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Distributed Generation Optimization in Future Smart Grids

by

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Declaration

The dissertation is my original work, hence proclaim it as such. It has not been partially or wholly submitted to any other university pursuant to a similar qualification.

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Abstract

Ever-surging global power(energy) demands coupled with the need to avail it in a reliable, as well as efficient manner, have led to the modernization of legacy and current power system grids into Smart Grid (SGs) equivalents. This is mostly achieved by blending the existing systems with an information subsystem that will facilitate duplex communication, i.e., electrical power flowing towards the end users while information characterising the grid's performance can also be relayed, mostly in the reverse direction. Thus, the information subsystem interconnects other core (key) entities such as generation, distribution, transmission, and end-user terminals to interrelate in real-time, and in the process, achieving a well reliable, robust as well as efficiently managed SG power system.

As such, in the emerging distributed power systems of the future, Demand Side Management (DSM) will play an important role in dealing with stochastic renewable power sources and loads. A near-unity load factor can be secured by employing Demand Response methods with storage systems as well as regulatory control mechanisms. Increasing deployment of Renewable Energy generation and other forms of unconventional loads such as Plug-In Electric Vehicles will aid DR implementation with attendant better results for both prosumers and the utilities. The central objective of DSM is to minimize peak-to-average ratio (PAR) and energy costs by switching to cheaper RES as well as reduction of CO_2 emissions. This work focused on emergent techniques and microgrid optimization with special attention to load scheduling. Techniques for DSM, mathematical models of DSM, and optimization methods have been reviewed. State-of-the-art methodologies entering the DSM mainstream are data science, advanced metering infrastructure, and blockchain technologies. An improved atom search optimization technique is applied for DSM to substantially reduce power and energy costs in typical standalone or grid-tied microgrids. Further the day ahead dispatch problem of MGs with DEGs subject to a non-convex cost function is solved and simulated using quadratic particle swarm optimization. In the later case, the objective function includes the DEGs 'valve-point' loading effect in the 'fuel-cost' curve. The impact of DSM on convex and non-convex energy management problems with different load participation levels is investigated. Ultimately, it is demonstrated that the quadratic particle swarm optimization algorithm efficiently solves the non-convex energy management system (EMS) problem. In addition, we propose a

hierarchical optimal dispatch framework that relies on several objectives to achieve the overall design goal of a reliable and stable power supply, coupled with economic benefits to prosumers who elect to participate in power trading. Evaluation of the proposed framework is carried out analytically and by way of simulation.

Overall, it is deduced from the obtained analytical as well as simulation results that the combination of appropriately sized battery storage systems (BESS) and renewable type generators such as PVs and WTs will help achieve a stable and reliable power supply to all users in the SG (or MG) and at the same time, it affords resilience. Finally, in our closing chapter, we also spell out possible future research directions.

Conference Publications

1. R.F Chidzonga, B. Nleya and P. Khumalo, "Power Demand and Supply Optimization in Islanded Microgrids with Distributed Generation," *2022 30th Southern African Universities Power Engineering Conference (SAUPEC)*, 2022, pp. 1-6, DOI: 10.1109/SAUPEC55179.2022.9730694.
2. Richard Foya Chidzonga, M. Gomba and B. Nleya, "Energy Demand and Trading Optimization in Isolated Microgrids," 2020 Conference on Information Communications Technology and Society (ICTAS), Durban, South Africa, 2020, pp. 1-5, DOI: 10.1109/ICTAS47918.2020.233994.
3. Mutsvangwa, B. Nleya, M. Gomba, and R. Chidzonga, "User and Microgrid Energy Optimization in Cooperative, MGs," 2019 International Multidisciplinary Information Technology and Engineering Conference (IMITEC), Vanderbijlpark, South Africa, 2019, pp. 1-6, DOI: 10.1109/IMITEC45504.2019.9015861.
4. R.F. Chidzonga M. Gomba and B.Nleya "Energy Optimization in Rural Cooperating Microgrids," 2019 IEEE PES/IAS PowerAfrica, pg.47-51
5. Richard Foya Chidzonga and Bakhe Nleya, "Energy Optimization for a Smart Home with Renewable Generation, " 2019 IEEE PES/IAS PowerAfrica, pg. 694-699.
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7. Masimba Gomba, Bakhe Nleya, Richard Chidzonga, and Philani Khumalo, "Balancing between Demand and Trading in Microgrids," SAUPEC 2020, 978-1-7281-4162-6/20/$31.00 ©2020 IEEE.
8. Richard.F.Chidzonga and Nleya Bakhe, "TOU and CPP Driven Power Scheduling In Smart Homes," icABCD2019 Conference.
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9. Richard Foya Chidzonga & Bakhe Nleya, Perspectives On Impact of High Penetration of Renewable Sources on LV Networks, IEEE's 3rd International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), 6-7 August, Durban, (virtual), 2020.

10. Philani Khumalo, Bakhe Nleya, A. Mutsvangwa & Richard Chidzonga, Quality of Transmission Aware Routing and Wavelength Assignment Algorithm for Blocking Minimization in Translucent Optical Networks, IEEE's 3rd International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), 6-7 August, Durban (virtual), 2020
11. Masimba Gomba, Bakhe Nleya, Andrew Mutsvangwa & Richard Chidzonga, Evaluation of Wavelength Congestion in Transparent Optical Transport Networks, IEEE's 3rd International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), 6-7 August, Durban (virtual), 2020.
12. Masimba Gomba, Bakhe Nleya & Richard Chidzonga, Availability and Operability in Optical Transport Network Architectures, IEEE's 3rd International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD), 6-7 August, Durban, (virtual), 2020
13. B.P. Numbi, S.J. Malinga, R.F. Chidzonga, T.C. Mulangu, Energy Cost Saving Potential in Educational Buildings-Case Study of MUT Campus, 2017 International Conference on the Industrial and Commercial Use of Energy (ICUE), pg. 1-5, DOI: 10.23919/ICUE42687.2017, 15-16 Aug. 2017.
14. R.F Chidzonga, B Nleya, P Khumalo, Power Demand and Supply Optimization in Islanded Microgrids with Distributed Generation, 2022 30th Southern African Universities Power Engineering Conference (SAUPEC).

Journal Publications

- Richard Chidzonga and Bakhe Nleya, On Demand and Supply Management in Domestic Microgrids, in Turkish Online Journal of Qualitative Inquiry(TOJQI), Vol. 12 No. 6 (2021), pp.6525-6542.
- Bakhe Nleya, Mlungisi Molefe, Richard Chidzonga, An Energy Efficient Resources Allocation Scheme for Flexible Translucent Optical Transport Networks, PSYCHOLOGY AND EDUCATION, Vol. 58 No. 2 (2021), pg.10409-10415.

- Richard Chidzonga, Bakhe Nleya, "Energy Optimization for a smart prosumer." International Journal of Sciences and Research, Apr 2020, Vol. 76, Issue 4, Apr 2020. DOI: 10.21506/j.ponte.2020.4.7, pg.71-83.

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Table of contents

List of figures

List of tables

Chapter 1 Introduction

1.1 Current Power Grids and Future Systems

The electrical power grid is a complex robust system that distributes electrical energy between the usually remote bulk power stations and the millions of consumers further downstream. Substantial unavoidable ohmic losses occur due to conductors' resistivity between sources and consumers.

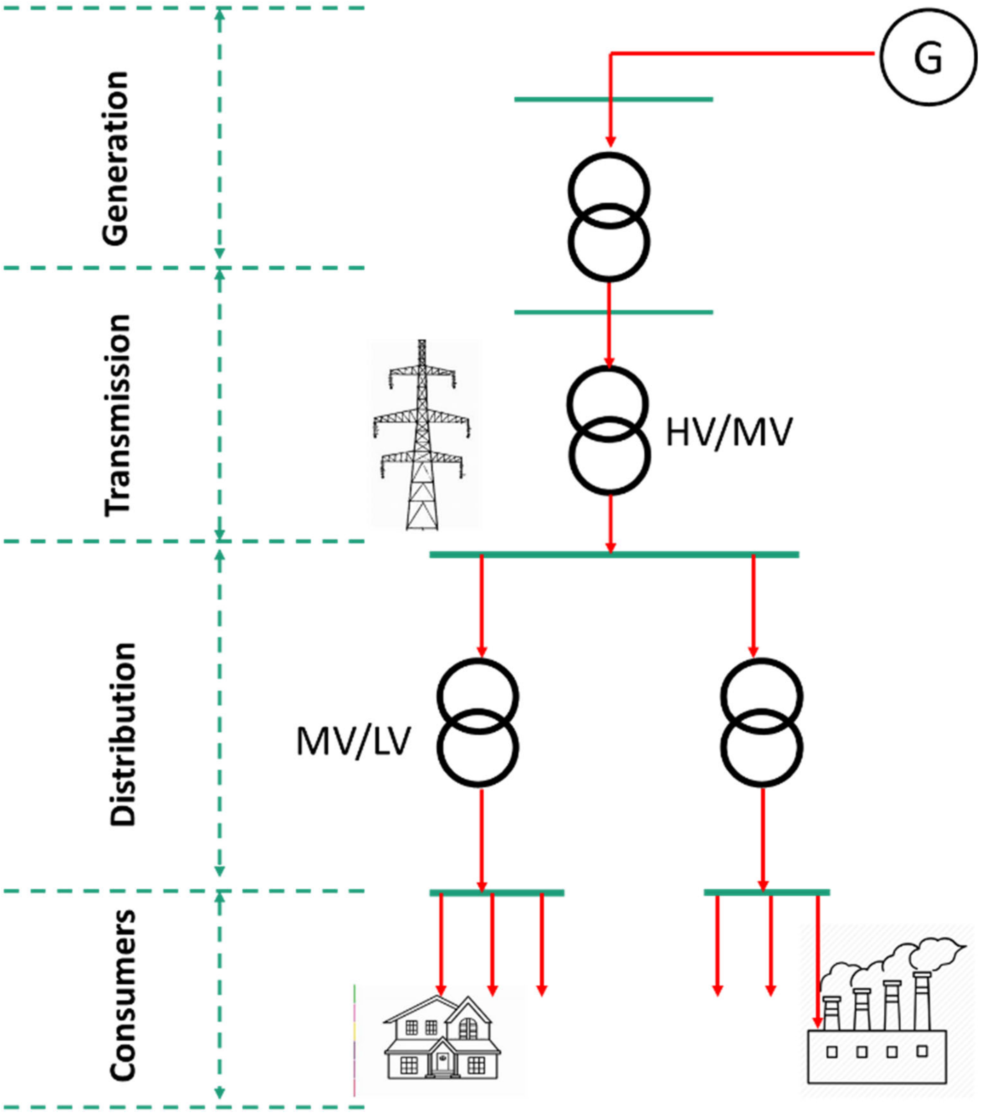


Fig. 1-1. Legacy Electric Power Grid

This compromises efficiency. Traditionally the grid is divided into four sections namely generation, transmission, distribution, and consumption, Fig. 1-1. At power stations sending end voltages are raised to high Tension (HT, HV) levels, then reduced to Low Voltage (LV) at final consumer points. Each section of the power system then operates at specific voltage levels. At the bulk power stations, non-renewable energy sources such as coal, oil, gas, and nuclear power or renewable sources such as solar, wind, hydro, bio-mass, and wave energy are converted to electrical energy. Transmission and distribution networks transport electrical energy at Extra High Voltage (EHV), High Voltage (HV), and Medium Voltage(MV) from the power stations to distribution substations from where energy is sent to end consumers over MV and LV networks. Consumers are usually categorized into four sectors or categories i.e., Residential, Commercial, Industrial, and Transportation.

Table 1-1. RSA % Energy source contributions projections [1][2]

SECTOR/YEAR	2014	2017	2030
Coal	92.6	83	29.7
Nuclear	5.7	4	17
Hydo	0.5	1	7.2
Gas	0.1	6	12.9
Wind	0	0	16.3
Solar	0	0	14.9
Pumped Storage	1.1	6	0
CSP	0	0	
Other			
TOTALS	100	100	98

Electrical distribution networks in industrialized and developing countries are undergoing far-reaching rapid greening and ITC-driven technical changes [3][4][5]. These changes are the result of increased demand, congestion, and other network constraints [6], the liberalization of the electricity markets[7], and the increase in the implementation of renewable energy or Low Carbon Technologies (LCT) [4][8][9]. Since the 20th century the legacy network topology Fig. 1-1, of the electrical systems has remained structured top-down. This paradigm, where energy flow is nearly unidirectional has over the years guaranteed safe and reliable power transmission and the design methodologies which are well-understood textbook material. With ever-increasing world energy demand Fig. 1-2, the advent of energy market liberalization and the rapid, and almost exponential growth of ‘green energy’ technologies many producers of electrical energy are appearing especially at the LV level, Fig. 1-3. These developments coupled with environmental imperatives like reduction of greenhouse gases, and redress of global warming have seen many governments set sectorial targets of green energy mixes to as much as 40-50% renewable generation by 2050 [10][11].

Globally, Denmark is a leader in Wind Turbines (WT) implementation— 46.7% of its electricity demand in 2019 comes from wind. The country is targeting a 70% reduction in its greenhouse gas emissions by 2030 and to have 100% of its energy needs supplied from renewables by 2050 [11]. New thinking on 100% Renewable, '24/7' is emerging [12]. The idea is that the goal of achieving a 100 % RES grid, rests on the question of whether renewables can meet demand at any given time. The "24/7" 100% RE approach seeks to match consumer hourly demand to renewable energy in the locality and same hour.

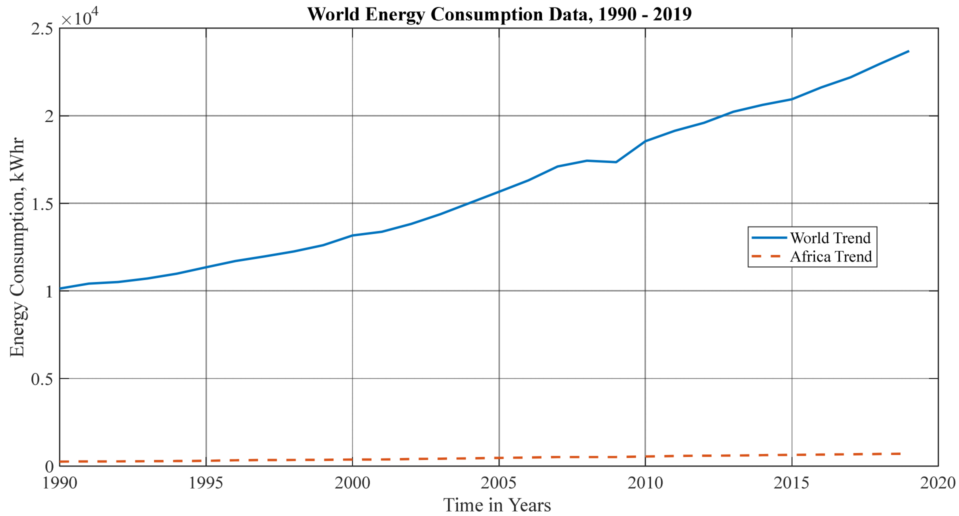


Fig. 1-2. World and Africa energy consumption trends, 1990 - 2019

Another major driving force toward renewable energy is the incessant rise of global average temperature [13]–[15] and the increased volatility of damaging extreme weather events. On average the earth's surface global temperature will rise by a further 0.3°C to 1.7°C in the lowest emissions scenario, and 2.6°C to 4.8°C in the highest emissions scenario by the end of the 21st century [14]. As a result, the electrical generation, transmission and distribution systems should address the emerging societal challenges encompassing; the old and ageing networks, the advent of PEV as new electrical loads, growth in demand and severe peaking due to rapid urbanization and population growth, the deployment of intermittent and/or decentralized renewable resources [16]. Since these developments' prosumers and IPP are actively seeking technology solutions that will not only revolutionize the ways power has been generated but also the ways it will be consumed, marketed and the business models to be followed.

The future electricity markets will be more flexible and highly integrated with an increased footprint of intermittent renewable production, Fig. 1-3 and the deployment of ICT to guarantee system reliability. Taken together these factors have seen the emergence of the concepts of Smart Grids (SG) and Internet of Energy (IoE), to optimize the management and consumption of the electrical system [17], [18].

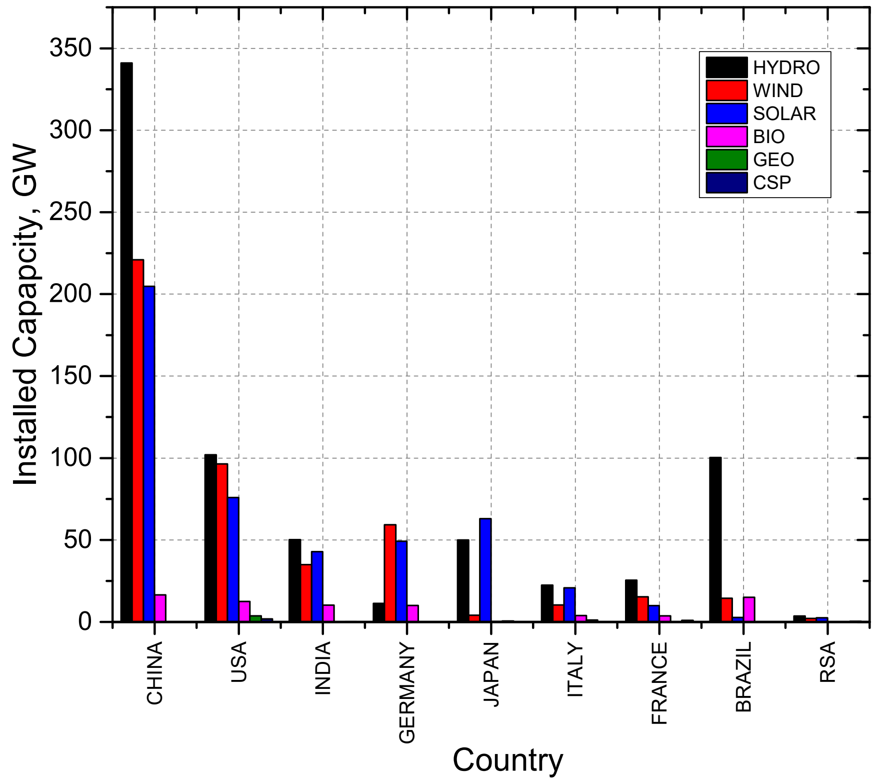


Fig. 1-3. 2019 Statistics of DEG growth in various major countries

SGs result from the integration of the electrical networks and the ICT systems. These deployments allow bi-directional communication between DSO, consumers/prosumers, the decentralized distributed generators, EVs, and other elements of the emerging electrical networks. The embedding of intelligent components at points of energy consumption and bi-directional flow of both energy and information via Smart Meters (SM) has given new impetuses to demand-side management (DSM) as a means to control consumption and thus avoid expensive new investment to increase supply [19][20]. Throughout the world buildings generally consume as much as 40% of generated electricity [21]. Of particular note is the domestic sector which on average consumes about 25-30% of all produced electrical energy [11]. Locally, electrical energy consumption is dominated by three sectors, namely; commercial, residential & public service, and industry for which the share of consumption is in the ranges of 15-31, 20-27, and 64% respectively [22],[1]. The predominant utility is Eskom [23]. The 2030 National Development Plan envisages decommissioning 35 GW (of 42 GW currently operating) of thermal power capacity. In addition, at least 20 GW of the additional 29 GW of electricity needed by the economy will be derived from RES and gas [23] sources.

This dissertation looks at the critical role DSM will play in the imperative to balance supply and demand in the emerging grid with high penetration of renewables. Optimal techniques to schedule the overall grid load(s) are investigated and applied to reduce PAR and overall costs of energy consumption while securing user comfort. An improved BFO technique is shown to outperform other widely used heuristic methods.

1.2 Distributed Generation

As demonstrated in Fig. 1-2, power demand is growing steeply in both developed and developing countries. By 2030, a 40% and 50% increase in consumption is expected in Europe and USA alone. By the same year (2030), China and India's demand is expected to triple and overall double in the rest of the world [24],[25],[26]. Against this demand growth, the availability of fuels can no longer be regarded as a given. Even if these resources were available, the long-term impact of CO_2 emissions should be avoided [14]. Aside from these global challenges alluded to above, the electricity grids are in dire need of upgrades and modernization. The only viable alternative is the addition of decentralized or intermittent generation sources with new technologies embedded for control and management. This approach has ushered in distributed generation, microgrids (MG), and ultimately the smart grid (SG) concepts.

They are no universal definition of Distributed Energy Generation (DEG), otherwise also referred to as embedded generation or dispersed generation or in some parts of the world decentralized generation. This term, however, generally describes various technologies that generate electricity nearer the points of consumption [27][28]. Examples are solar panels (PV), wind turbines (WT), diesel generators (DG), and combined heat and power (CHP). Interconnected distributed generators acting as single controllable entities concerning the main grids, serving homes or business entities may be part of Microgrids (smaller grids tied to the utility grids), industrial facilities, college campuses, or hospital facilities in remote areas. Two classification categories for DEG are suggested in the literature [29]. The first classification uses DEG capacity, and the second uses technology as depicted in Fig. 1-4.

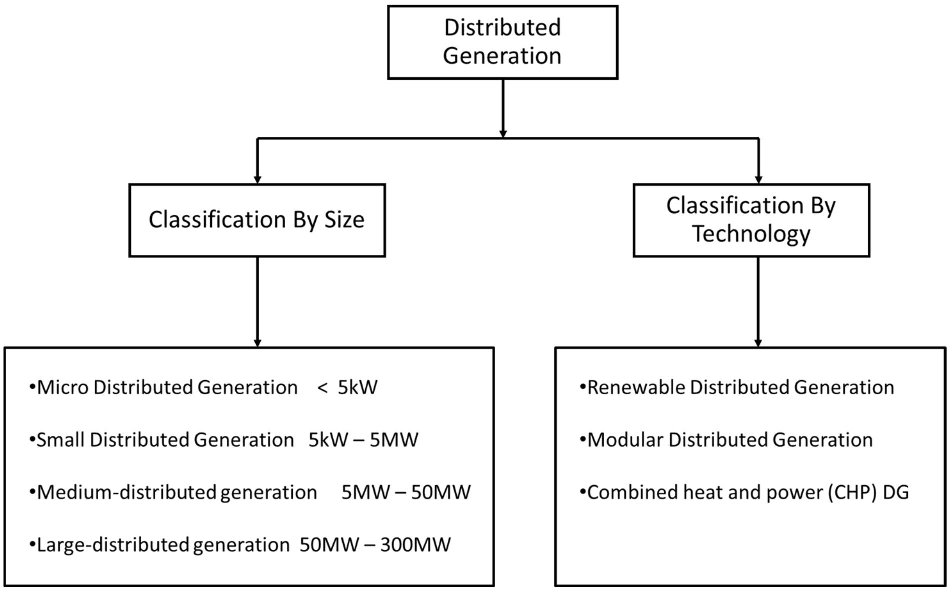


Fig. 1-4. Distributed generation size or type classification

When connected to utilities, LV power supply networks, and distributed generators support the delivery of green power to remote customers. This reduces electrical losses in the long transmission and distribution networks. For residential areas, common distributed generator technologies include PV, WT, and Fuel cells whereas in the industrial sectors additional distributed generation systems may include biomass and reciprocating combustion engines. Due to the power industry deregulation and the move to clean renewable energy sources, many Independent Power Producers (IPP) and prosumers are entering the power supply market. Benefits of integrating DEGs into power grid networks [30] include;

- Saving on CAPEX for new T&D lines and upgrades to the present power systems.

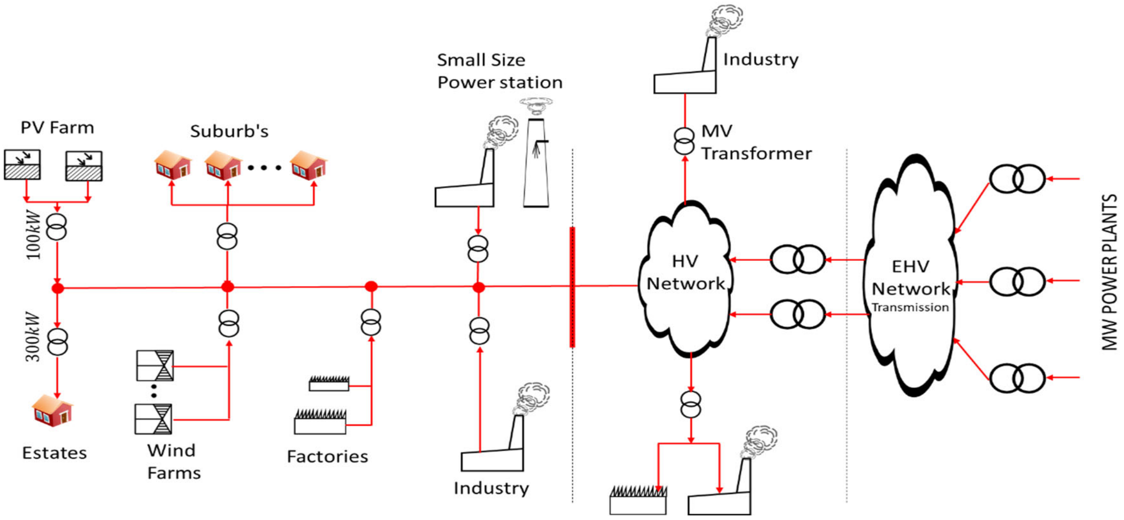


Fig. 1-5. The General layout of a modern distributed generation system

- proximity to consumers implies the reduction of transmission copper losses.
- Flexibility in locating sites to install DEGs compared to complexities and delays associated with servitude land rights for traditional networks.
- DEGs injection of kW and kVAr into the power grid improves voltage profiles and load factor. This means fewer voltage regulators and capacitors are needed.
- Lead times from conceptualization, design then implementation of modularised DEGs are short. This carries lower investment risk. DEGs are easier to translocate and operate on a plug-and-play basis.
- DEGs are environmentally friendly and come in sizes from a few kW to 15 MW. Installations can be affected on MV to LV levels.
- When properly operated and coordinated, the distributed nature of DEGs boosts system reliability, unlike one large, centralized generation station.

Integrating DEGs into power networks can also have a downside in distribution networks. Instances of high voltage may occur by injecting currents that are more than the lines' thermal limits, harmonics distortion, voltage flicker, and instability of the voltage profile at the consumer ends. The two-way power flows can induce voltage profile fluctuations and affect short circuit ratio(SCR) wreaking havoc on protection coordination when not properly set. Distribution System Operators (DSOs) may also experience revenue drops.

Against continuously increasing demand [31], conventional electricity grids face many other challenges depending on demand and generation mix scenarios. The universal problems are market deregulation meaning the entry of multiple players, sustainability, aging infrastructure, and the rising costs of depleting fossil fuels [27]. Wind and solar have very strong growth potential, Fig. 1-3 [32]. IPP initiatives [33],[34] are reshaping the monopolistic business model of electricity from generation, transmission, and distribution [33]. Energy management and scheduling are assuming new and exciting dimensions due to the increase of new processes of continuous energy monitoring and bidding in the utility market of which the unpredictable flows from prosumers or demand for electricity do not make this any easier. A 10% penetration of wind energy is possible without major changes in grid infrastructure [35]. However, the heterogeneous and stochasticity of solar and wind energy production brings many integration problems hence the requirement for ICT infrastructure for effective management and control.

1.3 Impact of DGs on the Grid: Hosting Capacity

Possible negative impacts of excessive DG penetration are discussed in the previous sections. Competing and conflicting interests arise between DSO on one hand and IPP or prosumers wishing to connect more DG into the distribution network to increase profits of selling power. The concept of Hosting Capacity [30] is a means to evaluate a grid's capacity to host additional DG's taking cognizance of the capacity limitations of the system beyond which performance, as measured by various metrics, degrades. S.M. Ismael et al [30] discusses rules of thumb applied by different utilities in various countries to limit the size of DG connected to LV or MV networks. Many utilities use the rule of thumb "*that penetration levels of a system higher than 15% of its peak load should be avoided and should be investigated through supplemental studies*." Additionally, various formulations of Hosting Capacity (HC) indexes are discussed in the survey. We note the results.

i. For voltage rise, the voltage drops with no DEG, and the voltage rise at the maximum DEG penetration have approximately the same value, (1.1).

$$\left|\Delta V_{drop}\right| \cong \left|\Delta V_{rise}\right| \tag{1.1}$$

$$P_{DG} = 2P_{load} + (1 - S_{load}) \tag{1.2}$$

$$F_d = \left|\frac{N_a}{N_{tot}} + a\left(\frac{N_b}{N_{tot}}\right) + a^2\left(\frac{N_c}{N_{tot}}\right)\right|, \quad a = e^{j0.5\pi} \tag{1.3}$$

ii. In the feeder, the maximum DEG capacity for a feeder not to exceed its current limit is estimated by (1.2).

iii. Overvoltage and voltage unbalance problems may arise due to high DEG penetration. These problems are compounded by the number of DEG units connected, respective ratings, locations, and nature of the connection. The factor F_d (1.3) was proposed to estimate the unbalance in radial distribution systems due to DEG integration. $N_a, N_b,$ and N_c are the number of DEG connected to the ABC phases of the 3-Phase system and $N_{tot} = N_a + N_b + N_c$.

iv. The impacts of DEG penetration on the voltage profile are estimated from the voltage rise ΔV_{rise} at different buses, as given in (1.4). The X/R ratio being constant for a given line, P or Q is available to control voltage. The option for P means power curtailment or storage.

$$\Delta V_{rise} \cong \frac{PR + QX}{|V_n|} \tag{1.4}$$

We know that power flow in a distribution system can change at any time depending on the depth of penetration of RES and instantaneous loading levels. Given this dynamism in the grid, hosting capacity is a time-dependent variable. It is a very useful evolving tool for planning and monitoring [36][37].

A robust optimization approach for maximum hosting capacity is discussed in [38] and results point to the fact that other factors such as storage and power reverse flows also matter. The addition of DEG to the grid may lead to overvoltage, thermal overloading, QoS, and protection problems. Overvoltage is the main issue with high DEG penetration. These four criteria plus losses can be used by DSOs in estimating HC. However, uncertainty in the HC calculations may arise due to unknown DEG locations and ratings, the intermittent nature of the DEGs' output powers, alterations of loads, and lack of data. Further work is required on HC to realize affordable, reliable, and deeper penetration of RES as grid systems transition from the traditional legacy network with a high carbon footprint to green technologies. DEG curtailment approach [37] with network dynamic reconfiguration and DSM can improve deeper RES penetrations in the grid but they are practical limits and no standard methodology for HC computation is yet available in the literature.

CIGRÉ, workgroup WG6.22 has stated that portions of the electrical system, containing DEG such as DG, ESS or PV, WT, etc., or controllable loads constitute a microgrid [39]. Such a microgrid can be either a part of the main grid through a switchable point of common coupling (PCC) [1] or it operates in standalone mode. This arrangement is exemplified in Fig. 1-11 of the next section which discusses MGs. The integration of RES and MGs is a very pertinent problem to deal with in the looming energy crisis. However, the adaptation of existing grids consistent with a fully distributed, efficient, and reliable system at minimum cost is still an unsolved problem. The Global installed capacity of DEG is accelerating at a fast pace and is expected to contribute a cumulative 40 - 50% of overall energy consumption by 2040 [40],[41].

1.4 Microgrids Concepts

The development of interactive and artificially intelligent networks will require the corresponding development of new systems to be retrofitted into the existing framework. A Microgrid as defined by the U.S. Department of Energy is "*a group of interconnected loads and distributed energy resources (DERs) with clearly defined electrical boundaries that act as a single controllable entity concerning the grid and can connect and disconnect from the grid to enable it to operate in both grid-connected or island modes*" [42] [43] [44].

Many other alternative definitions of an MG from various bodies exist. The EU definition [45] emphasizes issues of components, architecture, and operation of microgrids, as *"Microgrids comprise low voltage distribution systems with distributed energy resources (micro-turbines, fuel cells, PV, etc.) together with storage devices (flywheels, energy capacitors, and batteries) and flexible loads. Such systems can be* *operated in a nonautonomous way if interconnected to the grid, or in an autonomous way if disconnected from the main grid. The operation of micro-sources in the network can provide distinct benefits to the overall system performance if managed and coordinated efficiently."* In[46], it was proposed that:

"Microgrid can be defined as a low to medium voltage network that contains an aggregation of certain loads and distribution generation units, which is connected to the main grid system through a point of common coupling. It can operate in either grid-connected or islanded mode. In grid mode, it remains connected to the main grid and is seen as a single aggregate load or source, while in the islanded mode it separates from the main grid, due to a major disturbance, becoming self-sustained and continues to serve certain loads."

CIGRE's WG6.22 working group defined the microgrids as *"portions of the electrical system, containing the so-called distributed energy resources (such as distributed generators (DGs), energy storage systems (ESS) or controllable loads). Operation of the grid is done in a controlled fashion, and this can be in either one of two modes: connected to the main power grid or islanded"*. Not only the constituent elements but also the extent of operational flexibility define the microgrids [39].

Thus, the common building blocks of MGs or DEG systems are PV, WT, BESS, loads, etc. These are normally installed within the locality of the electricity consumers to enable the local supply of loads. DEGs have three characteristics to qualify as a microgrid: clearly defined electrical boundaries; the local RES with a local master controller to control and coordinate all local resources as a single entity; and lastly generation capacity installed should exceed the peak load to enable the islanded operation mode.

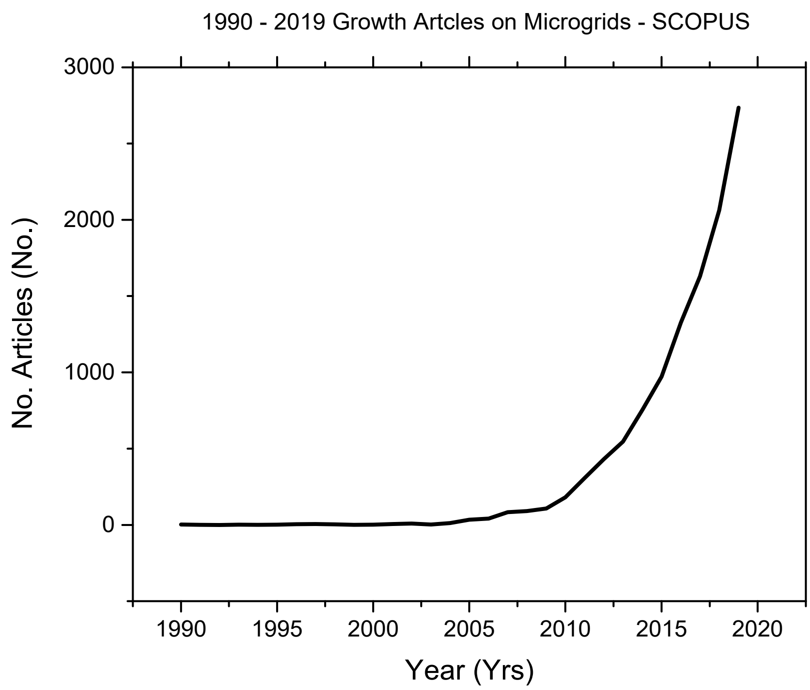


Fig. 1-6. Growth of Microgrids According to the number of SCOPUS published articles

In this context, microgrids can be regarded as small-scale power systems with the functionality of self-supply and islanding, which can generate, regulate, and distribute the flow of electricity to local loads. Microgrids' characteristics and topologies are still very much the subject of open research. In Fig. 1-6 the exponential growth of research articles in this field is self-evident.

Microgrid Architectures

About a hundred years ago Thomas Edison established the first electric utility [47] which was essentially an MG. A representative schematic is shown in Fig. 1-11. Due to the unregulated output voltage, and the inherent intermittency of the renewable energy sources, power electronic converters are employed to control the power from DEGs, and interfacing [48],[28] to the main grid. In grid-connected mode, the operating voltage and frequency are regulated by the stiff main grid. In standalone mode, MGs regulate their frequency and voltage to achieve demand-generation power balance. The microgrid concept is a central building block of the future SG.

MGs are a flexible and powerful construct for the integration of DEGs, BESSs/ESSs, and other DERs, whiles maintaining the fundamental objective of satisfying demand in a locality. The combination and sizing of MGs components is a complex optimization problem that depends on user requirements, preferences, regulatory constraints, and economic cost-benefit factors. A combination of both renewable and non-renewable sources such as diesel generation can be used in MGs. The MGs can be connected either directly to the grid by electrical rotating generators via transformers or can be interfaced by inverters as is the case with DC/AC coupled systems. Generally, the DEG elements of the MG are situated near a local LV power grid network to which they can couple or decouple. They are instances where a portion of the MV network can be part of an MG [15].

In a majority of cases, we find that the DEGs are small units with power ratings of less than 200 kW [49]. MGs though can have components of various sizes, compatible with MV-to-LV grids, LV feeders, or just a single LV facility like a homestead, commercial building, or infrastructural facilities like a communication tower or research post. In general, the capacity of MGs, specified in terms of peak load demand is limited to a few MW [15]. Due to the multiplicity of MGs equipment manufacturers and lack of universal standards, MGs end up having various heterogeneous components. These components are required to be intelligent and with sophisticated communication abilities for management and control purposes. At the HV scale, MGs can be interconnected to form multi-microgrid (MMG) systems.

In grid-connected mode, consumers or prosumers anticipate supplying or consuming certain amounts of energy optimally and cost-effectively. The obvious strategy is to schedule and use energy from the cheapest DEGs and minimize intake from the utility grid during times of high tariffs. In this mode, the utility grid balances consumption and generation and controls the supply frequency. When the MGs operate in islanded mode, the local DEGs and any power from storage systems should be regulated to meet demand at any time instant by way of fast and flexible V/f control techniques. These techniques are implemented via active and reactive power control. The general practice however is that except for MGs isolated from the main grid, such as the examples given above, MGs near main grids always operate and are configured in grid-connected mode. This improves reliability and resilience. In emergencies, MGs are switched to islanded mode [50]. As would be expected without the 'buffering' capacity of the main grid, the choice of islanded or off-grid operation does play a significant role in the sizing of the MG. The need to ensure continuity of supply often plays into the oversizing of components as in this way greater autonomy is obtained.

MG Technologies

The RES technologies deployment from the 1990s to early 2000 has been rather incremental. The same cannot be said beyond 2000 as evidenced by Fig. 1-7, in practically all world regions growth is in leaps and bounds. The share of RES in the energy mix of most countries is growing strongly.

Micro-turbines (MT). These are small electricity generators that burn natural gas, propane, and other liquid fuel to drive an electrical generator at high-speed [39]. MT generators are most attractive in distributed power generation applications and their capacity ranges from 20 kW to 500 kW and efficiencies of more than 80% can be attained when the CHP application is used in the system.

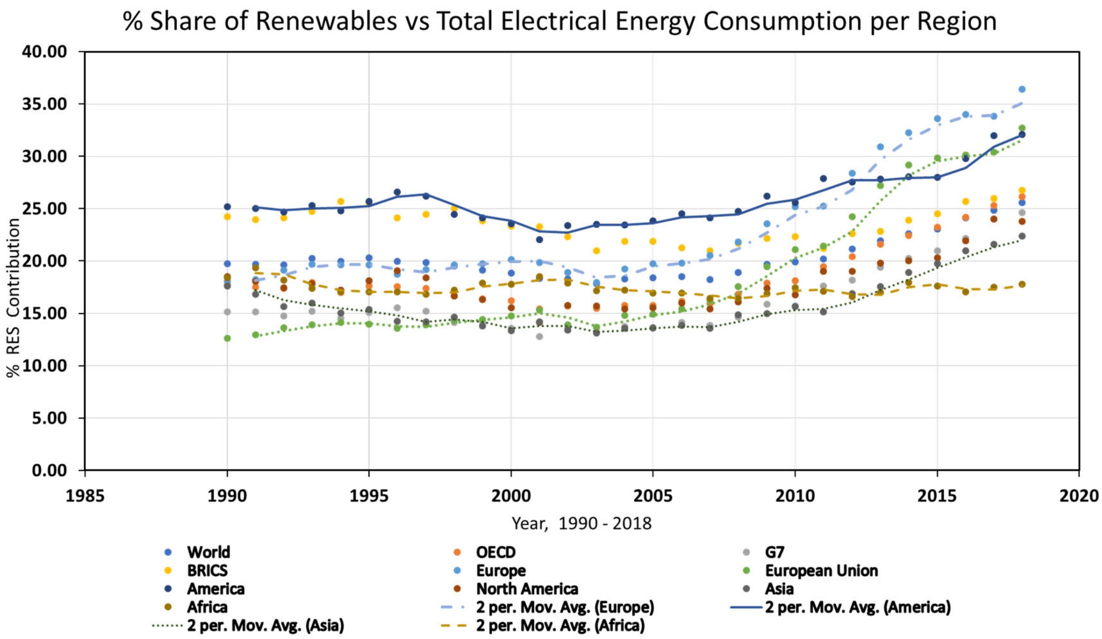


Fig. 1-7. World RES % share of the total electricity consumed

Photovoltaic (PV). These are stationary semi-conductor photocells that turn solar radiation into DC electricity. Four types of PV cells are in the market namely monocrystalline silicon (efficiency 15%), multi-crystalline silicon (12%), thin-film silicon (6%), and hybrid (17%). PV or solar farms are prevalent in MGs, Fig. 1-3.

Wind Turbines (WT). A wind turbine is a rotary machine that converts wind kinetic energy to the mechanical energy of a turbine and then electrical energy. WTs are among the most prevalent RES in the world with a wind capacity of over 591GW, and 3000 WTs being built each year since 2005, [51]. Currently, the 260m tall, 12 MW GE's Halide-X offshore turbine is the largest WT[52]. Problems with integrating these DEGs include intermittent generation and dynamic variations in the turbine's torque caused by wind, which reflects as disturbances on power output. China, the USA, Germany, and India have 221GW, 96.4GW, 59.3GW, and 35GW wind installed capacity respectively [2]. Denmark has the highest penetration of wind energy, at 43.4% of its electricity consumption as of 2017.

Fuel Cells (FC). These are electrochemical package devices that use a continuous flow of gaseous fuel such as natural gas, methanol, hydrogen, propane, etc. to produce electricity. They are many types of fuel cells such as Proton Exchange Membrane Fuel Cells (PEMFCs), which operate at ~90°C. Phosphoric Acid Fuel Cell (PAFCs) operate at about 200°C with efficiency in the range of 36-40%; and the high temperature (1000°C), high efficiency of about 60%, Solid Oxide Fuel Cells (SOFCs), molten carbonate fuel cell, phosphoric acid fuel cell, etc.

Storage Systems. Energy Storage systems (ESS) are critical in microgrids due to the intermittency of energy sources. Energy storage compensates for the mismatch between demand and generation [53]. Technologies in common use are special *Ni*-Cd, Na-S, Na-NiCl2, Ni-MH, Li-Ion, etc. Such battery types are characterized by nominal voltage, energy density, cycle life, and elongated lifetimes. The battery storage capacity can go up to the Mega Amp Hour scale. Li-Ion batteries have higher energy densities and a lifetime of 1000 -10000^{+} cycles or 5- 15 years. Flywheels store kinetic energy for levels up to 500MJ and have ultra-fast response times. They are thus well suited to absorb or release energy to balance shortfall. Flywheels don't have the disadvantage of battery (BESS). Pumped storage is the storage of energy in reversible hydro plants. During off-peak times excess electricity is used to run the generators in pumping mode thus transferring water to an upstream reservoir. During peaking times when energy is needed the turbines run in generation mode to produce electricity. Supercapacitors have greater surface area hence more energy storage capacity to the region of 4Whr/kg. Their main advantage is that they can supply energy in a short period. Other ESS systems exist such as compressed air energy storage systems, thermal energy storage systems and superconducting Magnetic Energy Storage (SMES), mini-hydro plants, etc. [39].

MGs Topologies / Architecture

Due to the intense penetration of LCT in the LV distribution grids, the planning, operation, and management of these grids are transforming substantially [54]. Main electrical grid networks are configured into basically three topologies with a goal of greater reliability. Depending on size, MGs can interface into any of these topologies, which are;

- Interconnected network – For HV transmission networks where interconnectivity provides multiple paths to transport power and hence better reliability.
- Ring topology – Has Links, typically with an open-loop arrangement. The open point is situated between two interconnected radial feeders to ensure the radial operation for each feeder in isolating a faulty section.
- Radial topology - Used in LV networks where the maximum voltage level is 1kV, but the common range is 120-240V single phase or 415V three phase. This radial network can be reconfigured into a weak mesh to link two buses.

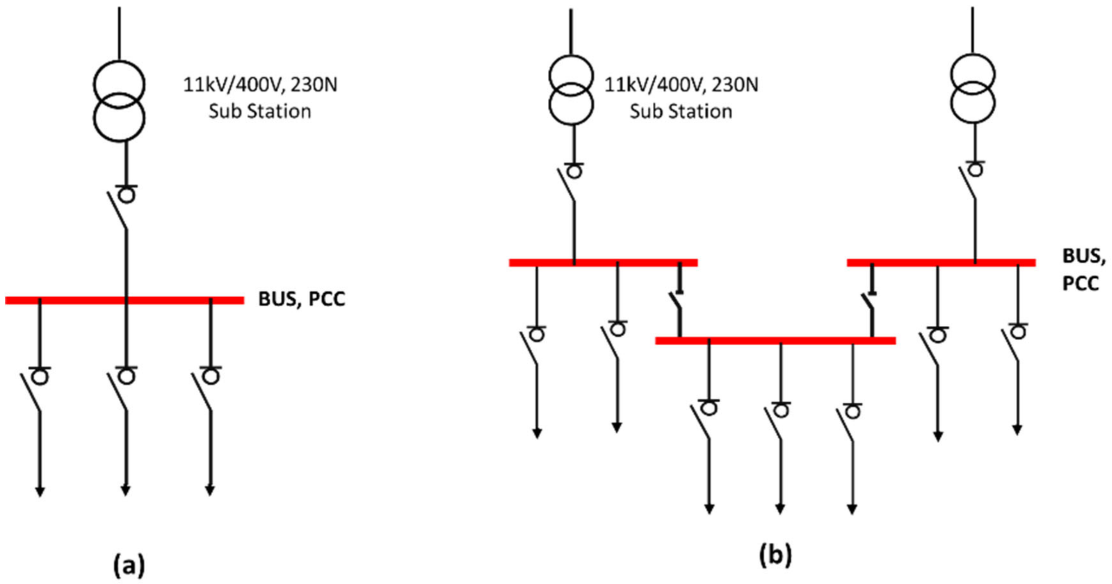


Fig. 1-8. Radial and parallel-connected network topologies

On the other hand, the LV distribution networks are characterized by having;

- Many nodes corresponding to the many consumers.
- No monitoring. Metering is still predominantly the old type and AMI is in very early stages hence uncertainty of the state of the network prevails.
- Radial or weakly meshed topologies.
- High R/X ratios compared with HV and MV networks. Predominantly resistive with constant voltage angle.
- Highly varying load patterns with a high degree of unbalance and uncertainty.
- Reverse power flow due to DG in LV network which may also raise voltage levels on the load side.

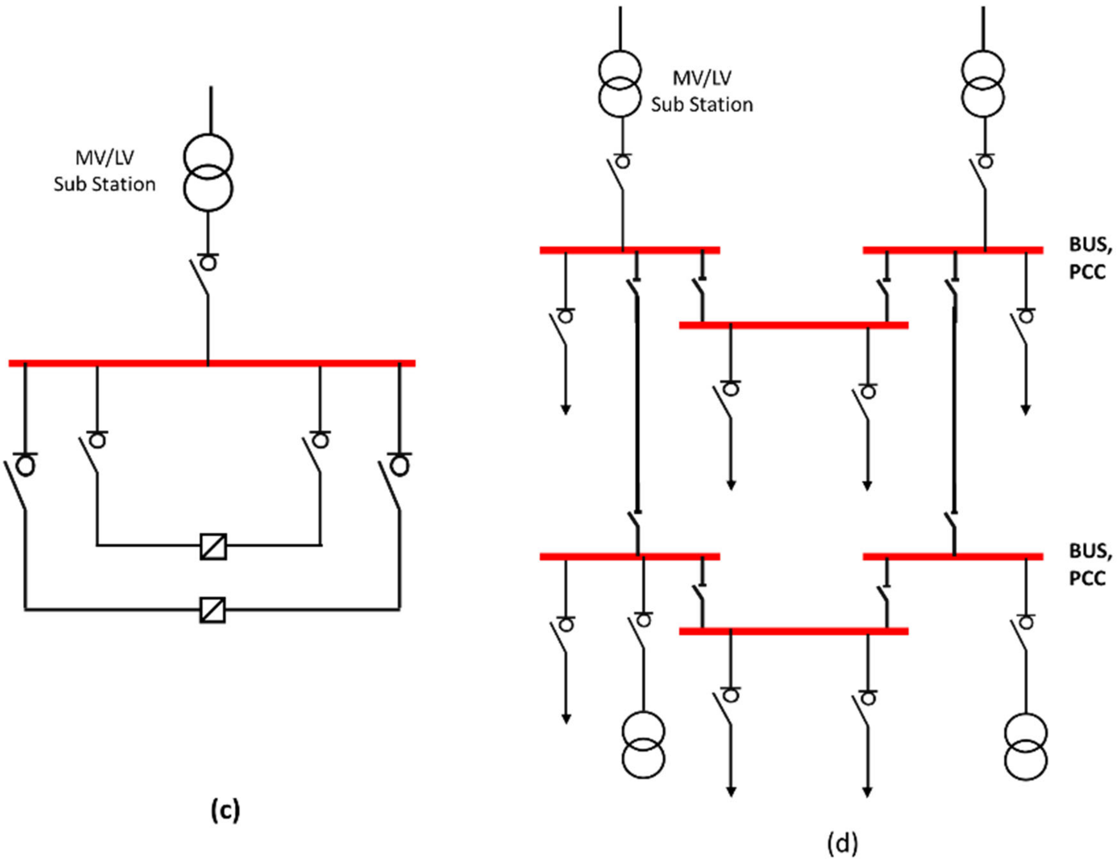


Fig. 1-9. Ring and Mesh LV network topologies

Deciding on the MGs technologies to combine, their sizes in terms of generating capacity, location, or placement of these components of MG is a complex optimization problem dependent on specific consumer or prosumer needs, grid code requirements, and many other economic imperatives [55][56]. Both renewable and conventional sources are used in microgrids. A majority of the DEGs are composed of units whose size range from 5kW - 200kW [27]. MGs occur in various architectures but essentially can be put into three main categories according to the way their components are configured: DC coupled microgrids, AC-coupled microgrids, and hybrid coupled AC–DC microgrids [57],[50],[58]. Various underlining factors determine the choice of possible architecture as depicted in Fig. 1-10.

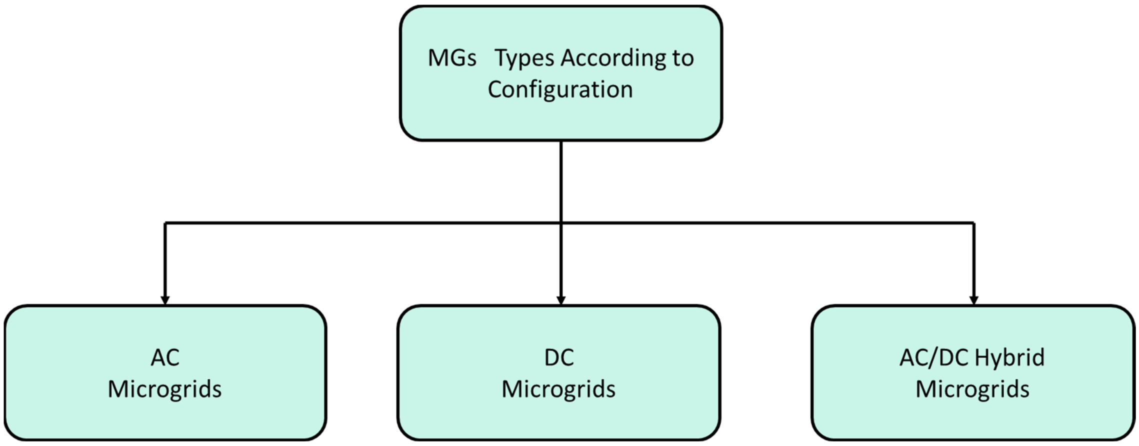


Fig. 1-10. Microgrids Types AC, DC & Hybrid Configurations

It is common to connect alternate generation systems in the MGs to improve the availability of power given that the other DEGs are dependent on random weather elements. Some of the DEG output DC power such as PV solar panels; DG or Bio generators output AC. This has a bearing on the configuration of the MGs. As outlined above, the choice of MG operation between islanded and grid-connected impacts the OPEX for the system and components sizing. Additionally, MG services to be rendered to the operator's grid and the users of energy also influence the type and size of installed components, and hence the architecture. MG architectures are also influenced by intended applications, e.g., military, industrial, commercial, or residential applications. Several compressive architectures are proposed in [18] [50].

The AC MGs integrate easily with the ubiquitous AC networks and thus they are most pervasive in the literature. Such MGs are radial, Fig. 1-8 whereby feeders connect the DGs components as in Fig. 1-11. At the PCC, an islanding switch is normally installed. Due to its simplicity, this configuration is deployed in mass [54][59]. This radial configuration is studied and carefully tested by Consortium for Electric Reliability Technology Solutions (CERTS) [50][60]. The studies and robustness tests on a radial three-feeder grid with components: RES DGs, CHP, and some loads on islanded MGs were demonstrated. Further studies on prototype radial microgrids such as the Industrial Park

[61], which utilize the concept of integrated demand response (IDR) to coordinate different DEG in an MG greatly enhance both overall utilization and efficiency.

Work on MGs has been undertaken in many countries. Hossain et al. provide an extensive review of the current state of the art for prototype developments [62]. Early pilot or prototype MGs schemes have demonstrated for the most part that AC coupling with centralized control is economic. The DC MGs framework is not very prominent, but most MGs tests incorporate electric storage which means DC-to-AC conversion stages. However, they are still practical hurdles concerning the stability of the DC MG system with less conventional sources like diesel generators during fault conditions [63].

MGs with one or more DC feeders are classified as DC microgrids and their merits compared to AC systems are explored by Shahid Ullah in [63]. AC-to-DC converters are normally installed between the MGs and the main grid at the PCCs. This architecture uses fewer AC-to-DC converters which in turn implies reduced conversion losses and an increase in overall efficiency. Further, there is no reactive power circulation and no need for synchronization to the main grid which results in simpler control implementation [62]. However, in some instances, DC/DC or AC/DC conversion may be required to match voltage levels to the loads, DG and ESS. DC MGs are becoming popular as new DC applications increase. Most commercial or household loads are AC powered whereas DC MGs would be suitable for industrial applications with DC loads, such as charging bays for Electric Vehicles, Electric forklifts, etc. In some cases, the CESI RICERCA proposed testing a DC-MG in LV DC linked to the MV network [64].

The hybrid AC-to-DC architectures have advantages over both the purely AC- and purely DC-coupled architectures. Hybridization enables efficiency to be increased through a reduction in multiple conversion stages as DC-based technologies and loads can be directly connected at appropriate voltages. In addition, as the DC components count increases, the economic feasibility of a hybrid MG becomes more suited than the AC equivalents [63]. On the other hand, the hybrid architecture requires complex management, due to the simultaneous control of AC and DC electronic power devices.

Deployment of ICT is a prerequisite for data exchange between the different market players in the evolving Internet of Energy (IoE) [18]. In the current form, the power grid's ICT is limited to the transmission and sub-transmission levels. A variety of standard protocols are in use at different voltage levels. MV and LV networks are characteristically 'mute.' Standardized, interoperable data exchange models and communication services in the electricity supply chain are being developed. The central problem is coordinating all these data streams in a simple, robust, secure, and flexible communication infrastructure down to the consumer. Much of the transmission network provides services such as power flow analysis to ensure constraints are satisfied. Contingency analysis and balancing are required at the distribution level[7] congested with DEGs. Intelligent building energy services in residential and commercial spaces, need to use SG to support main grids' V/f characteristics. This is one of the more compelling reasons for strong ICT control of the distribution grids which thus need to operate in fast real-time multi-dimensional formations providing information to prosumers, customers, aggregators, and all other players in the electricity generation value chain.

Other Opportunities & Challenges in MG

Active DG grid's IoT devices should allow timeous decision making and information flow, hierarchical and distributed control architecture to integrate with existing network control techniques. Besides real-time control, the Active Distribution Network (ADN) will be enhanced with new functions e.g., AMI will enable utility-consumer and consumer-consumer two-way communication. The explosion of big data analytics will also enhance the modelling of uncertainties, energy yield prediction, and demand forecasting in planning and operation. Standard communication protocols and data models to ensure inter-operability of various vendor equipment so that reliability and costs effective networks are built will also evolve.

At hardware level, the power electronic converters used to interface DEG units to the grid lack the smoothing effect of inertia [65] found in traditional rotary synchronous machines. Fuel cells, PV sources, microturbines, etc. are slower and hence cannot provide stiff frequency regulation. This deficiency can be mitigated by fast-acting energy storage devices such as batteries, supercapacitors, or flywheels. The later components duplicate the effect of the rotating mass inertia found in the conventional grids [66]. The fast response of the energy storage devices enables the DEG units to react to transient imbalances in the generation/load demand while regulating the operating frequency and voltage [66][67].

BESS in the MGs are a buffer that either supplies or absorbs power as necessary. Overall, they are regulated as well as controlled to supply power during peak periods when the demand increases beyond generation. When the converse is true, they absorb the surplus power from the REGs. A DEG system that generates reactive power improves voltage stability whereas one that absorbs reactive power compromises it. Proper coordination and control of reactive power compensation devices are required to mitigate some of these negative effects. Excess real power may occur during high winds or high solar yields when demand is low. This leads to spillage power *(the amount of e.g. PV or WT power generated more than that utilized due to some limitations)* that can negatively affect voltage stability, especially in weak grids i.e. those with low short circuit ratio(SCR) [68][69].

The development of intelligent multiple and interconnected microgrids (MIMG) also known as a community of microgrids(CMGs) with various distributed energy resources (DERs) is one of the hottest research topics of our time cutting across different disciplines. Though today's grid is quite complex its overall monitoring, sensing, communication, and control have not yet attained "smart" levels. Efforts are being made to further enhance smartness, e.g., [3]. [39], [64]. Proper operation and control of MGs are thus very crucial within the context of SGs. New techniques for this are still very much an area of active research.

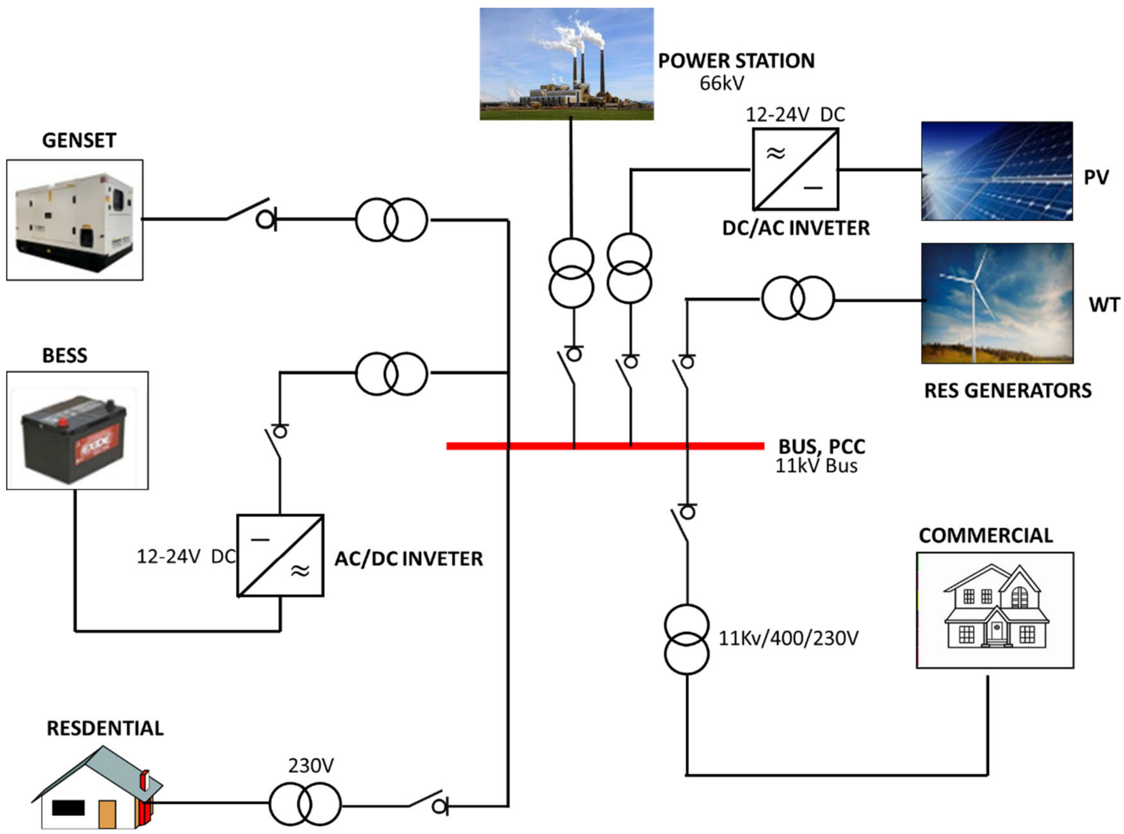


Fig. 1-11. Typical microgrid radial schematic

The smart grid addresses the surmounting problems of the current energy. The next section captures the key aspects of this concept and then introduces the focus of this work.

1.5 The Smart Grid & Smart Home

Today they are many things that are described as being "smart" for example smartphones, smart cities, etc. In [70] an attempt is made to characterize these systems by defining ten attributes related to smartness. The Smart Grid embodies the extent of present and future power grid ICT-driven transformation to meet the challenges of future and current electricity supply. They rely on ICT to provide reliable electrical energy supply to consumers, and high power quality, whiles deploying DER like PV, WT, and CHP, in electrical grids. The main feature which distinguishes the concept of an SG from the traditional power grid is the penetration of DEGs. In this way, the SG can manage, coordinate and control connected distributed energy resources to achieve optimal performance. At a local consumer level, small RES, like households or commercial entities do not possess enough capacity to directly participate in electricity markets or to be of use when grid contingencies arise. Furthermore, both consumption and renewable energy yield at this level are stochastic and often difficult to predict in comparison to variation at higher, aggregate sub-station levels. This means the DERs, ESS, loads etc. within a locality need to be organized into a coherent subsystem for purposes of control and management.

The traditional architecture where electricity flows from big generation stations to consumers via long and complex generation, transmission, and distribution networks spanning vast areas is no longer adequate for the 21st-century demands. Factors relating to the rise and demise of the legacy grid are summarized in [3]. Current technological advancements require power grid control to incorporate new appliances such as electric vehicles and photovoltaic or microgrids in general [3],[71]. Managing such complex grids has become increasingly important for research and practice, since, for example, grid reliability and cost benefits are endangered by the ever-increasing appearance of microgrids at the distribution level.

The controllability and operational management of such a new grid structure, based on mini-grids or microgrids and common aggregation control points, is a technical feat calling for the development of novel distributed and efficient methodologies. The methods should be able to support network operation by deploying flexible and scalable systems. The multi-agent concept or construct is an up-and-coming new technique for designing and developing complex distributed systems such as SGs. The focus of this chapter is the introduction of SG building blocks, architecture, management, and control methodologies in the current literature.

The term SG refers to the entire 'intelligent' electrical system from generation and transmission to distribution as well as the terminal consumers [72]. It is a dynamically interactive real-time system encompassing diverse power systems [73]. Hassan [5] discusses the technological evolutionary path current grid to the SG. The IEE's Smart Grid Study Group 3, SG3 [74] defines an SG as "the concept of modernizing the electric grid. The SG integrates the electrical and information technologies in between any point of generation and any point of consumption." Many research articles have been written on SGs and continue to grow [75]. Compared to the old legacy power grids, SGs are distinct in their use of modern ICT to provide bi-directionality in both information and power flow. This potentially saves energy, and cost and increases reliability [9]. Remote control of appliances and general optimizations over how the energy is managed and consumed is possible. Several organizations are coordinating international standardization of architectures to enable seamless integration and interoperable ecosystems [76].

Essentially SGs will evolve into cyber-physical systems with various wireless communication technologies forming the network. Abstract SG architectures are discussed in [77],[78]. The fastest growth of SG is expected in the residential and commercial sectors [79], Fig. 1-14. In the residential segment, from a bottom-up view the smallest intelligent unit is the Home Area Networks (HANs), then Neighbourhood Area Networks (NANs), and finally the Wide Area Network (WAN). HANs connect the intelligent energy-consuming devices of specific consumers. NANs connect multiple HANs communicating behavioural data, and networking applications for smart grids. The collected information is channelled to the WAN gateway for aggregation. WANs are the communication backbone between smart cities, renewable energy sources, and smart grids. Connectivity between devices is increasingly wireless, especially with the advent of super-fast 5G technology [80]. Fig. 1-13 is a typical hybrid physical layer depicting various energy sources at the components layer of the future grid with interconnected distributed generation sources.

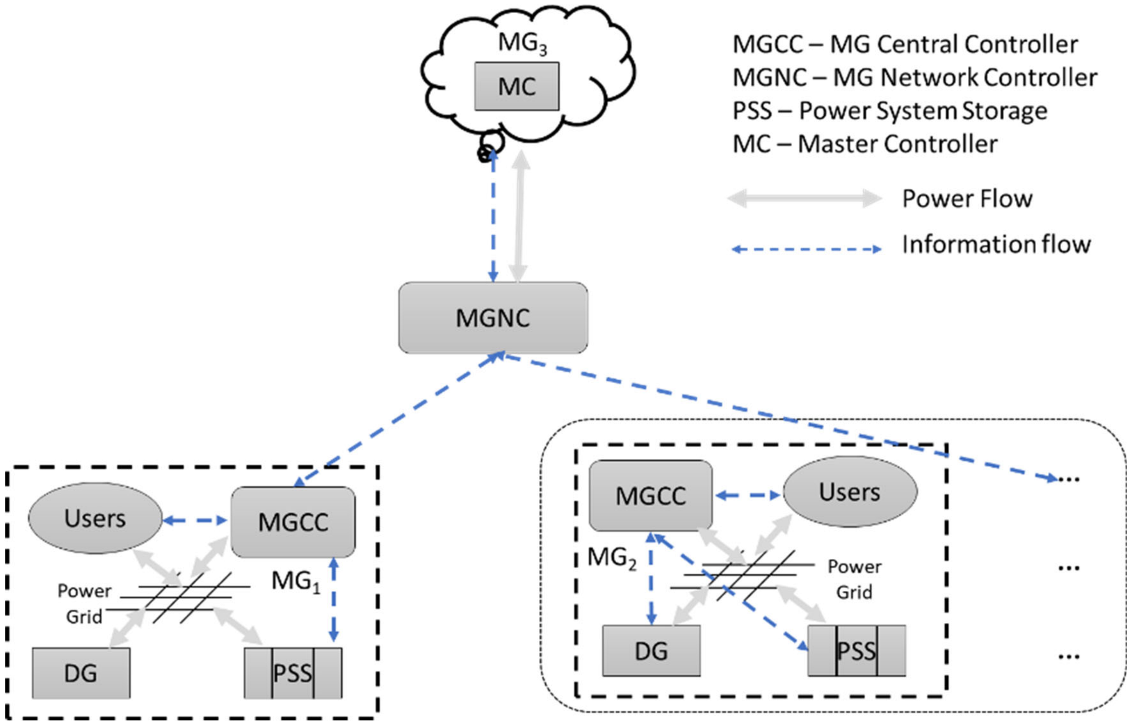


Fig. 1-12. General SG Architecture

The EU's Smart Grid Architecture Model (SGAM) Fig. 1-13, is outlined in [78]. SGAM is a 3D model with five interoperability layers, five domains, and six zones. It has a diverse range of power, communication, electronic equipment, and devices, ranging from Smart Meters (SM) to Phasor Measurement Units (PMUs), wind turbines, and Photovoltaic to mobile Plug-in Electric Vehicles (PEVs). ICT technologies enable connectivity, automation, and coordination between suppliers, consumers, and networks that perform long-distance transmission or local distribution tasks [81]. By using the concept of virtualization [82],[83] together with Software Defined Networking (SDN), these electronic devices and SG infrastructures can be shared among multiple parties with each party having full control over their portion of the resources. The cyber-physical nature of the SG leads to the virtual sub-station concept [8].

The proliferation of microgrids has attendant challenges and opportunities. Desirable opportunities are [11]; ability to involve consumers in DSM initiatives, high reliability, and power quality to offset the intermittency of RES as the quality of the power must not degrade consumer experience; high resistance to cyber and physical attacks and ability to grow microgrid on a ‘plug and play basis. Attendant challenges that have been extensively dealt with in the literature are voltage and frequency control, islanding, stability, power quality, and economic optimization [84].

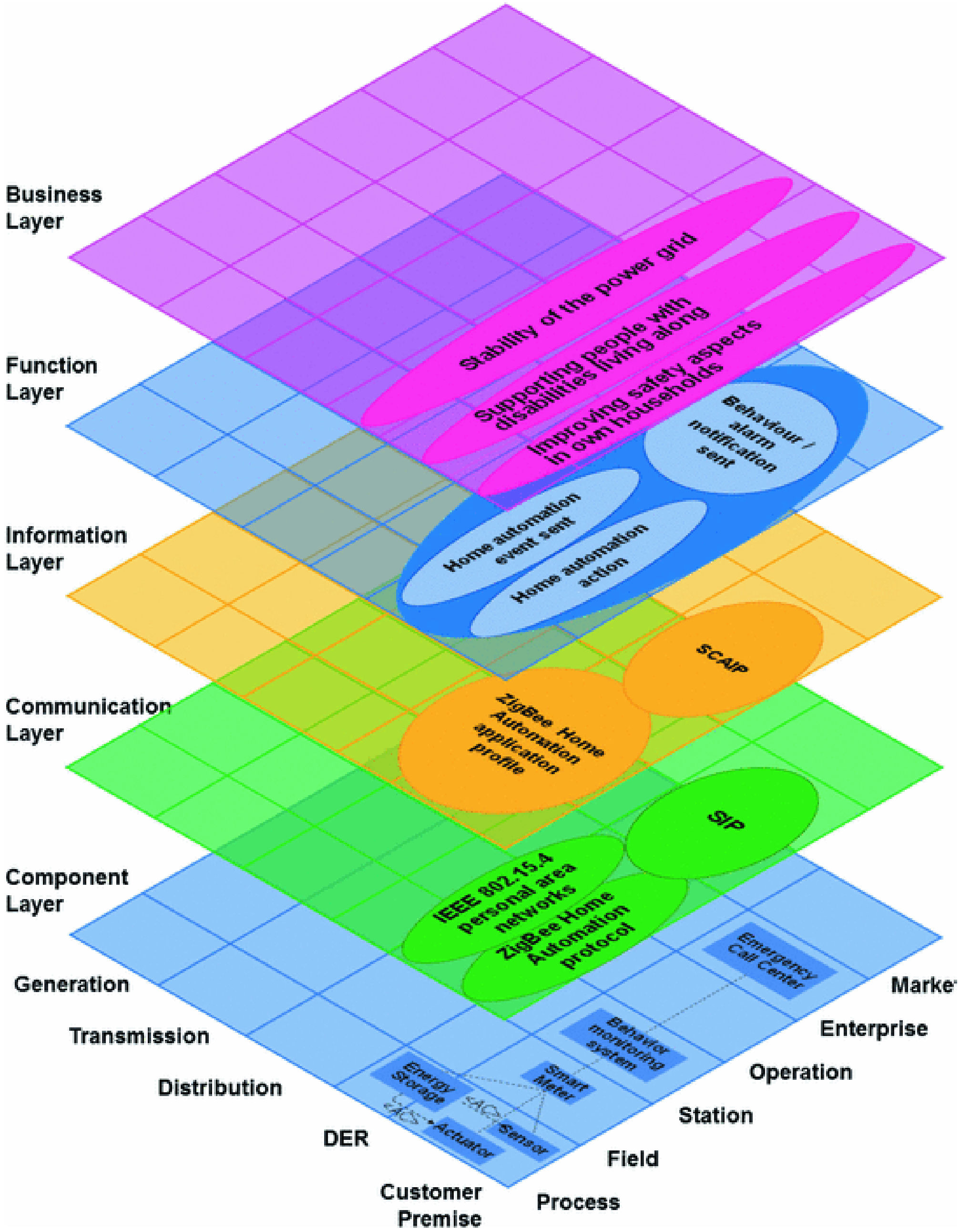


Fig. 1-13. EU Smart Grid Architecture model[85]

Various SGs research initiatives are ongoing in different parts of the world [72],[73],[76],[86],[87] such as the EPRI IntelliGrid project established to facilitate the transformation of the electric infrastructure into cost-effective MGs [73]. This project focus on enabling modelling and fast simulation of communication, distribution, and monitoring systems. The EPRI Advanced Distribution Automation [71] is a sub-group focusing on QoS, integration of distributed generation and storage, and integration of customer systems [87]. The National Institute of Standards and Technology (NIST) and the European Telecommunications Standards Institute/European Committee for Standardization/European Committee for Electrotechnical Standardization (ETSI/CEN/CENELEC) are working towards providing a taxonomy of future SG standards [76]. Denmark leads in implementing SG solutions [88]. In China, extensive SG research projects exist [26]. A summary of international projects and specific SG integration studies is given in [8]. Keys focus study areas identified by M. H. Rehmani et al. [8] in the implementation of the SG are; planning of the integration of RESs into the SG, scalability, regulatory environment, the standardization of universal protocols, and standardization hardware for seamless operation of SGs.

1.6 Motivation for SG Energy Management.

A combination of reasons covering; electrical grid infrastructure nearing its life span, capacity, and the need to accommodate increasing embedded RES generation; Increasing demand vs dwindling fossil fuel resources and the emergence of new forms of electric loads; Pressure to reduce CO_2 emissions and arrest greenhouse gas emissions; The imperative to manage intermittency and lack of inertia of RES and the need to deal with integration and de-regulation problems due to growth of IPP with RES and new market models with greater consumer flexibility have among others spurred the rapid development of energy management research [89]. Fig. 1-14 illustrates the growth of literature on "Household Energy Management" since 1990. The statistics were scanned from three literature databases namely SCOPUS, GOOGLE SCHOLAR, and IEEE XPLORE. This is indicative of high research activity in this space.

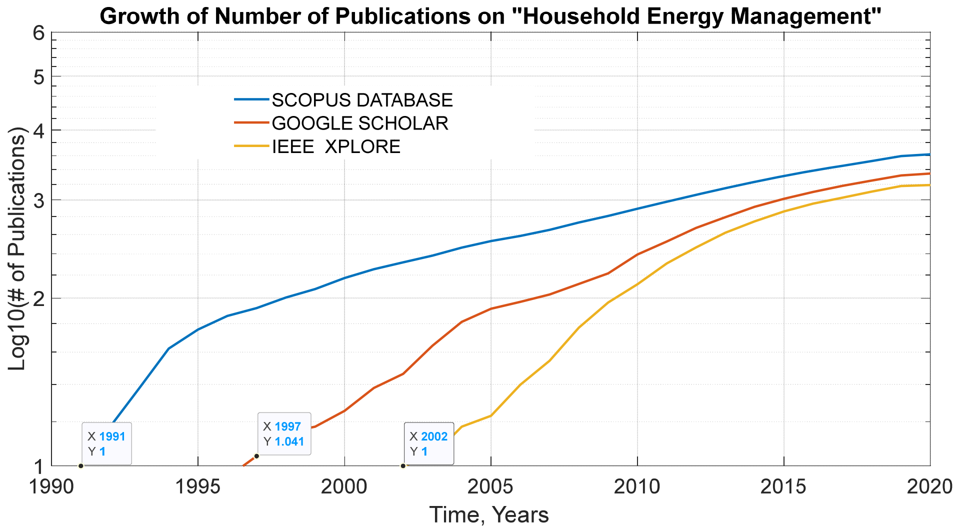


Fig. 1-14. Growth of Research Activity on Household Energy Management

The key to energy utilization efficiency is DSM with time-related pricing. Intelligence in the SG with "closed-loop" control of demand implies the small and numerous RES will be easier to control and coordinate. However, the intermittency and geographic spread of RESs require high computing power. Various researchers have identified various key research questions for the successful implementation of SG concepts [8]. The scope of this research covers Demand Side Management, Load Shifting, and Dynamic Energy Pricing for domestic electrical energy consumers. The broad range of MG research has dealt with islanding, small-signal stability, power quality improvement, scheduling, and economic optimization.

Energy optimization using scheduling alone is limited by the flexibility of schedulable loads and the consumers' willingness to compromise their comfort due to appliances' switch-on time delays. The residential tariffs should directly offer monetary incentives for PAR reduction strategies to work, otherwise, customers will have no desire to flatten their peaks on the load curves. Besides shifting base load appliances, a complementary method of optimizing households' energy consumption is the deployment of electrical storage. If ToU tariffs and electricity storage are used, then consumer electricity costs can be reduced by storing energy during low-cost off-peak times and then discharging the stored energy for use during high-cost on-peak times so avoiding expensive grid supply. Energy storage is effective at lowering electric bills without direct user involvement but the impact of large-scale energy storage adoption on-grid electricity demand needs to be quantified and understood.

In South Africa, the residential sector's share of total national electricity consumption increased from 16% in 1993 to 27% in 2015 [1]. Energy-intensive mining operations which are less flexible account for about 60% of national electricity consumption. The cost of generation and corresponding tariffs are expected to grow very steeply [90] as access to basic electricity increases. Supply constraints are a major concern. National rotational load shedding introduced in early 2014 is now a permanent feature for the foreseeable future [22]. According to studies in [22] electricity prices which stabilized at low levels in 2001, have from 2008 steadily risen in real terms. Going into the future the average price of electricity for local residential consumers is on a steep upward trajectory [91] and will not be relenting anytime soon. The article [22] provides an extensive historical and current context of the state of affairs of electrical energy supply locally. An average home now pays about R1500.00/month on utilities which includes electricity. Today's prices exclude negative externalities connected with electricity production, namely climate change, and air pollution, the actual cost in all likelihood is higher than prices projections today.

The main instrument available to utilities to stimulate energy-efficiency initiatives is escalating electricity kWhr unit costs. Another alternative and quick way to alleviate electrical energy supply constraints is improving energy efficiency on both the supply and demand sides. This is economically and socially attractive but operationally difficult to implement. Energy efficiency and DSM initiatives also benefit the environmental impacts associated with electricity generation. Demand peaks have a very lop-sided effect on generation costs as they drive CAPEX—by dictating the number of power plants, transmission lines, and substations—and operational expenses since "peaking" generation is expensive to operate [92]. High peak demands also imply greater transmission I^2R copper losses stand at about 10% of the 45.5GW of the local installed capacity [93]. This loss translates to about US$1.4 billion which is approximately 0.4% of the GDP. In comparison, the world average is 0.113% of GDP thus local (South African) losses are 3.5 times higher than the global average in percentage terms. Given such a scenario any small reductions in peak demand will positively impact generation costs in a big measure.

In attempts to decrease PAR, utilities are moving from Flat Rate Tariff (FRT) which charges a flat fee per kWh to ToU tariffs which better reflect the true cost of electricity according to peak or off-peak times. The ToU is already adopted in commercial and industrial sectors with rough-grained ToU structures. For instance, the local eThekwini Municipality ToU tariffs are depicted in Fig. 2-11**.** To extend this tariff to the residential sectors where more flexibility to manage energy resides, utilities will have to deploy AMI [89]. To be truly beneficial DSM should place no burden on consumers to be part of the 'control loop' through monitoring prices, and then adjusting their consumption to decrease energy costs in line with minimal disruption to routine home consumption patterns. Such tasks are onerous. Most consumers have no interest in knowing how much power appliances consume, and do not desire to plan their electricity usage. Thus, DSM in this basic form cannot yield the cost-saving benefits of PAR reduction. However, even if consumers were to respond to electricity market signals, new peaks may appear elsewhere. Difficulties in consumers' behavioural changes in electricity usage in switching to market-driven tariffs will also place a damper on customers' acceptance of DSM.

To mitigate these competing problems, a DSM scheme for intelligent energy management in Smart Home is proposed. The scheme relies on the maximization of RES energy in terms of consumption and charging and discharging of the BESS system. The scheme also determines how much and when to store low-cost energy for use during high-cost periods based on Day-Ahead (DA) predictions. The strategy seeks to also optimize the consumers' utility function under ToU tariff regimes. The strategy will seek to reduce costs by appropriately switching home appliances between grid power, stored power, and RES power. The problem is formulated in the context of multi-objective linear programming optimization given DA electricity costs and predicted load profiles [94]. DA consumption is predicted using Machine Learning (ML) models based on predictive data such as weather, time of day, day of the week, etc., and an improved Bacterial Foraging Algorithm is used to solve the optimization problem [95][96]. We hypothesize that ToU can reduce electricity costs for consumers over time as penetration of RES increases and that as AMI technology is deployed, average electricity prices will see a significant fall due to PAR reduction. Utilities will however need to design their tariffs to incentivize the deployment of DSM, behavioural changes in energy usage, and installation of storage. The Dissertation makes the following contributions.

1.7 Contributions of the Dissertation

The following is a summary of the key contributions of this work.

- Algorithm to re-shape electrical load profile in a household consumer and SG to reduce PAR, consumer bills, and costs to the utility. To perform this, we draw from the new ASO and QPSO heuristic algorithms and machine learning for predictive load forecasting. Simulations are used to evaluate the effectiveness of the methodologies based on real power consumption data sourced from internet sources and — real data logger installed at a university substation. The contributions are in energy optimizations in buildings and energy optimizations in SGs. The key contributions and systems developed for energy optimizations in buildings are as follows:
- Flattening electricity demand profile by dynamic 'base' load scheduling while identifying and minimizing discomfort on frequently active low power appliances. Simulations show that base electrical appliances consume more than half of the total energy in a household hence, we formulated an appliance scheduler that flattens peak load by scheduling only the base appliances thus minimizing consumer discomfort. The average deviation from mean power can be decreased by as much as 20% throughout the day.
- Application of RTP with storage optimization.
- Optimization of local RES for household consumption to reduce electricity costs while ensuring optimal operation of aggregate MG. Simulations are done that look at aggregate load optimization.
- Demonstrate operability of BESS charging-discharging algorithm with ToU tariffs and minimum utility electricity consumption.
- We investigated the effectiveness of energy storage in lowering electricity bills and peak demands without direct consumer participation. Using DA electricity prices, and machine learning (ML) consumption prediction model simulation results show that 10-15% in electricity bill savings can be realized.
- Finally, in the concluding sections, the work proposes and analyses a hierarchical optimal dispatch framework that relies on several objectives to achieve

the overall design goal of a reliable and stable power supply, coupled with economic benefits to prosumers who elect to participate in power trading.

Note that, however, the adaptability and robustness of MG networks are still open research issues that are not directly addressed in this research.

1.8 Dissertation structure

Overall, the dissertation's chapters are laid out as follows; Chapter 1 is an introductory section covering power grid evolution, global trends in developing such future systems, and motivation for the overall research. We further explore challenges on demand growth amid gradually ageing power systems networks. Chapter 2 looks at energy management, as well as consolidating the key research aims and objectives already identified in the previous chapter. In the same chapter, we explore the sustained utilization of limited resources. The following chapter introduces and reviews the concepts and techniques of optimization applicable to the problem of discrete energy optimization and load scheduling with a special focus on domestic energy load scheduling. Chapter 4 is dedicated to modelling REG components. In Chapter 5, the problem of household load scheduling in the presence of MG with REGs is modelled and simulated. Further extensive scheduling optimization and household load modelling are dealt with in Chapter 6, wherein a new meta-heuristic technique based on the Atom Search Optimization(ASO) technique is applied in household energy optimization in a bid to improve the overall power system grid's demand and supply balancing. In chapter 7, the work proposes and analyses a hierarchical optimal dispatch framework that relies on several objectives to achieve the overall design goal of reliable and stable power supply, coupled with economic benefits to prosumers who elect to participate in power trading.

Chapter 8 outlines the conclusions, main contributions of the Dissertation, and possible directions for future work.

Chapter 2 Energy Management in MGs

2.1 Introduction

Microgrids with DEGs are growing in many areas of society spanning residential, commercial, and industrial sectors. They are some isolated systems servicing special installations e.g. telecommunications, military, and remotely located research infrastructures [8]. In residential or commercial sites interconnections, of these DEGs aggregate into larger multi-level electricity MG systems [97]. Larger DEG architectures help to overcome vulnerability due to climatic changes. To maintain energy balance between supply and demand, the key issue is control and coordination of the various DEGs which are inherently random, unlike traditional fuel-fired power stations. Expectations vary. From consumers' viewpoints, MGs are expected to provide electricity efficiently and economically while promoting eco-friendly technologies. In the process of time, more DEGs will be deployed as investments by Distribution Systems Operators (DSO) in the sector grows. However, given the problem of intermittency, DEGs can at the same time induce problems on the power grids on such parameters as voltage and frequency. The work in [98] provides an extensive account of these challenges and limitations. Such problems are mitigated by proper integration of DEGs into the grid so that the MGs act as coherent entities that support the grid network.

Advances in smart grids and AMI implementation have opened doors to the concept of managing the demand curve in sectors where it has never been done before wherein consumers are involved in generation. Such developments in SGs empower consumers to shape their electricity consumption. This ability to shape consumption to attain certain goals is what embodies and encompasses the core DSM problem. DSM is strategically implemented by Utility operators with the sole objective of shaping the load profile on the use of electricity or reconstructing the load curve by levelling the demand or optimizing it to a specific desired profile so that the load factor is closer to unity. DSM helps to maintain equilibrium between load and supply thus achieving overall reliable operation of the power supply grids [99]. It also results in reduced energy losses, increases grid hosting capacity, or strengthens congested grids. Such is the concept of a

Virtual Power Plant (VPP) as reported in various research works. The VPP refers to a fully integrated SG with sufficient control in keeping with healthy and reliable grid operation [45],[100],[101] comparable to the legacy grid. In [101] the SGAM EU model of an MG is used to expand on the architecture of VPP and Demand Response, investigating core functionalities, information and communication needs, as well as required standards and technologies.

Presently they are several MGs implementations, control, and management challenges emanating from regulatory, markets or technical reasons [98]. Technically, MGs complexes contain multi-vendor components of different technologies which may hinder interoperability. The interests of e.g., DSO, consumers, and prosumers may conflict and compete with one another. For example, in the market models discussed in [102], the interest to feed more renewable energy into the distribution grid may conflict with the DSO requirement to curtail power infeed to maintain network voltages within certain limits. The result is a management environment where the inter-communication burden for control becomes computationally intensive and complex. Protection coordination and settings to take care of both main grid and MGs in the event of faults become complex too [54] with bidirectional flow of power.

Within a regulatory framework, the mechanism for cross-interaction between the various MGs players needs to be defined so that all stockholders are made aware of how their activities impact others when looking at the system[103] as a whole. Electricity like any other commodity will have to be traded in the marketplace to boost MGs competitiveness. With competitiveness, costs can decline, and new services may appear to benefit all. Pursuit of the MGs control and energy management challenges gave birth to the concept of a Smart Grid. New control methods and strategies, architectures, and algorithms, to ensure the sustainability of future SG are needed [104]. Successful deployment of these ICT-based capabilities will set apart future MGs from the traditional ‘passive’ distribution grids with DGs elements. The architecture of MGs optimal control must meet many operational constraints, such as mode of operation, users’ objectives, limits imposed by the existing grid etc. Issues to be resolved include where and how to control decisions are taken, control strategy applied, competitive vs collaborative control, and information exchange or transparency within the microgrid eco-system.

MGs can be configured either in a centralized, decentralized or hybrid architecture [105]. A centralized control architecture is suitable where extensive collaboration among microgrids is required. The central controller oversees all interconnected MGs and can control them within system-wide constraints as determined by individual micro-sources and energy consumption patterns. In this configuration, the MG Central Controller (MGCC) gathers data from the SM. The MGCC makes decisions and performs computations to determine the control actions of the individual components in the MG. This approach calls for wide communication between the MGCC and the controlled sub-units. In a centralized MG, strong coupling allows collective optimization and control, which minimizes OPEX. However, a disadvantage of this architecture is the need for widespread communication, which may span larger geographic areas, require big data analytics, and high-end computing to handle the many system components. They are also privacy issues to contend with as in-depth knowledge of the system is needed such as component models, consumption data and patterns etc. The downside is that the centralized system is not easily scalable.

Decentralized architectures by implication do not have a central command for decision making but rather an MG-Local Controller (MGLC). In such systems, each participant can make local decisions based on their circumstances [59]. Collectively the system behaviour is the total responses of all the individual responses, like how peoples' groupings where each makes limited decisions, and these decisions influence everyone around. With this configuration, the MG local controllers act on local information and they are not fully aware of system-wide variables or other sub-controllers actions. This approach entails lower communication overheads. It is suitable for heterogeneous components in the MG and poses greater resiliency. In complexes of residential or commercial apartments with e.g., various shiftable appliances, it is difficult to formulate a model for comfort utility requirements and include appliance constraints in one optimization problem. As complex constrained optimization problems are handled locally, this lowers computational capacities and communication requirements. The downside is that a global optimum operational point may not be easy to find with this paradigm.

The hybrid configuration is a mixture of the two methods above. The dominance of one or the other structure is detected by design choices. In the hybrid control structure, the main defining strategy is that the process control is shared between several nodes in a hierarchy whereby decisions are made at different levels and by different subsystems using partial system knowledge.

Within the DSM context, the focal point is the interaction between overall microgrid control vs demand experienced in different end-user sub-microgrids. Exact load demands are hard to know, and the elasticity of the systems will be low without demand management and power quality may worsen. Direct Load Control (DLC) methods can be used to deal with unpredictable load changes, but these compromise users' comfort. Various microgrid control methodologies have been enunciated in the literature [106][107] with the heuristic techniques [108] dominating the landscape. Demand compensation and proper energy marketing models are still subjects of much active research [97].

The development of smart ways of energy utilization at the consumer end is a top priority across the globe e.g., the European Strategic Energy Technology Plan [109] and by extension realisation of Renewable Energy Directive II [10]. Current efforts on energy efficiency are focused on the concept of Smart Homes (SHs) and Demand Response (DR) in general. SHs refer to residences, apartments, etc. [110] equipped with smart meters, controllable loads, RES or BESS systems making up autonomous, and reliable energy supply systems [86], [111],[70]. Key variables in these systems i.e., RES yield, electricity market price, and residential consumers' energy demand are all stochastic. Home Energy Management Systems (HEMS) to schedule local generation and consumption are therefore a must. HEMS is a generic term referring to the techniques or control methods to regulate energy consumption with the objective of improving energy usage efficiency, minimizing costs, and maintaining consumer utility and sustainability [112]. Many techniques are employed in the literature as depicted in Fig. 2-1.

Various DR methods targeted at load flatting and peak clipping Fig. 2-5, have made it feasible for prosumers in the residential and other sectors to accrue financial benefits by selling electricity to the grid or optimizing the usage of costly grid electricity [113]. An algorithm for utilities and prosumers to reduce demand at specific times when aggregate network load demand is high is proposed in [94]. The latter algorithm is based on Day-Ahead (DA) energy cost minimization via optimizing energy consumption in an SH equipped with SM and smart appliances. In this instance, the optimization algorithms only flatten the load curve. The dual problem of cost reduction still requires matching ToU tariffs carefully designed by the electricity utility. The success of the optimization plus attractive tariffs can entice consumers into flexible and payless energy-saving DSM schemes. Various challenges still faced by utilities in the delivery of energy are summarized in Fig. 2-2.

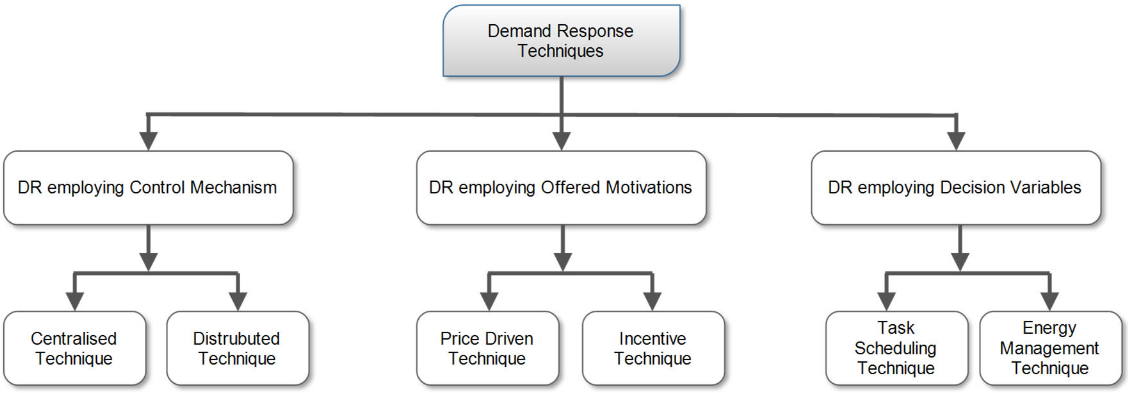


Fig. 2-1. DR schemes classification based on motivation or decision variables [72][8].

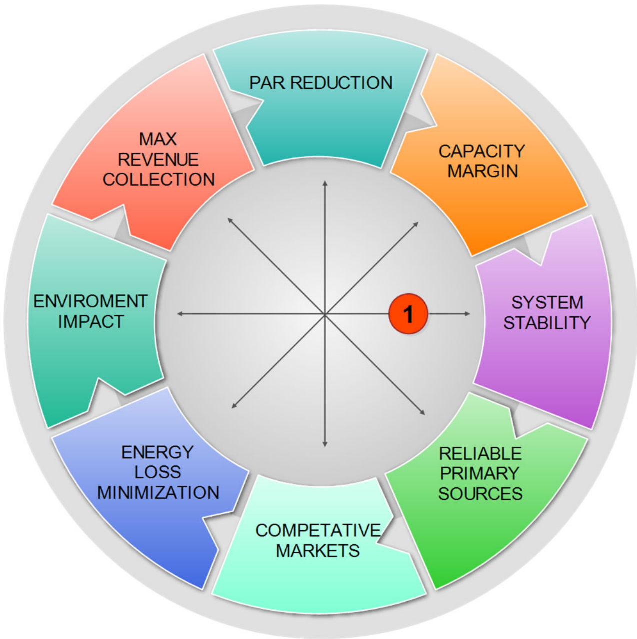


Fig. 2-2. Priority challenges faced by utilities in energy supply

2.2 Load Profiling for DSM

Electrical energy is such that at any given time you supply the quantity that is needed for use hence load forecasting is crucial to balance supply and demand. Many techniques with some strengths and weaknesses [8][9] are in use for load prediction. Installation of SM means household electricity consumption data becomes easily available hence the prediction techniques can be made use of to foretell domestic load and validate it. It is important to note that the demand curve at the aggregation level is quite dissimilar to that of an individual household or commercial entity corresponding to e.g., a University

Campus. Fig. 2-3 shows a typical load profile as seen at a substation of a typical commercial block hosting several activities. This was recorded on the 1st of August 2017 over two hours [114]. Fig. 2-4 and Fig. 2-5 show the same profiles over 24 hours and extended days as indicated. The longer periods are smoothly shaped with relatively reduced electricity consumption during the night hours. Peak times are clearly during business hours and thereafter demand falls. As shown in Fig. 2-5, the general profile shapes change for different days of the week and over the year due to the seasonality of commercial activity and fluctuating working patterns of occupancy.

The objective of DSM techniques is to bring down the high peaks and fill the valleys of the demand curve so that energy consumption is used more efficiently by eliminating or mitigating the need for peak plants or spinning reserves in the power plants. Successful deployment of DSM programs leads to one of the following demand reduction objectives namely peak clipping, valley filling, load shifting, and energy conservation as shown in [115].

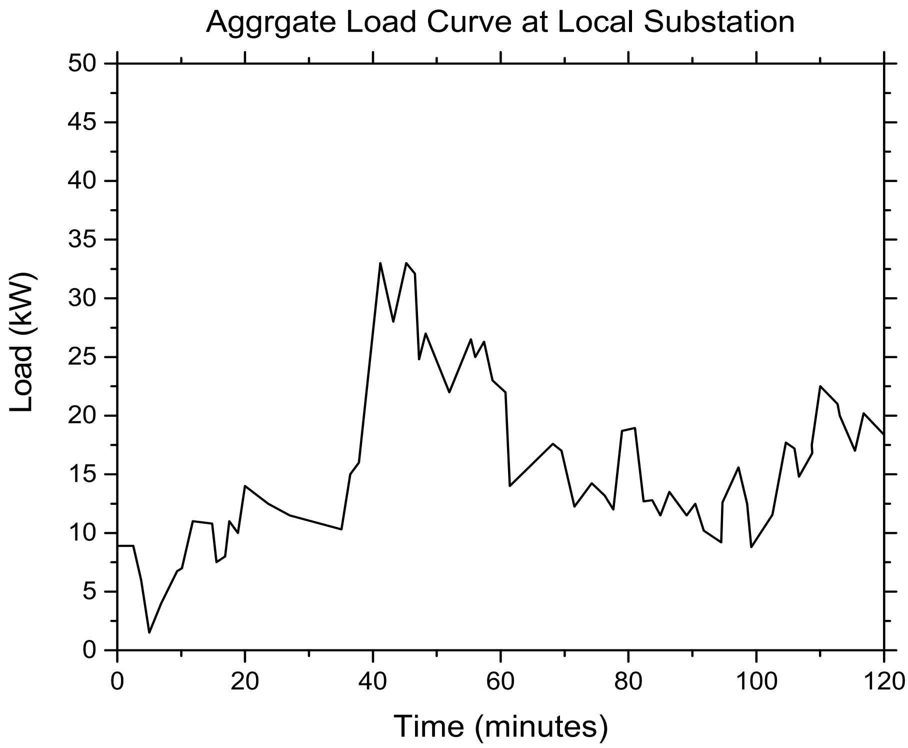


Fig. 2-3. Typical aggregate load at commercial building substation

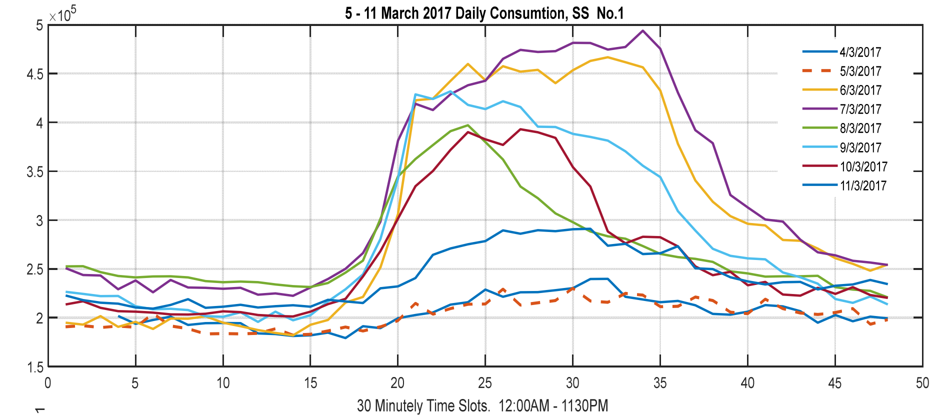


Fig. 2-4. Daily energy consumption for a Campus Unit at various times

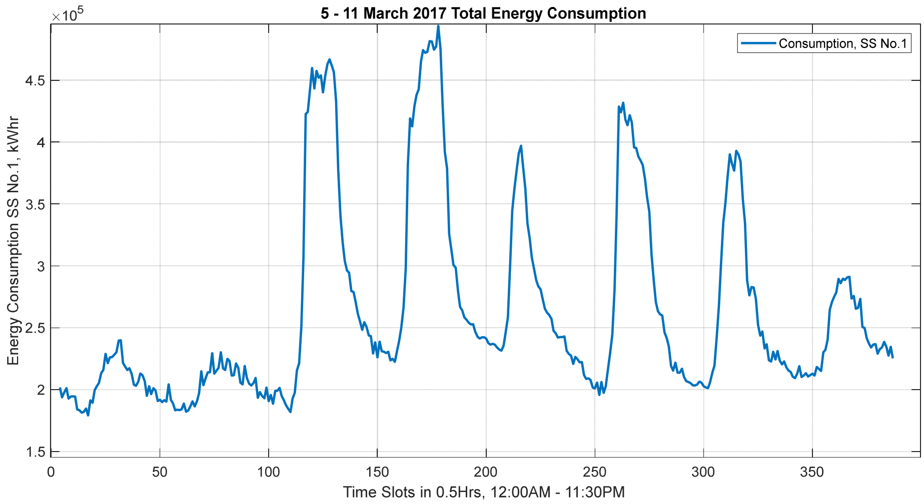


Fig. 2-5. Daily load variation stretched out 5-11 March 2017, Sub Station No.1 - Commercial

Peak Clipping

Peak clipping is illustrated in Fig. 2-6b. This is a reduction of total load demand during a high peak period. This is attained by Direct Load Control (DLC) or switching off the low-priority loads to increase the grid's stability. Both energy consumption and generation are reduced.

Energy Conservation

Energy conservation is illustrated in Fig. 2-6d. This refers to a change of paradigm where the total amount of energy consumption or load is reduced to match the supply. For the successful implementation of consumer participation and smart metering, intelligent networks are required. Recently, smart phone-based human activity recognition is also enabling efficient energy conservation in the residential sector [15].

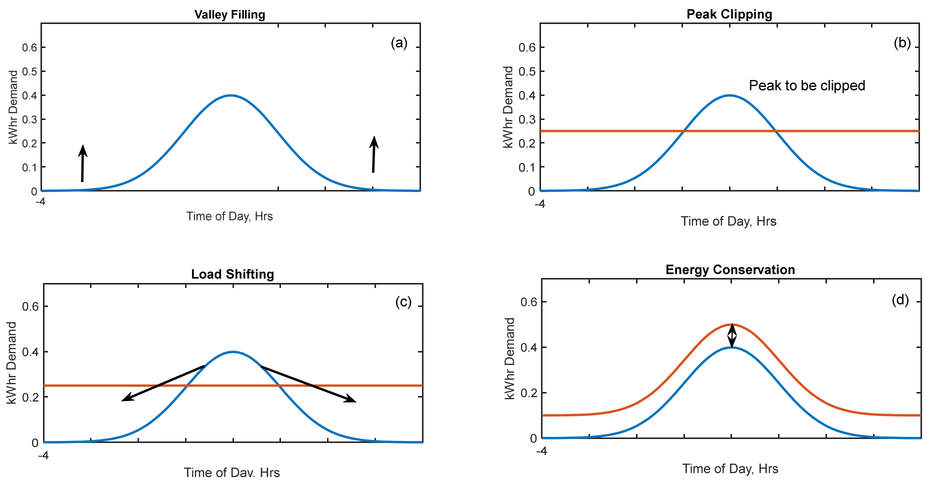


Fig. 2-6. DSM Techniques Valley filling, Peak Clipping, Load Shifting and Energy Conservation

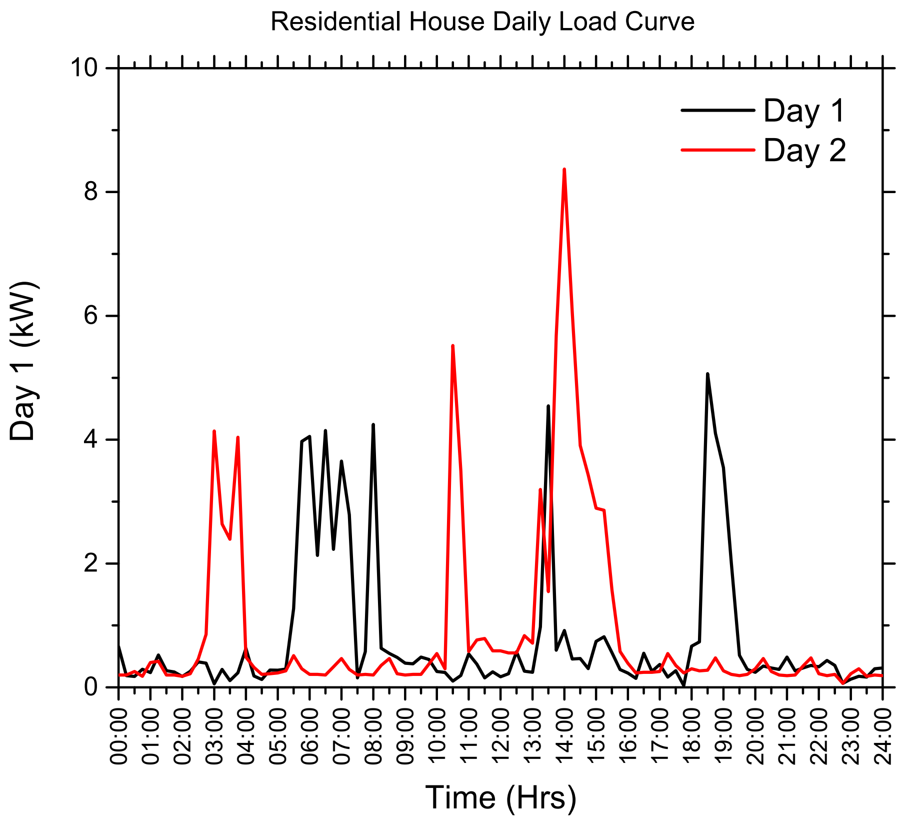


Fig. 2-7. Daily load curves for Household

Load Shifting

Load shifting is illustrated in Fig. 2-6c. Shifting the load from high peak to low peak hours can be termed load shifting. In this case, total energy consumption remains the same at the end of the time interval. DSM and incentive-based techniques are used to shift the load from high-demand to low-demand hours by encouraging the customers.

Valley Filling

Valley filling is illustrated in Fig. 2-6a. Load factor is the ratio of average electricity used to maximize electrical demand for a given period. A low load factor is indicative of inefficient electricity usage relative to what it would be if peak demand was controlled. Valley filling is akin to building the load during off-peak hours to balance the system load factor. High energy generation and low demand reduce utility revenue because energy cannot be stored. For example, battery or Plug-in Hybrid Electric Vehicle (PHEV) charging mechanisms can be used at night when there is less energy demand by the customers, especially in the residential sectors.

Benefits of DSM

DSM programs benefit all stakeholders in the value chain from generation to consumption. By adapting DSM-compatible appliances consumers lower their bills, especially where HVAC, lighting, motors, and fans are heavily in use. From a power utility perspective, DSM programs help in deferring capacity expansion programs in the face of growing demand. These strategies are easy and cheaper to implement compared to building new power stations. By de-stressing the system, DSM strategies reduce the risks of grid failure due to unpredicted high energy demand. The carbon footprint of utility companies is also reduced. Consequentially the environment and hence society benefit from fewer carbon emissions and uninterrupted power supply. Utilities are also under regulatory pressure to provide clean green energy. This is one of the major reasons why improvements to harvesting renewable energy are continually being sought [116][117].

Electricity is difficult to store economically on a large scale which implies at any given time instant total generation should equal demand. Marginal Cost (MC) i.e., cost to produce one additional 1.0 kWhr is very variable due to continuous fluctuations in consumption. This variability of MC is to the order of 15-60 minutes. Domestic consumers are mostly charged static average prices. This creates a disconnection between the real electricity production unit cost and the selling price paid by consumers; hence this is an inefficient pricing mechanism with negative repercussions for the limited generation resources of utilities. On fixed block tariff, consumers are shielded from the variable real cost of power and thus they see no benefit to participating in DR initiatives[86]. In other words, the Flat Rate Pricing (FRP) tariff of electricity encourages inefficient consumption of electricity when electricity prices are higher than average or when selling prices are lower relative to the average rate as in all cases generation must equal demand. To discourage unresponsive consumers, power producers increase power prices above going prices at certain times or have more stringent DR programs. Effective DR programs mitigate the risks of capacity upgrade investment to cater for peaking generation power plants. The latter approach is difficult in terms of both time, cost, and servitudes acquisition.

The improved efficiency of the overall energy network enabled by the two-way interactions between utility and consumers is the biggest achievement of the DR program. This mutually beneficial symbiotic relationship is not limited to a single party because customers and utilities equally participate in energy management programs. They are takeaways for all, the utility, customers and society. Consumers benefit in terms of low electricity bills. Alternatively, participants of market-based programs receive benefits according to their performance. Market Benefits with reduced demand and utilities spend a lot less on strengthening up capacity. The CAPEX can be directed elsewhere. Reliability benefits. By implementing DR programs, utilities can provide uninterrupted energy to customers. Energy management programs significantly reduce the risk of grid failures which ultimately reduces the probability of power outage.

2.3 Tariff Options for DSM

As RES penetration in the power grid increases, the share of 'easily' adjustable power generation with natural load/frequency balancing inertia to stiffen the system is declining as a result challenges of energy management are aggravated [74]. To mitigate these problems, a paradigm change of "generation following load" to "load adapting to generation" is required, Fig**.** 2-8. This entails greater load management to balance generation and demand at each instant to maintain the stability of the power supply systems grid than has been required in the past. DR is a utility methodology that seeks to manage energy consumption to align with supply conditions whereby customers reduce load levels at certain times when the grid is stressed thereby curtailing the system's peak demand [118]. Alternatively, demand response can be viewed as steps effected by utilities to lower demand through tariff instruments such as variable electricity prices [119]. With DR, utility online demand devices shut off certain targeted loads when a contingency event in the grid is sensed. This may occur at unfavourable times for the consumers. As an incentive mechanism for cooperation between consumers and the electricity utility to modify consumption behaviour, DR is limited by the design of incentives [120].

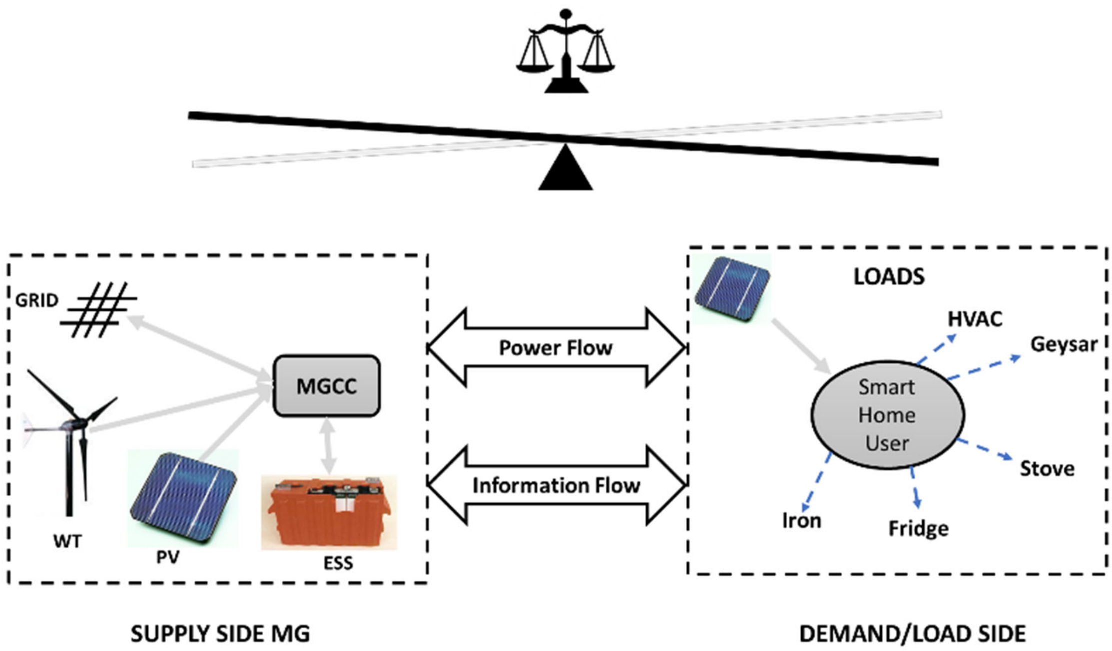


Fig. 2-8. DR in an MG -Continual interaction between the supply & demand sides through AMI enabling two-way flows of information and power.

Continuously balancing demand and supply requires faster control through fully automated closed-loop systems. The consumers in these instances need to be seamlessly integrated with the grid via Advanced Metering Interfaces (AMI) deployed in an area [121]. Load management and demand response are then realized through these programmable interfaces installed at customer premises to control individual loads or appliances. In real practice the load shaded during times of system stress can be pre-agreed with consumers subject to certain contractual obligations or real-time price signals used to incentivize change in customers' behaviour. Consumers can opt to change or not change their consumption therefore these systems are unable to support rapid energy consumption balancing, thus they can only support energy management.

A secondary problem with demand management based on inducements is the choice of the optimal incentive in monetary terms [122]. Electrical energy being a necessity, conflicting scenarios arise between fairness and the margin of the price differential between times of low and high-power availability which determine when DR kicks in. Monetary incentives alone will not be enough instruments for energy balancing and thus direct intrusive control mechanisms will still be required [123]. Integration of power grid and AMI automation offers measures that make possible the modification of the consumer's energy consumption profile, both in shape or time or to suit prevailing supply constraints. DR schemes are either centralized or distributed [124],[125] architecture. Illustrations given in Fig. 2-9 and Fig. 2-10 depict the two strategies.

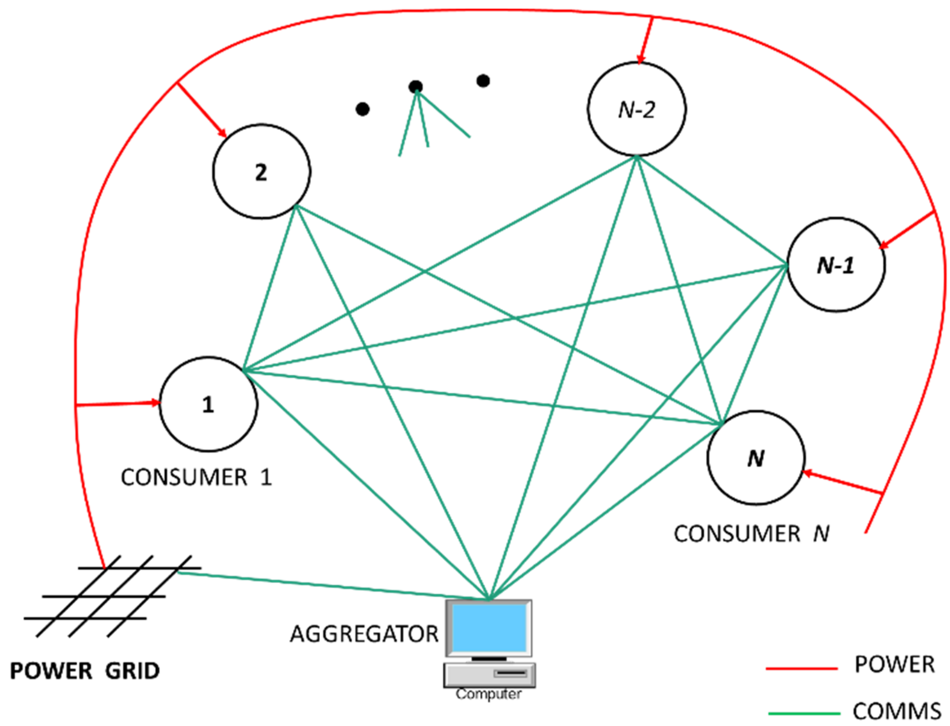


Fig. 2-9. Centralized DR system

Realizing DR achieves multiple objectives visa vee costs reduction, peak load reduction, and the load profile flattening. Current research does not fully address algorithms that encompass these multiple objectives [105]. In this work, we design a multi-objective DR optimization algorithm and propose solution strategies for DSM. It is assumed that a microgrid has bi-directional communication and that customers willingly participate in DSM. The authors in [126] have shown that a 20% reduction in consumption of electricity can potentially reduce electricity peak hours prices by a colossal margin of 43%. This has big repercussions for the economy.

For the centralized DR system, consumers have individual lines of communication with the power utility, they are no direct consumer-to-consumer interactions. Users send their consumption information to the utility [124]. In Fig. 2-9, DR is performed centrally by an aggregator. This distributed system is inspired by wide internet connectivity.

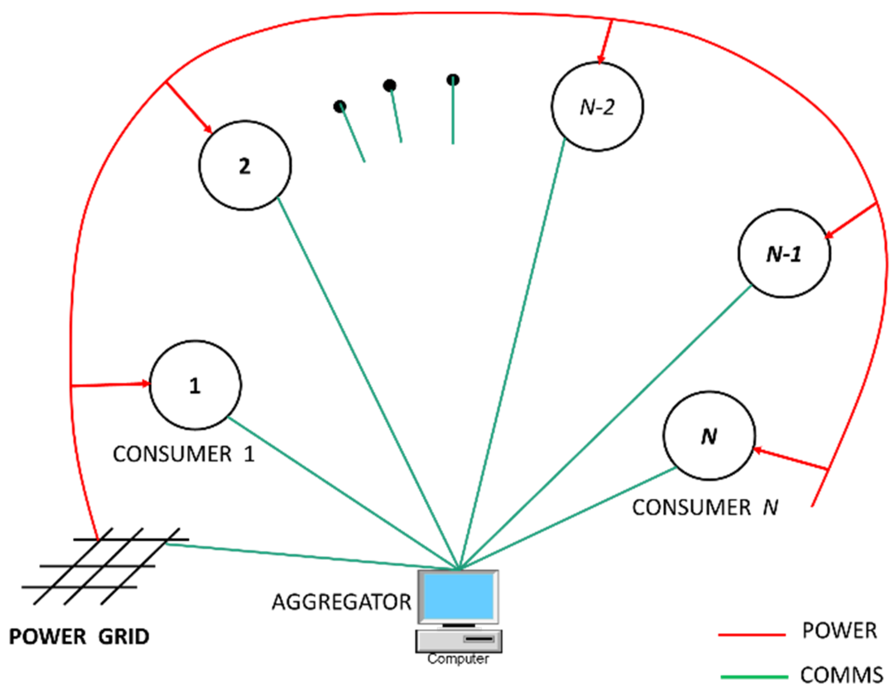


Fig. 2-10. The distributed control DR system

Full connectivity allows users to inter-communicate and with such a scheme the utility's cardinal role is to send real-time price information, which is dependent on the overall system load. Local users interact within the NAN to achieve a total load reduction and DR can be achieved using e.g., decentralized congestion control for IP networks mechanism [127].

DR programs fall into two broad categories [128],[129] i.e., (i) price and (ii) incentive-based. Price-driven schemes are based on the time-variability cost of electricity at different times of the day. Incentive-based schemes have fixed or time-varying rates to encourage the decrease of load demand times when the supply grid is stressed [124] due to high demand. The latter scheme penalizes customers for lack of compliance with the contractual DR program [130]. Various time-pricing strategies have been proposed to implement demand response. Some of the schemes are [131];

- Time of Use (ToU),
- Flat Rate Pricing (FRP). Customers are charged fixed prices/kWh.
- Real-Time Pricing (RTP),

ToU Pricing. In this tariff model the billing period, normally a day is divided into time intervals e.g., 15, 30 or 60 etc. minutes, and prices are pre-set depending on the seasonality. Customers optimize daily electricity consumption for lower bills according to the low, high, or mid-tariff periods. For example, from 7 am to 10 am [37] the electricity tariff rates are high, and customers are expected to minimize load during these hours. Practically, electricity rates cannot be fixed for a long time and change according to the varying load demand and supply. This is the essence of DR programs. Thus, in ToU tariff models, if consumers want to minimize electricity bills, they should of necessity schedule their load accordingly. Generally, tariff rates profiles are fixed monthly or seasonally, Fig. 2-11.

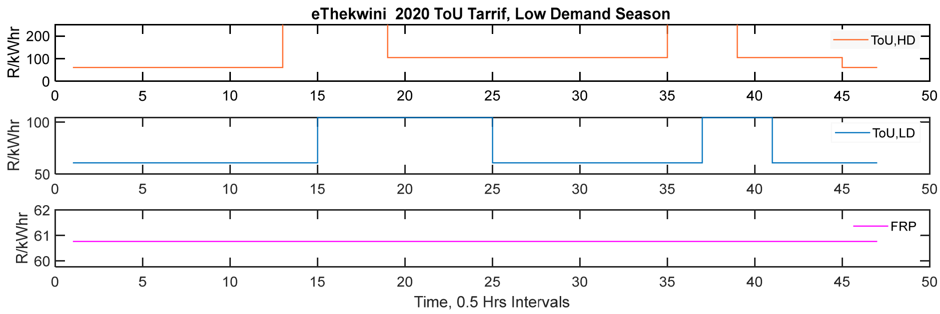


Fig. 2-11. 2020 ToU Tariff differentiation according to time and season

RTP Pricing. To maintain a balance between energy demand and supply, an SM aggregates demand and then re-schedules the working times of appliances to low price periods. Effectively consumers with the same load may see variable electricity bills due to having different consumption patterns. Care is needed not to create peak load elsewhere during low price hours due to customers' tendency to turn on maximum load during these hours. When prices vary hourly RTP is like ToU. Utilities generate price signals by summing the total load of individual networks. As mentioned above prices are high during high demand periods and vice versa. Dynamic pricing creates energy management problems in the system since shifting operational times of certain appliances might discomfort some consumers. As energy consumption cost is directly proportional to the net energy requirement, this problem is convex.

Critical Peak Pricing (CPP). In this scheme, utility customers are incentivized through price signals when the system operator deems it necessary to balance supply and demand. CPP tariff is used in an emergency to arrest grid instability threats. Its ability to reduce load is well proven [122],[132]. It works by increasing the electricity price on system-constrained days and reducing the prices on days the system is not constrained. The system-constrained days are days in which the utility notifies customers of the occurrence of critical peak days as predetermined by the System Operator to balance supply and demand. During critical peak times, after a warning notification is sent a day ahead, the energy tariff rates that will be applied will be significantly higher. The warning signal is for customers to either curtail consumption failing which they pay the critical peak day rates [132].

Incentive-Based Programs. With incentive-based DR programs, customers are contractually expected to curtail consumption during critical peak hours. In a **DLC** tariff regime**,** utilities can shut down electricity for short periods after sending prior notifications [128]. Loads such as HVAC, water pumps, etc can be targeted.

Interruptible Programs. In this DR strategy customers receive incentives in bills. Utilities request consumers to curtail loading over given periods when the supply is under stress. Customers are expected to respond within a half-to-one hour after which penalties are levied depending upon the terms and conditions of the programs.

Demand Bidding. Here customers bid the price for load curtailment or total shutdown. Once agreed, utilities levy heavy penalties for any deviation from the agreed curtailment targets. With such regimes in place, supply is maintained obviating the need to disconnect the load during peak price hours. Some techniques apply to HVAC systems.

Emergency Programs. Here customers are given incentives to reduce the load in emergencies. Participation is open to any customer [133].

Capacity Market Programs. Customers agree to shut download during overload and utilities pay incentives. This strategy is based on day-ahead predictions sent to participants. Penalties apply for no compliance.

The third way of DR is driven by decision variables used [128]. The variables are either Task-scheduling or energy-management based. In task scheduling DR, the strategy is to control the switch-on time of specific loads, whose operation can be moved to times when demand is low. Reduced power consumption during high-demand hours is achieved by reducing the consumption of specific loads [134]. Locally, electricity pricing is set by a government regulatory urgency, NERSA which has to balance the interest of the public and that of the utility [22]. Enabling consumers to participate in DR can spur economic growth fuelling further innovative DR programs. Consumer involvement contributes to energy management solutions which also contributes to the UN's Sustainable Development Goals (SDGs) to reduce carbon footprint, fluctuations in peaks, and increased effects of distributed generation due to its heterogeneous nature.

A properly controlled microgrid constitutes a VPP whose power can be further used to optimize consumption-generation power balance in the grid system. VPP opens the means of integrating building and home automation within the modern power grid environment. Critical features of a responsive and successful DR regime lie in distribution management, smart metering technology, automating building energy consumption or generation prediction engines and transparent pricing information. Real-time measurements of current load and generation will also be imperative.

2.4 DSM Control Algorithms Review

There is a phenomenally exponential rise in published work on DSM for microgrid optimization [135][136][137][138]. General constraints, various objective functions, problem formulation methodologies, and topologies of the smart grids exist in the literature. Vardakas et. al., [72] identified five typical microgrid optimization objectives and outlined a matrix of these criteria vs twenty-two optimization techniques. The characteristic optimization problems in the area are summarised as;

- Electricity cost minimization,
- Consumer utility or comfort function maximization,
- Aggregate power usage minimization,
- Minimization of both cost and total power consumed.
- The comfort maximization and aggregate power consumption minimization.

A typical constrained multi-objective function formulation of the optimization is considered in [139]. This achieves multi-objectives of cost savings, load flattening and peak load reduction. Under certain conditions and assumptions, a Pareto-optimal solving strategy can be formulated, but the optimization model becomes too complex.

Early literature on DR is available in [126][140][141] and the authors present a survey bibliography on pricing signals as they have evolved in electricity distribution systems, and briefly review the growth of some demand-side programs. Studies on relevant demand response smart technologies and markets are covered in [100] [101], and they demonstrate the extent of energy savings and other efficiency metrics that have been achieved in the electricity markets. Descriptions of demand response architectures are presented in [142][143][144][145]with highlights on their requirements, benefits, costs and implementations progress in the USA, Europe and China. The surveys [39],[146],[147] focus on enabling technologies such as SM, Energy Controllers (EC), and cyber-physical communication systems needed for the deployment of DR in SGs.

Traditionally demand side was applied to energy-consuming loads. With the SG hosting easily controllable sources such as PV, WT and ESS, more flexibility for DR is introduced from the generation side. The operation strategy of MGs in the context of DR involves optimization, which means considering all the components in addition to the traditional loads. An optimization simulation done by Yongli Wang et. al.,[148] using the GA algorithm shows that DR based on traditional load curtailment can achieve a reduction of grid power whiles simultaneously increasing RES grid supply.

Of these numerous exact, game theory approaches and metaheuristic DR algorithms techniques [136],[128], the literature is not clear as to which methods are specifically suitable for certain classes of problems that arise in real-life situations. An extensive account of state-of-the-art methods for power scheduling in smart homes is provided as well as possible future research directions in [128],[135]. Simpler optimization models dealing with single-time instant have solutions that can be computed easily in closed-form or by polynomial algorithms [149]. Nevertheless, the class of optimization that investigates multiple intervals discrete-time problems, is characteristically solved by heuristic techniques that may result in suboptimal results. Andras Kovacs [149] introduced the concept of the Simple Multi-Period Energy Tariff Optimization Problem and prove that all such problems are NP-hard. The area of application has mainly been around residential appliance scheduling using price-based DR programs and inputs of;

- Electricity price ToU or day ahead RTP signals obtained from utility or energy retailer SM.
- Consumer utility function from which the optimization algorithm makes decisions.
- Environmental factors such as temperature, occupancy, luminance intensity, etc.

Dispatch in large-scale transmission systems is a typical minimum cost-optimal power flow (OPF) problem. Agent-based distributed algorithms have shown superiority compared to centralized approaches as they require a minimum amount of information sharing. Various offline techniques for distributed optimization and power flow models are summarised in [135]. The Dual Decomposition, Alternating Direction Method of Multipliers, Analytical Target Cascading, the Auxiliary Problem Principle, Optimality Condition Decomposition, and Consensus Innovation are some of the promising methods for finding solutions to a variety of optimization and power control problems. Most of the methods have been applied offline in the literature. Adaptation to online optimization still requires a great deal of work. Surveys of several meta-heuristic optimization techniques and their limitations as applied to offline microgrids are available in [49][150][151].

The population-based meta-heuristic optimization methods that have found application in power system optimization generally belong to three classes namely swarm intelligence (SI) [152], evolutionary algorithms (EA) and the hybrid of the two techniques [150]. Popular evolutionary methods cover Genetic Algorithm (GA), Evolution Strategy

ES), Differential Evolution (DE), Evolution Programming (EP), etc. An extensive discussion of the limitations of these methods and possible research leads can be found in [153]. Firefly, Particle Swarm Optimization, Artificial Bee Colony, Ant Colony Optimization, etc., [108] are some of the most popular SI methods. Other natural phenomena-inspired methods are e.g., Gravitational Search (GSA), Harmony Search (HS) algorithm, Flower Pollination (FPA), Biogeography-Based Optimization (BBO), etc. Fig. 2-12 is an anatomy of commonly applied DR optimization techniques well elucidated in the literature.

Meta-heuristic techniques can tackle multi-objective optimization problems without gradient information and can recover from local optima as they are inherently stochastic. Certain standard benchmark multi-modal, mixed-modal, and unimodal model functions are used to assess the performance of these techniques subject to tuning certain parameters. Standard deviation values of solutions obtained and convergence rates are measures used to compare the performance of the various methods. The weakness of GAs is that they are prone to get stuck in local optimum and their search spaces are small. DE methods though they have been shown to possess average convergence rates, and a greater degree of complexity, in their favour, is easy applicability to a wide variety of problems that include practical scheduling [108],[153].

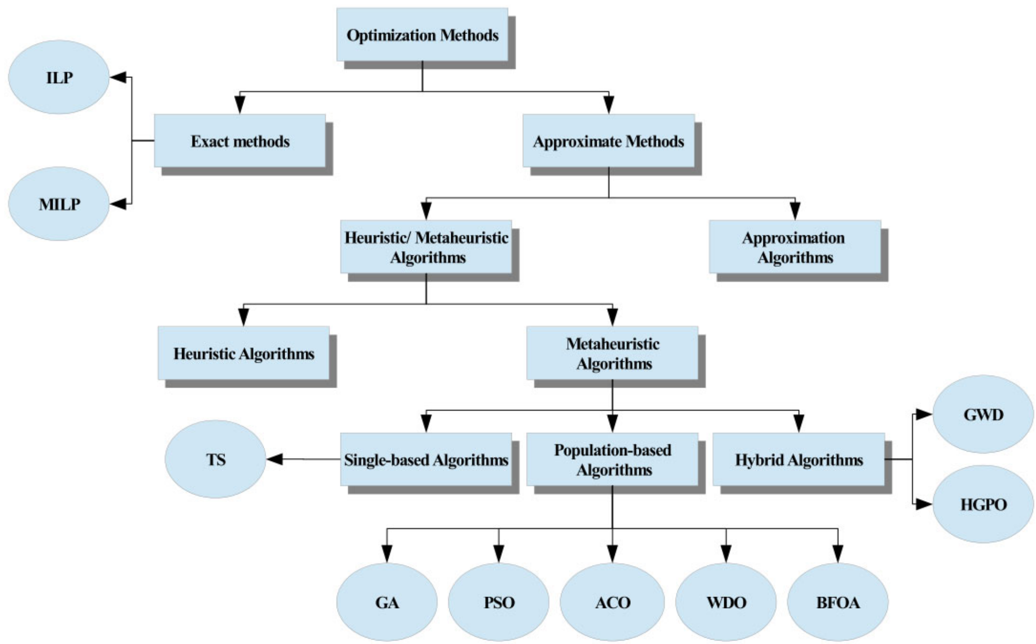


Fig. 2-12. Optimization Techniques Applied in DR[135]

Currently, there is no single method that is well suited for both standard and practical formulations. There is, therefore, a need to find such standard benchmark functions to help with selecting appropriate optimization methods for general cost optimization problems [128].

Gamarra and Guerrero [49] provide an extensive review of other optimization techniques applied to four common micro-grid optimization problems of power mix selection, sizing, siting as well as scheduling which is the focus of this dissertation. Mathematical methods such as linear mixed-integer(LMI) programming take more time to find the optimal solutions compared to the heuristic techniques [154].

Observability, controllability and security are imperatives for successful MG operations [155]. If these can be fully achieved, possible benefits that can be accrued are system performance, customer satisfaction and availability of data to close off gaps in uncertainties. Challenges that persist are lack of real-time system controls, societal barriers to market deregulation, and insufficient time to avail consumers of the time-varying pricing information. Load prediction and control state estimation can be employed to enhance observability in intelligent distribution networks using e.g., agent-based control approach whose architecture derives from distributed control rather than a traditional centralized paradigm. The resultant DEG networks will have enhanced flexibility and adaptability of automation systems hence generally contributing to speeding the progress of Smart Grids. What is needed now is an effort to develop a standardized and integrated vision for SG [156]. Electric vehicle technology will also in the future have a great impact on SG development. Consequently, there exists a huge potential for research both for backup and DSM as well as the provision of flexibilities for main grid management [18] [157].

2.5 Hierarchical Agent-Based Control

Agents are local, and autonomous, yet decentralized to the extent that they can communicate with each other and make control decisions by themselves. The multi-agents [158], integrate to perform and accomplish certain tasks in a complex system. A hierarchical or distributed agent control method based on game theory architecture can capture the ability of self-organization and self-steering to realize individual goals typical of a consumer serviced by a specific microgrid. Multi-Agent-based technology has been successfully used to control microgrids comprising PV plants, batteries, and adjustable loads [158].

A typical autonomous multi-agent system is designed and implemented in [159]. The agents can be sensitive to upstream outages and respond accordingly to allow islanded operation of microgrids. Open source modelling and simulation tools for power systems such as GridLAB-D, UWPFLOW, TEFTS, MatPower, PST, and InterPSS [160][161] are available and help to integrate detailed grid systems and consumer models. These tools enable fast simulation and modelling [39] as they are specifically tailored for MGs studies. A special case of MG at the rural distribution level is considered in [162]. The results illustrate how SG technologies improve rural distribution systems management in terms of energy management.

2.6 Smart Homes (SH) Control Algorithms Review

With appropriate HEMS, optimal scheduling of smart appliances and REG according to specified criteria optimal energy management performance is achievable. The pivotal role of HEMS is to solve the objective function so that the costs, energy consumption, consumer utility or comfort, CO_2 emission etc., are optimal. The HEMS has the dual functions of minimizing the cost of grid energy and the extent of energy curtailment [163] consistent with required comfort levels. Voltage control techniques have been used in some HEMS to reduce power consumption and simultaneously minimize load shifting to avoid consumer discomfort. The load scheduling problem in SH is proposed by various researchers. In [121] using an opportunity-constrained programming model, the problem is solved by stochastic simulation and particle swarm optimization. Different energy tariff models, i.e., ToU, RTP and IBT, FRT etc., for controlling home appliances are considered [118], [164]–[166]. Dynamic pricing is used in DA energy scheduling, whereby prosumers share energy to cut electricity bills, [147].

Model predictive control and identification techniques are also widely employed for automatic control in SH [167][168][169]. Heuristic techniques such as GA [170][171], particle swarm optimization [172][173], Tabu search [174][98], binary backtracking search algorithm [175][176], hybrid algorithms [177][178][153], [179] and evolutionary algorithms [173][180][181] are also in use for optimization. Other mathematical energy management techniques have been employed such as mixed integer programming(MIP) or dynamic programming[182] and game theory optimization as outlined in [61][151], [183]. In these game-theoretic approaches, consumers play different 'tactics', changing day ahead demand predictions, continuously adapting demand to reduce cost, and then evaluating optimality at each step. Alternative concepts, modeling and methods for different HEMSs for SH are reviewed in [20], [151], [184]–[186].

Optimal load scheduling relies on knowledge of price, demand, and REGs yield at specific times. Forecasts of consumption, PV generation, and energy prices have a large degree of uncertainty due to being random as previously alluded to. An optimal scheme for minimization of consumer electricity bills as well as peak demand of homes with BESS using multi-objective optimization demand response programs is presented in [44][187]. The uncertainty of load behaviour is modelled by a normal probability distribution function. To cater for these uncertainties in energy control, stochastic programming (SP), robust optimization approach and chance-constraint optimization [173][188] are also commonly used.

A framework for grid-tied optimization in buildings integrated with EVs, BESS and PV modules to effect demand response control is proposed in [129]. Uncertainty of PV energy output and EV driving patterns as they affect overall energy dynamics are also formulated employing statistical programming. A multi-objective optimization approach is proposed in [189]. Uncertainty is handled using a scenario-based conditional value at risk constrained framework.

A scheme for SH optimization with diverse loads, PV and BESS systems participating as prosumers in DA and RTP markets is proposed in [158]. Stochastic Programming and interval optimization are used to characterize the uncertainties of PV generator output and power RTP scheme fluctuations. A two-stage SP for the participation of the SH in local DA and RTP markets considering EVs, WT generation and controllable demand is then solved. The authors [189] have presented a robust optimal algorithm for SH aggregators to take part in the DA power markets. These aggregators have access to PV generation and storage systems data. The focus of this work is scheduling management of smart homes subject to demand and input uncertainty. Uncertainty of DA pricing is regulated by a ROA scheme rendering the schedule risk-averse. We note that the worst constraint is imposed by limited PV generation.

The information gap decision theory (IGDT) method for optimal energy management of HVAC systems without considering other load types of energy management of SHs given price uncertainty is proposed in [189], [190]. Both advantages and disadvantages of market price uncertainty on consumption costs are investigated. Furthermore, [20][191] present a robust optimization approach to schedule smart buildings with multiple energy generation and storage. The maximum and minimum limits of the time-variable market selling price are used in the risk-opposed scheduling scheme. Due to the use of multiple REGs, these buildings are considered prosumers who can participate in energy markets. To minimize the expected cost of a residential consumer with the uncertainty of RES generation, a two-stage SP is proposed in [192]. Market prices and non-controllable appliances are modelled by the probability scenarios. The weakness of these methods is the requirement for a prior knowledge of statistical parameters which in the case of domestic consumers is still difficult to source.

2.7 Discussion

The chapter has reviewed the techniques for microgrid energy management which are either decentralized or centralized. Centralized optimization uses available information without coordination between sub–MGs. On the other hand, the decentralized technique utilizes partial information for coordinating the MG sub-grids. Each sub-MG sets its optimal settings. Centralized MG control relies on metaheuristic techniques, and decentralized MG management is commonly based on multiagent control. Though many researchers have proposed the centralized approach for managing MGs, the growth of DEG translates to high information demand which in turn means high computational overheads due to the large volume of data.

Distributed energy management is a viable architecture as it solves the problem of high computational burden when using centralized control. Real-time distributed systems control of MGs requires communication layers which result in added costs by way of e.g., Bluetooth, Wi-Fi, wireless networks etc. Successful energy management in MGs entails data acquisition, friendly HMI, and data analytics for meteorological parameters. MG optimization is a single objective optimization problem when a single cost function is considered. The latter function typically corresponds to the OPEX of the MG. The scenario turns into multi-objective when it is required to satisfy multiple optimization criteria visa vee technical, economic, and environmental factors among others. Many researchers have attempted solutions using methods such as the classical LP and NLP, numerous heuristics, agent-based methods, and lately artificial intelligence paradigms which have been elucidated above. Storage systems in MGs are very much an ongoing critical concern. Cost-effectiveness ESS solutions so far have been elusive. Research on the optimal ESS is still required to account for accurate failure models able to accurately predict the battery life in realistic operational conditions.

The concept of SH equipped with smart devices to cope with stochastic optimization approaches is widely being implemented to manage energy consumption where SH is connected to the DEG systems. The overall objective is to attain profitability in real-time (RT) markets through the scheduling of the DEG systems, loads, and storage units. However, the uncertainty of energy cost, PV or WT etc. yield, and consumption need careful consideration too. Some studies in the literature have considered deterministic demand and DEG generation with uncertainties in energy price. Accounting for uncertainties in DEG generation and market prices and a variety of controllable loads results in accurate predictors and hence profitable prosumers. BESS arbitrage between off-peak and peak periods. Deployment of ICT infrastructure will improve energy risk management for smart buildings as well as provide access to consumption data for use in load modelling.

Energy management also encompasses QoS metrics for the smooth operation of MGs especially when the buffering effect of the main grids is absent. To this end mitigation of power QoS in MGs operation through coordination of energy scheduling and an iterative power quality improvement technique are required. Typically, optimal scheduling algorithms seek minimum cost, and the power quality algorithm monitors the MGs for possible voltage deviations, harmonic distortions, and voltage unbalance during operation. Stochasticity for DEGs, loads and electricity prices are still to be fully integrated into energy management tools, [193]. Based on the overall literature review the five conceptual and functional variables of smart energy conservation systems in SH encompass the microgrid, HEMS, demand response, consumer behaviour and forecasting [194].

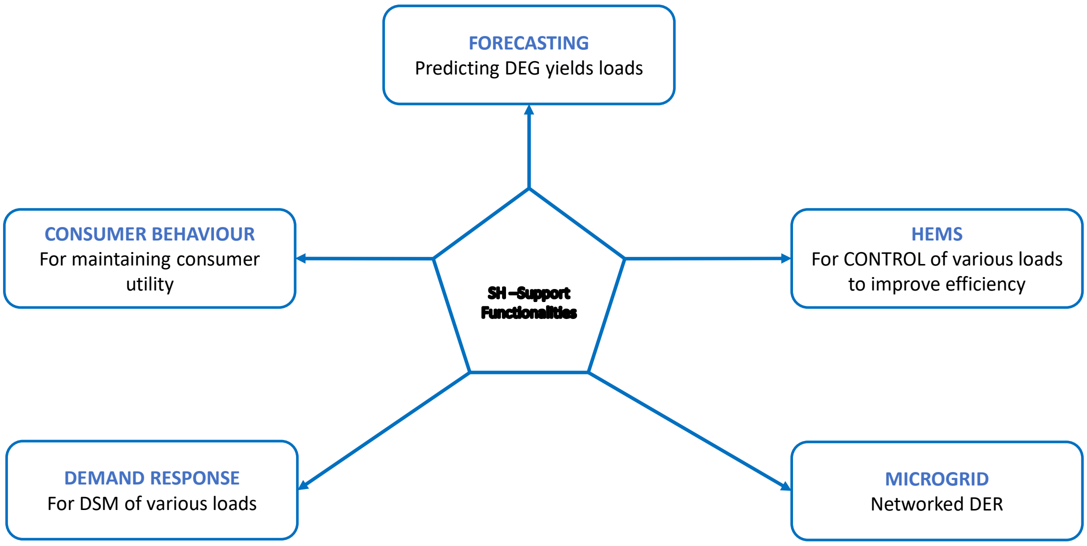


Fig. 2-13. Critical Areas Needing Research in realising fully functional SH

Demand for DEG and BESS should be accompanied by appropriate operating, and management control systems including scheduling to match specific demand profiles. Scheduling strategy will be guided by consumption patterns, and performance objectives such as economic, environmental etc. The research focusing on SGs has three perspectives (i) development of real-time energy monitoring and control systems at the consumer and Neighbourhood Home Networks (NHN)-level taking consumer dynamics into account; (ii) integration of intelligent HEMS energy management; and (iii) interconnection of MGs to form larger energy IoE networks to improve resilience and reliability. Information on the DEGs output coupled with consumption data collected in real-time can assist in reducing PAR via optimal operation algorithm developed using various decision-making tools to realize overall energy efficiency.

2.8 Gaps in the Literature

- Linear Programming (LP) has been used to minimize electricity costs whereby the day is divided into time slots of equal lengths with varying prices of electricity [53]. Uniform length time slots can be replaced with varying time intervals according to the schedules of home occupants and dynamic prices. The objective remains the minimization of energy costs via scheduling. In this scenario input to the optimization engine are consumers' switch-on requests, dynamic power unit cost and the output is optimal load schedule. Further priority subdivision of load to get optimized energy consumption is still possible.

- A scheme for domestic energy management, in-Home Energy Management (iHEM), is presented in [54]. Unlike the LP model, consumers' requests are processed in near real-time. Turn-on requests are made without regard to peak hours concern as iHEM control the actual start time. A user utility index may be incorporated to eliminate manual control.

2.9 The research questions

End-user SG technologies critical for successful DSM being developed cover smart meters, HEMS, EVs systems etc. High-end and bi-directional ICT networks form the framework for real-time optimal control of power systems from generation to consumption. Distributed control, especially at the consumer end, will enable SGs to timeously self-regulate. This boarders well for the grid supply quality, overall stability, and reliability. Both wireline and wireless communication protocols and technologies working on long or short-range have been proposed for HANs and NANs, respectively. However wireless systems coupled with wireless sensor networks in SG open greater implementation possibilities for optimal control, real-time appliance scheduling and DR management.

Stakeholders of the imaging SG are many. These cover utilities/IPP, central regulatory bodies, consumers/prosumers, markets, and DSOs. These stakeholders need fast and reliable interconnection. Consumers demand reliable and economic energy compliant with quality and strict environmental specifications. The SG is expected to embrace and satisfy these diverse demands dynamically as markets, input factors as well as consumption change. Expectations for utilities and consumers may conflict but they are commonalities detected by the global imperative of environmental sustainability.

Peaking demand exacerbates the stress on any electric generation system and if not controlled can induce system instability which widens supply-demand mismatch resulting in unfavourable economic conditions and possible grid collapse. SGs with DSM enhance grid efficiency by peak load shaving. Several techniques for optimization have been proposed for peak load shaving and cost minimization(2.1). However, the major limiting factors to attain the objective function are available capacity and fulfilment of total demand from the combined available sources (2.2).

$$\min_{h} C_{cost} = \sum_{i=1}^{H} \left(\text{ToU}_{tariff} \cdot P_{grid} - e_{g}.P_{DEG} \right) \tag{2.1}$$

$$P_{demad} = \sum_{j=1}^{N} \left(P_{grid,j} + P_{DEG} \right) \tag{2.2}$$

The optimization problem (2.1) can include various parameters like minimization of PAR, appliance waiting time, minimization of CO_2 emission etc. Nevertheless, great research potential exists with more realistic constraints for better optimal results. Ongoing research is looking into HEMS architectures employing various optimization techniques and cloud computing platforms that dynamically allocate priority to controllable appliances. The latter depends on the type and status of the controllable appliances. Dynamic priority allocation is successfully tested and achieved a reduction of 7.3 % in average power consumption with a limited range of appliances. Occupancy sensing-based control strategies introduced in [51] have also received limited attention in the literature.

This research focuses on energy management through scheduling wherein loads are divided into categories to enable more flexibility and attainment of minimal costs in the utilization of power. We also look at various tariff options such as ToU, RTP, and CPP for more user and utility choices. Alternative optimization techniques are compared to provide insights concerning energy cost minimization. Furthermore, we consider multiple DEGs models in the context of the local energy landscape. These contextual aspects make the proposed energy management scheme novel and comprehensive. The problem is simulated in MATLAB using partial data measured at a commercial entity sub-station interfaced with an energy meter.

2.10 Contribution to Knowledge

Work in this dissertation centres on smart grid DSM alongside optimization techniques. The work presents the design and simulation of HEMS typified by multiple appliance scheduling and cost minimization characterized by clear load discrimination. The idea of partial baseline load is implemented in HEMS for further energy cost minimization. The dissertation also looks at a unique scheduling algorithm with the inclusion of a partial baseline and risk index [195] load in the optimization model. Multiple pricing schemes ToU, RTP, CPP etc. are also included in this scheme. The novel idea of risk index load ensures pre-defined slots for the operation of a specific load.

2.11 Conclusion

This chapter has presented background discussions, and a literature review spanning the conventional electrical grid to the SG. The different subsystems of the emerging electrical grid are briefly described as well as the challenges that affect the sector and constraints this new network faces. The SG concept is presented with its DEG components such as generation units, customer/prosumer, communication, and the market. We have also dealt with the main aspects that will allow the transition from the current power grid to the SG. Subsequently, several optimization techniques have been discussed in the context of SGs and SHs are evolving. The next chapter explores concepts of smart home energy optimization.

Chapter 3 Optimization Review

3.1 Introduction

This chapter provides a preliminary review of mathematical techniques applied in this work. In the beginning, the general classical formulation of constrained and unconstrained optimisation problems is outlined. In science, engineering, finance and general business questions often arise problems wherein the 'best' way to achieve some defined objectives [196] is sought. The travelling salesman problem (TSP)[197][198] is a well-known case that seeks the optimum route to be taken given a set of points and distances that must all be visited. For communication networks, the problem can be finding the most efficient route for ingress traffic to travel between various network nodes. For the electrical SG or the energy system, this interrogation can be the question of deciding on the production resources to be operated in a specific period and how much energy should each produce. In an SH the best combination of appliances to be switched on for maximum benefit or minimum cost can be sought. Such kinds of difficult problems belong to a mathematical set of problems under the banner of mathematical optimization for which numerous optimization techniques exist.

Generally, optimization refers to mathematical techniques for finding the best solution in some sense that satisfy specified optimality criteria of a given problem from a set of possible solutions. The function for which the optimum value is sought is called the objective function, fitness function, loss function or cost function. These names arise since the purpose of optimization is usually to reduce costs. In other words, optimization involves discovering the best values of an objective function within a defined domain subject to some specified constraints. This best solution if found satisfies the optimality conditions and minimizes or maximizes the objective function. They are many different types of optimization problems and solution techniques depending on the decision variables, objective functions and nature of the constraints, [199]. The points at which the best values are obtained are collectively called optimum points.

In Calculus, we find they are four types of optimum or 'stationary' points i.e., maximum, minimum, inflexion and saddle [199] points. Given $x \in R^{\mathbb{1}}$, a single variable function $f(x)$ has a local interior minimum stationary point at $x = x_{opt}$ on the interval $[a, b]$ if

$f(x) \le f(x_{opt} + \Delta x)$ for all incremental values of Δx. By the same token x_{opt} is a local maximum if $f(x) \ge f(x_{opt} + \Delta x)$ for all incremental values of Δx . A point x_{opt} is an inflexion point if the function value increases locally as x_{opt} increases and decreases locally as x_{opt} reduces. The function has a global or absolute minimum at $x = x_{opt}$ if $f(x) \ge f(x_{opt})$ for all x in the domain over which $f(x)$ is defined. $f(x)$ has a global maximum at $x = x_{opt}$ if $f(x) \le f(x_{opt})$ for all x in the domain over which the function is defined? These points are illustrated in Fig. 3-1.

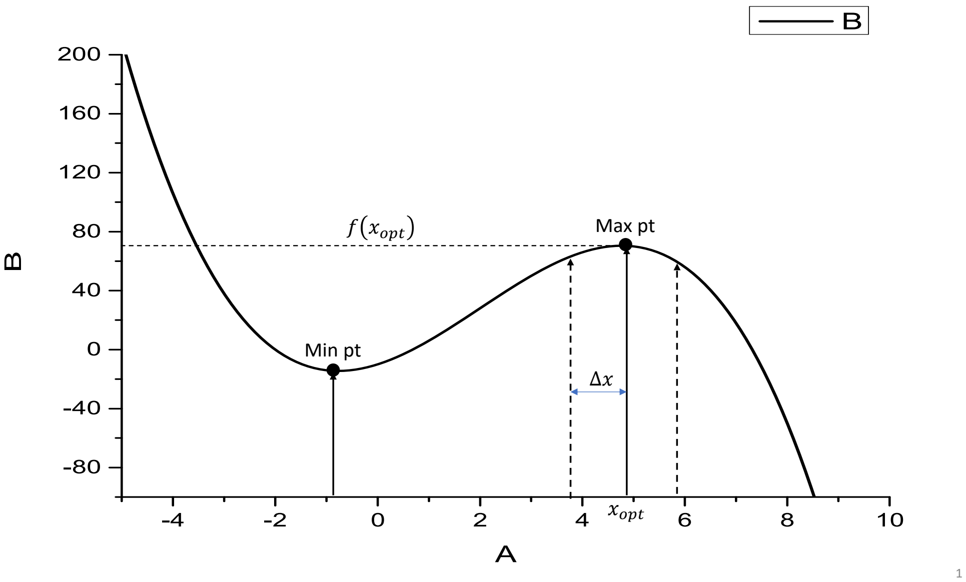


Fig. 3-1. Illustration of mini-max points for a single variable function f(x)

Another important concept in optimization is convexity. Mathematically, a real-valued function $f(\underline{x})$ defined on n-dimensional R^n interval is said to be convex if a chord drawn connecting any arbitrary two points on the graph of the function lies above the graph between the two points. This is illustrated in Fig. 3-2. The line segment from $\left(\underline{x}, f(\underline{x})\right)$, to $\left(\underline{y}, f(\underline{y})\right)$ lies on or above the graph of $f(\underline{x})$. Thus $f(\underline{x})$ is convex. A function is concave if - $f(\underline{x})$ is convex i.e., if the chord from *x* to y lies on or below the graph of $f(\underline{x})$.

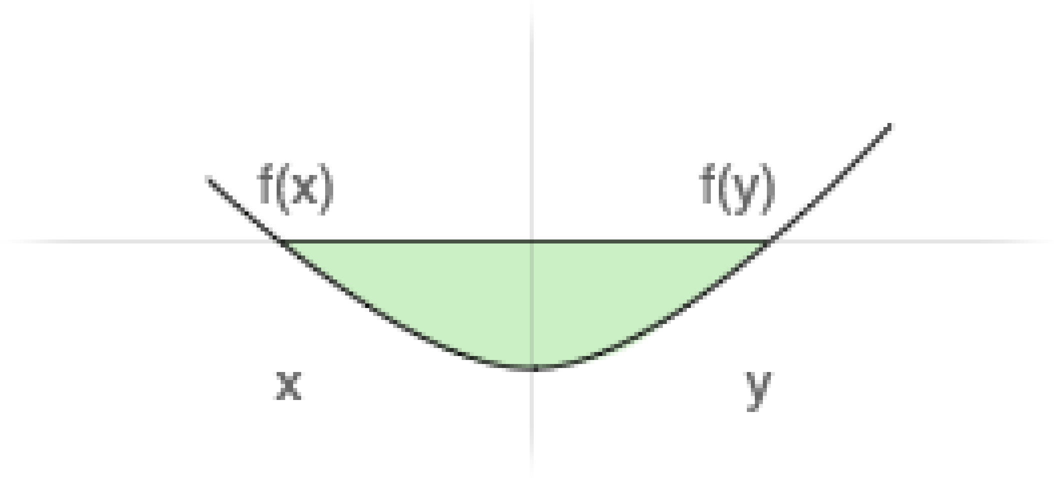


Fig. 3-2. Convexity of a function f(x)

Algebraically, $f(\underline{x})$ is convex if, for any x and y, and any t between 0 and 1;

$$\mathrm{f}(tx + (1-t)y) \leq tf(x) + (1-t)\mathrm{f}(y). \tag{3.1}$$

Convex optimization problems are solvable with a variety of techniques, but interior point or barrier techniques are appropriate for convex functions, as they handle linear, quadratic, conic, and smooth nonlinear functions in essentially the same way. They use a smooth convex nonlinear barrier function for the constraints.

Optimization problems are also solvable by either mathematical programming or (meta)heuristic methods. Traditional optimization techniques e.g., Newton-Raphson and interior point methods are well-grounded, but they cannot tackle large nonlinear (NL)real-world problems. NL problems have multiple stationary points whereby conventional optimization techniques easily get trapped at a local optimum. The modern Nature-Inspired Optimization (NIO) algorithms have greater success in attaining near-global optimal solutions. In this context, NIO algorithms do feature predominantly in the literature in handling real-world problems, [196].

The main heuristic optimisation methods are explored in Section 6.2. Unlike (meta)heuristic methods, mathematical programming techniques can guarantee optimality. However, heuristic methods can solve high-dimensional and complex problems whiles mathematical programming techniques fail as the dimensionality of the optimization problem grows. Combining these two approaches leads to better solvers for optimization problems. Early 21^{st}-century optimization developments have seen algorithms that merge mathematical programming solvers into (meta)heuristic frameworks and vice versa with demonstratable superior results in solving large complex optimization engineering problems. Optimization plays a significant role in smart energy management as far as achieving desirable load profiles is concerned. The energy management problem has various objectives and constraints.

3.2 General Multivariable Optimization

Fig. 3-3 illustrates a 3D plot of a function $z = f(x, y)$ with multiple optimum points depending on the domain of decision variables. $z(*)$ assumes scaler values depending on values of the independent variables (x, y). An optimization problem can either be constrained or unconstrained. Constrained problems have one or more equality and/or inequality constraints, with or without side constraints. Optimization techniques, or algorithms, used to solve these problems try to find the combination of decision variable values that maximize or minimize the objective function and simultaneously satisfy the equality, inequality, and side constraints.

Generally, the objective function is formulated in terms of $\underline{x} \in R^n$ decision variables. NL constrained optimization problem involves finding the best set of decision variables $\underline{\mathbf{x}}$, that minimize or maximize the scaler objective function $f(\underline{\mathbf{x}})$, Error! Reference source not found. (3.2) subject to certain constraints. The vector $\underline{x}^*_{opt} \in R^n$, of the decision variables that optimizes the objective function $f(\underline{x}^*_{opt}) = p^*$ is called the optimal vector. Typically, a constrained optimization problem has equality constraints (3.3), inequality constraints (3.4), and upper and lower bounds (3.5) on the decision variables $\underline{x}$ that must be satisfied.

$$\min_{\underline{x} \in R} f(x), \quad f(x): \mathbb{R}^n \to \mathbb{R} \tag{3.2}$$

subject to; $$h_i(\underline{x}) = 0, \qquad h_i(\underline{x}): \mathbb{R}^n \to \mathbb{R}, \;\; \mathrm{i} = 1,2, \dots, \mathrm{m} \tag{3.3}$$

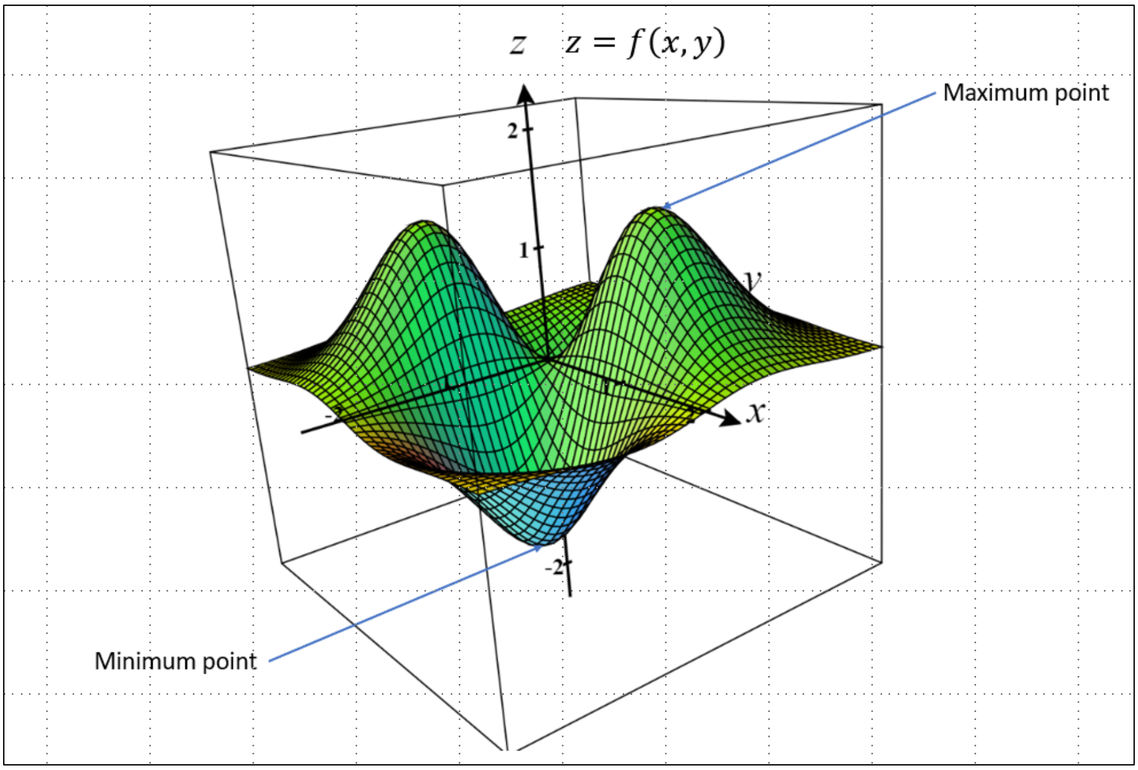


Fig. 3-3. General Illustration of Optimum points in $\boldsymbol{R}^3$

$$g_j(\underline{x}) \leq 0, \quad g_j(\underline{x}): \mathbb{R}^n \rightarrow \mathbb{R}, \quad \mathrm{j} = 1,2, \dots, r \tag{3.4}$$

$$x_{j,LB} \leq x_j \leq x_{j,UB}, \quad \mathrm{j} = 1,2, \dots, n \tag{3.5}$$

The first set of m equations is what is referred to as equality constraints and the second set of r equations is the inequality constraints. The feasible solution set is;

$$x_{feasible} = \{\underline{x} | g_i(\underline{x}) \leq 0, \, j = 1,2, \dots, r, \quad h_i(\underline{x}) = 0, i = 1,2, \dots, m\} \tag{3.6}$$

Wherein at a feasible point, $\mathrm{f}(\underline{x}_{feasible}) \leq p^* + \epsilon$, ϵ is a sub-optimal parameter, and the optimal value,

$$p^* = \inf\{\underline{x} | g_i(\underline{x}) \leq 0, \, j = 1,2, \dots, r, \quad h_i(\underline{x}) = 0, i = 1,2, \dots, m\} \text{ and if} \tag{3.7}$$

$$p^* = \infty, \text{the solution is not feasible} \tag{3.8}$$

$$p^* = -\infty, \text{solution is unbounded from below.} \tag{3.9}$$

They are problems where the decision variables $\underline{\mathbf{x}}$ only take on integer or discrete values, a situation that would give rise to what's referred to as integer or discrete optimization. Integer and/or discrete optimization problems are difficult to solve with local optimization techniques, but global algorithms are well suited to these problems. In a household, x_i for instance, could be the number of electrical energy-consuming appliances or the number of REG for a prosumer. The modelling of such problems includes integrality constraints i.e., $x_i \in \mathbb{Z}$, where $\mathbb{Z}$ is the set of integers. Such problems fall in the class of integer programming, which can be linear or non-linear. If some variables are not restricted to be integers, the nature of the optimization problems is defined as a mixed integer programming problem (MIP).

LIP problems are discrete optimization problems for which the parameters to be optimized are drawn from a finite set. In contrast, the feasible set for continuous optimization problems is usually uncountably infinite. Continuous optimization problems are smooth and amenable to the analytical solution. In discrete problems, the behaviour of the objective function and constraints may change drastically from one feasible point to another in a neighbourhood. Due to this, feasible points of discrete optimization problems exhibit an extreme form of none-convexity i.e., a convex combination of two feasible points is in general not feasible. The solutions are thus hard to find.

Generally, algorithms for optimization achieve local solutions, points where the objective function is smaller than at all other feasible nearby points. Finding an optimal solution in all search spaces i.e., the global solution is often difficult, and what is usually found is sub-optimal solutions. In convex programming problems, particularly for linear problems, local solutions are also global solutions. Generally, both constrained and unconstrained NL optimization problems may possess local solutions that are not global.

3.3 Types of Optimization Problems

Different ways of classifying optimization problems exist [150]. In this section, we review this classification. What influences the classification of the optimization problems is the nature of decision variables, the objective function(s), and the limitations imposed on the problem [16]. In some models' decision variables are discrete, or as often a subset of integers. In others, decision variables take on any real values. The classes are briefly described and illustrated in Fig. 3-4.

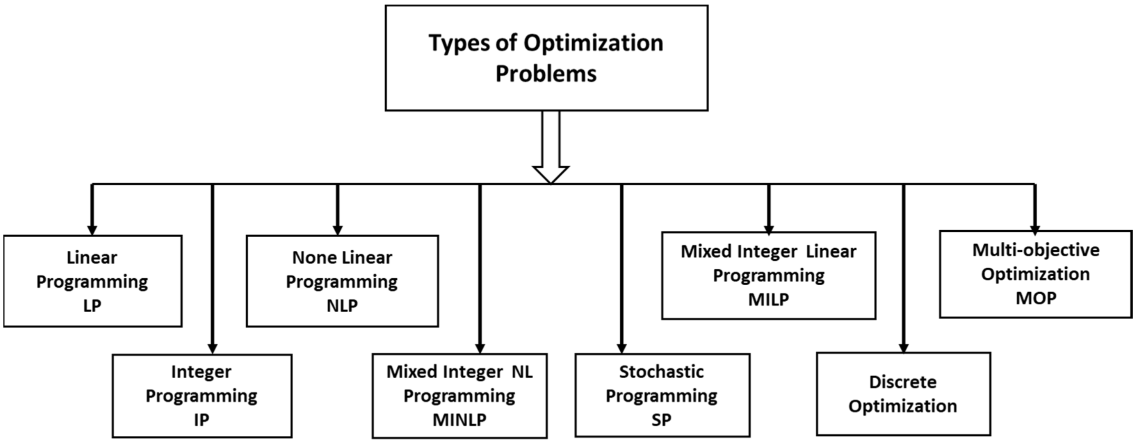


Fig. 3-4 Types of optimization problems

Continuous vs Discrete Optimization

In mathematics, a real-valued function is continuous when the graph does not have any breaks or discontinuity in its domain i.e. it's uncountable,[200]. On the contrary, a discrete function is one where a domain is countable hence a finite unordered set. For the discrete function, the *y*-variable is termed the class and its value is the class label. Discrete models are classification problems which means when the function is learned it is used to determine the *y*-values given the *x*-variables. Usually, the obtained function is a one-to-many i.e., for a given *x*-value the function returns a set of *y*-values. Its elements may be weighted, usually with their probabilities. Typical scenarios involve functions mapping from the problem space into a multidimensional continuous space such as weather forecasting.

Models with discrete decision variables give rise to discrete optimization, whereas models with continuous variables give rise to continuous optimization. Continuous optimization problems are easier to find solutions for than discrete. As continuous functions are smooth, the objective function and constraint function are amenable to gradient search techniques. However, advancements in ICT have increased the dimensionality and complexity of discrete optimization problems that can be efficiently tackled. Continuous techniques also play a significant role in discrete optimization. This is the case because many discrete algorithms generate a sequence of continuous sub-problems [176].

Constrained vs Unconstrained Optimization

Another important distinguishing characteristic is whether the optimization problem (3.2) has or does not have constraints or limitations on the decision variables, $\underline{x} \in R^n$. Constrained optimization problems occur in situations in which there are explicit limits on the variables such as resource allocation or specification limits. These constraints can be in the form of simple bounds, equalities, or inequalities representing relationships between the decision variables. Constrained optimization can still be classified according to the nature of the constraints e.g., nonlinear, linear, convex, and the differentiability of the constraint functions. Unconstrained optimization problems occur in some real situations. These can also arise when constrained optimization problems are reformulated such that the constraints are replaced by penalty terms in the objective function.

Classification Based on Several Objective Functions

Most optimization problems involve at least one objective function (OF), but there are also instances where no OFs are stated. Such optimization scenarios belong to the class of feasibility optimization. Here the target is to obtain values of the decision variables that meet the constraints of the problem without any specific objective function to be optimized. A complementarity problem is one of optimizing (minimizing or maximizing) a function of two vector variables with constraints which include the requirement that the two vectors are orthogonal. Such optimization problems are quite ubiquitous in engineering and the sphere of economics.

Another class of optimization problems has more than one objective function. In such instances, optimality must be attained as a trade-off between competing objectives such as when developing an engine competing requirement might be minimizing weight while simultaneously maximizing power at minimum risk. To make solutions tractable, multi-objectives optimization problems are often reformulated into a weighted single objective or part of the objectives are replaced by constraints. Peroto optimal optimization of multi-objective functions with the concept of Peroto front is yet another methodology for understanding multi-objective optimization problems.

Multi-Objective Optimization

Problems that involve the simultaneous optimization of several objectives exist in many applications [177][201]. Such multiple objectives may be of different dimensional units and often conflict or compete among themselves implying improvement of one objective deteriorates at least one or more of the other objectives. These kinds of problems belong to the class of optimization called Multi-objective Optimization Problems (MOPs) (3.6) as outlined in the section above. Multi-objective optimization problems do not have direct methods to determine if one solution is better than the other. The concept of Pareto dominance is used [177] and it results in a set of alternative solutions with different trade-offs between the objectives. Such solutions are called Pareto optimal solutions or non-dominated solutions. Multi-objective optimization problems are solved by either Multi-Criteria Decision Making (MCDM) or Evolutionary Multi-objective Optimization (EMO)[202]. Pertinent concepts are briefly outlined below.

Definition I Multi-objective Optimization Problem. Given m multi-objective Optimization functions $f_1(\underline{x}): \mathcal{X} \rightarrow \mathbb{R},\ f_2(\underline{x}): \mathcal{X} \rightarrow \mathbb{R}, \dots, f_m(\underline{x}): \mathcal{X} \rightarrow \mathbb{R}$ which maps a decision space $\mathcal{X}$ into $\mathbb{R}$, a multi-objective optimization problem is given by the following statement:

$$min\ f_1(\underline{x}),\ min\ f_2(\underline{x}), \dots, min\ f_m(\underline{x}),\ \underline{x} \in \mathbb{R} \tag{3.10}$$

The decision variables $\underline{x} \in \mathbb{R}^n$ must be determined. The feasible set $\mathcal{X} \in \mathbb{R}^n$ is implicitly determined by a set of equality and inequality constraints. The multi-objective functions $\underline{\boldsymbol{f}}(\underline{x}): \mathbb{R}^n \rightarrow \mathbb{R}^m$ is made-up of m-scaler objective functions $f_i(\underline{x}): \mathcal{X} \rightarrow \mathbb{R}$, $\mathrm{i} = 1,2, \dots, \mathrm{m}$ optimization. The set $\mathbb{R}^n$ is the decision variable space and $\mathbb{R}^m$ is objective function space. The image of $\mathcal{X}$ under the function $f_i(\underline{x})$ is a subset of the objective function space denoted by $Z = f(X)$ and referred to as the feasible set in the objective function space.

Deterministic Optimization vs Stochastic Optimization

When an optimization problem is deterministic, a strong assumption exists that data for the problem is accurately known. For various reasons in practical situations, the data is known with a degree of inaccurately e.g., due to measurement error, prediction failure or other difficulties, [203]. Optimization under such inaccuracies incorporates the uncertainty into the model and robust techniques often help when the uncertain parameters are known to certain error limits. Stochastic optimization (SO) refers to techniques for optimizing an OF given random behaviour of decision variables involved. The overall aim of SO is to find feasible solutions that are optimal in some sense. Stochastic programming leverages the fact that probability distribution functions relating to the data may be known or estimated to model the events under investigation. The optimization goal then translates to finding a feasibility policy for almost all occurring data points and optimization of the expected model performance.

3.4 Types of Optimization Techniques

One possible classification of optimization techniques is shown in Fig. 3-5. Depending on the complexity and the difficulty of the solution, exact or approximate optimization methods exist. The classical exact techniques are suitable for medium-sized problems. They have relatively short processing time but can encounter problems with more constraints [150]. Exact optimization techniques can be linear or NL. These can find optimal solutions when specified in a feasible region. The linear models are divided into three types, namely; LP, Integer Programming (IP) and a combination of the two i.e., mixed integer linear programming (MILP), according to the variables if they are real, integers, or both variable types correspondingly. The approximate methods can handle the NL constraints and NL objective functions. However, they cannot guarantee the optimality of results because they employ random search methods [84]. As the dimensionality of the problem increases, it becomes more difficult to find a global solution[204].

In stochastic optimization one or more of the input parameters is a random variable i.e., it behaves in a probabilistic way. Stochastic phenomena occur in many fields encompassing communications, energy utilization as well energy production involving renewable sources. Stochastic processes always involve probability, such as trying to predict solar insolation at a certain time based on random distribution of insolation incidence or estimating the number of on-appliances in each smart grid network based on random domestic consumer behaviour. In contrast, some phenomena either occur or do not occur, such is called deterministic. Stochastic optimization lends itself to real-life problems as many phenomena in the physical world involve randomness. In all instances, the objective is to maximize the cost function given the random decision variables.

Stochastic techniques have the advantage of flexibility in modelling both time-dependent and coupling constraints. Constraints handling and repairing mechanisms ensure feasible search space and increase the rate of convergence. These techniques are also easy to implement, they are simple in concept, and have the potential to achieve high-quality solutions. There is also the added flexibility to control the balance between global and local exploration. However, on the downside, they cannot guarantee the optimally of the provided solution and tend to have a high execution time [205].

Hybrid techniques employ multiple methods to enhance optimization characteristics [79]. They are easy to implement, have better convergence, and generally they are good at finding highly near-optimal solutions. However, their weakness is they depend on trials and fine-tuning.

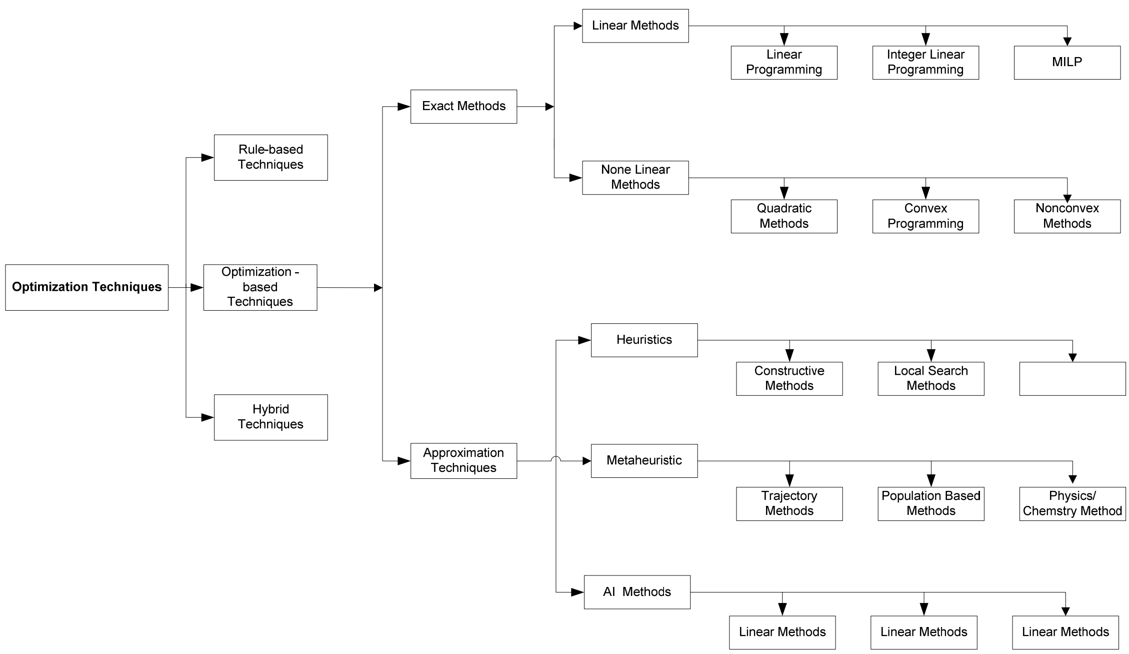


Fig. 3-5 Optimization techniques classification

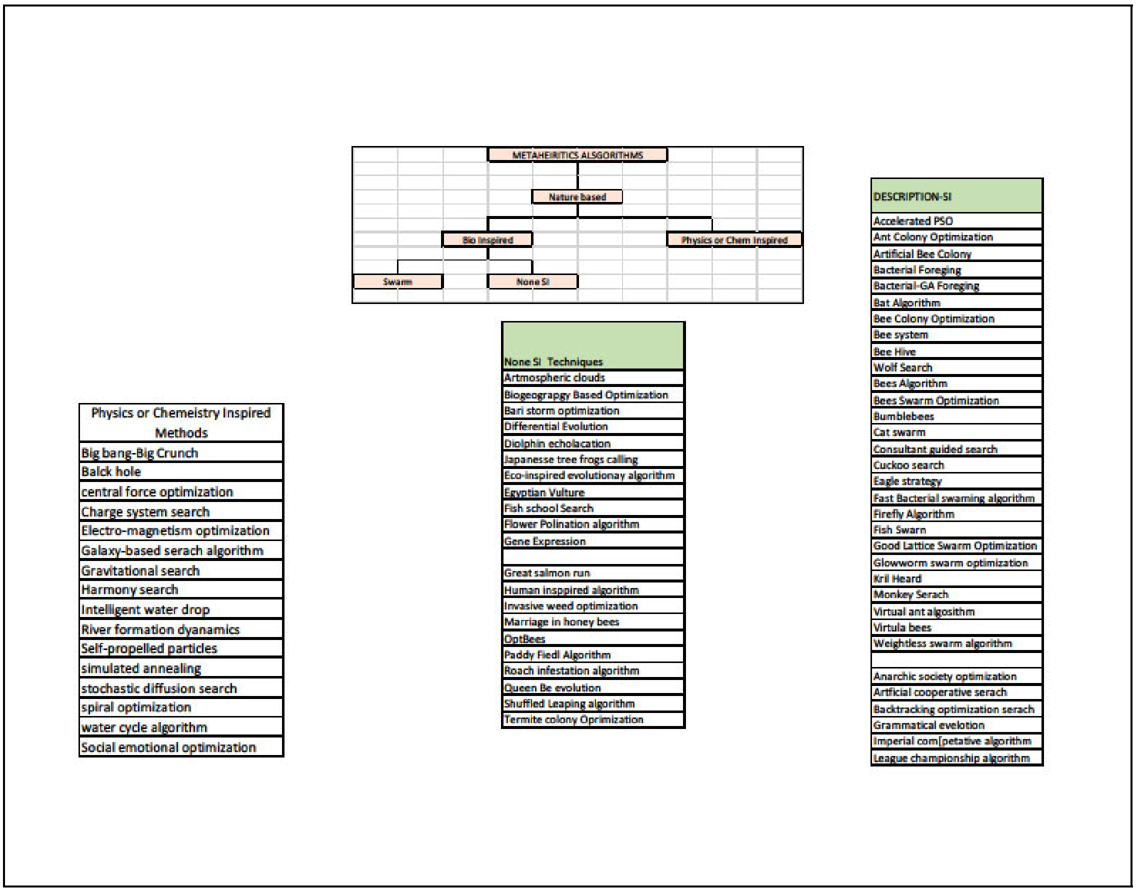


Fig. 3-6. Metaheuristics techniques[206]

Previous related research work on demand response optimization and computational intelligence techniques in an SG environment are reviewed in the subsequent chapter. The chief characteristics of the various techniques outline in Fig. 3-5 are summarized below.

- Linear programming: Objective function and constraints are linear and decision variables are scalar and continuous, (3.11) - (3.14).
- Non-linear programming: Cost function and/or constraints are NL and decision variables are scalar and continuous.
- Integer programming: Decision variables are scalars and integers.
- Mixed integer linear programming: Cost function and constraints are linear. Decision variables are scalar integers and others belong to the continuous domain.
- Mixed integer non-linear programming: Non-linear programming problem with integer as well as continuous decision variables.
- Discrete optimization: Involves integer decision variables.
- Stochastic optimization: The objective function and/or the constraints are random variables.

- Multi-objective optimization: These involve multiple cost functions.

Linear Programming Optimization

Problems in this class share three defining features; The decision variables are continuous i.e., $\underline{x} \in \mathrm{R^n}$ and the objective functions are linear combinations of the decision variables (3.11).

$$\mathcal{J}(\underline{x}) = b_o + b_1x_1 + b_2x_2 + \cdots + b_nx_n = b_o + \sum_{i=1}^{n} b_ix_i \tag{3.11}$$

where $b_i \in \mathbb{R}$. The equality and inequality constraints are all linear in the decision variables taking the form;

$$\sum_{i=i}^{n} \alpha_{ji}x_i = b_j, \qquad j = 1,2,\dots,n_e \tag{3.12}$$

$$\sum_{i=i}^{n} \beta_{ji}x_i \geq b_j, \qquad j = 1,2,\dots,n_g \tag{3.13}$$

$$\sum_{i=i}^{n} \mu_{ji}x_i \leq b_j, \qquad j = 1,2,\dots,n_l \tag{3.14}$$

Where $n_e, n_g \quad and \;\; n_l$ are the number of equality, greater than/equal to inequality and ($\geq$), less than/equal to inequality ($\leq$) constrains. A MILP will have the same general form as above with additional restrictions on the decision variables i.e. for some $n_{interger} + n_{real} =$ n and $\underline{x} \in \mathrm{R^n}$, $x_i \in \mathbb{R}, i = 1,2,..,n_{real}$ and $x_j \in \mathbb{Z}, j = 1,2,\dots,n_{interger}$. The latter is an integrality constraint. A general LP may include all or some of these constraints.

LP with integer decision Variables

Linear optimization problems where some decision variables are integers belong to the class of mixed integer linear programming (MILP). If $\forall j,\ j = 1,2,\dots,n \quad x_j \in \mathbb{Z}$ then the problem is purely an integer optimization problem. Further if $x_j \in \{0, \quad 1\}$ i.e., if decision variables are binary, then the problem is a pure binary linear optimization problem. Three characteristics define MILP problems;

1. Decision variables can be integer-valued and others real-valued i.e., $x_j \in \mathbb{Z}$ and $x_i \in \mathbb{R}$ respectively.
2. The objective function is linear in the decision variables (3.11),

3. Constraints are all equality or inequality constraints, linear in the decision variables. A MILP objective function can thus be written as;

$$\mathbb{J}(\underline{x}) = c_o + \sum_{i=i}^{n} \alpha_{ji} x_i , \qquad j = 1,2, \dots , n \tag{3.15}$$

St.
$$\sum_{i=1}^{n} \alpha_{ji} x_i = b_j, \qquad j = 1,2, \dots , n_e \tag{3.16}$$

$$\sum_{i=1}^{n} \beta_{ji} x_i \geq b_j, \qquad j = 1,2, \dots , n_g \tag{3.17}$$

$$\sum_{i=1}^{n} \mu_{ji} x_i \leq b_j, \qquad j = 1,2, \dots , n_l \tag{3.18}$$

Stochastic Optimization (SO) Techniques

Stochastic optimization problems are optimization problems involving uncertain data. Deterministic problems are formulated with known parameters, whereas in real life uncertainty in parameters is ever-present. Usually, the uncertain parameters behave according to a known probability distribution function(pdf), or the pdf can be deduced from observed data. Hence stochastic techniques fit unknown data to known pdf. The objective is to obtain a solution applicable to most of the observed data such that the expectation of an objective function of the decision variables used to measure the fitness of the solution is maximized or minimized. In [207] uncertainties associated with the duration of unscheduled islanding events in a microgrid with renewable generation, are modelled within a framework of multi-objective stochastic MILP.

The models introduced earlier assume determinism in the model parameters. They are limits to this assumption as some system parameters will always be indeterministic. However, in certain instances, the degree of uncertainty in a system renders the deterministic approach unsuitable. For this reason, uncertainty or random phenomenon is introduced into the optimization problem. If the set of the uncertain parameters is, $\chi = \{\mu_1, \mu_2, \dots, \mu_m\}$, the generic stochastic expectation $\mathbb{E}$, of an optimization problem, can be formulated as follows:

$$Min\ \mathbb{E}_{\mu_1,\mu_2,\dots,\mu_m}\{\mathbb{J}((x_1, x_2, \dots, x_m), (\mu_1, \mu_2, \dots, \mu_m))\} \tag{3.19}$$

Statistical Optimization with Recourse

In stochastic problems, the decision-maker decides in an instant and then afterwards tries to optimize the expectation of the objective function (usually costs) of a decision taken. This idea or concept is referred to as the recourse action or recourse modelling. The easiest form of recourse modelling comprises two steps: a decision is taken in the first step, then the suitability of the uncertain parameters is assessed at the beginning of the second stage, and further step 2 corrective recourse action is taken considering this new information. These simple modelling steps can be extended to multi-stage recourse actions. In a *multi-stage* scenario, a decision is made in the first step, then some uncertainty is resolved in the second step and then a new decision is made based on the knowledge deduced in the previous stage, and then some other uncertainty is resolved in that progression. At each step, the objective is to minimize the expected costs of the decisions[208].

Evolutionary Algorithms (EA)

Genetic algorithms have three functional operators which are crossover, mutation, and selection. *Crossover* involves swapping parts of the solution with another in chromosomes or solution representations. This enables the mixing of the solutions and convergence in a subspace. Crossover can only result in solutions in a subspace and the converged solutions/states will remain converged. *Mutation involves a* change of parts of one solution randomly. Mutation usually leads to a solution outside the subspace. This increases the diversity of the population and provides a mechanism for escaping from a local optimum. *Selection of the fittest, or elitism involves the use of* solutions with high fitness to pass on to the next generations, which is often carried out in terms of some form of a selection of the best solutions. In actual algorithms, the interactions between these genetic operators make behaviour very complex. However, the role of the individual components remains the same.

One important issue is the random selection among the population. For example, crossover requires two parents in the population. Do we choose them randomly or biased toward the solutions with better fitness? One way is to use a roulette wheel to do the selection; another is to use fitness-proportional selection. There are other forms of selection in use, including linear ranking selection, tournament selections, and others. Both crossover and mutation work without the use of the knowledge of the objective or fitness landscape. Selection of the fittest, or elitism, on the other hand, does use the fitness landscape to guide what to choose and thus affects the search behaviour of an algorithm. What is selected and how solutions are selected depend on the algorithm as well as the objective function values. This elitism ensures that the best solutions must survive in the population. However, very strong elitism may lead to premature convergence.

EAs belong to a class of heuristic techniques for solving problems difficult to solve in polynomial time. These algorithms as in Darwin's Evolution Theory [198], use the 'natural' selection process where the least fit members of a population diminish, and the 'species' or solutions with better optimal fitness values survive and 'reproduce' until solutions with better fitness are found. Thus, EA algorithms imitate biological evolution to solve highly difficult problems. Of the numerous EA [177], the most prevalent in the literature are Genetic Algorithms (GA) [153] and Particle Swarm Optimization (PSO). GA and PSO mimic the genetic processes of biological organisms' natural selection processes and intelligent behaviour of various swarms when e.g., foraging. Many of the EA based on swarm intelligence techniques such as Ant Colony Optimization, Bees algorithm, etc. are explored in [94].

The traditional optimization techniques using gradient search at best can solve local optimization problems. Irrespective of the complex algorithms [19] that now exist, the success of the traditional optimization techniques depends on the starting point. For simple LP they can attain the global optimum solution. However, for NLP problems, solvers get easily "trapped" in a local optimum point. Nondeterministic, high dimensionality problems require longer computational time and power to attain optimum solutions. For mildly difficult problems, a traditional optimization is a good option considering the attainment of optimality and lower computational power required.

EAs can be easily adapted to higher-dimensional problems. This easiness of adaptability of these algorithms is what attracts the most criticisms of EA techniques as different algorithmic configurations tend to give rise to different solutions. Another disadvantage is early convergence to local stationary points because of poorly configured algorithms not attaining the global optimum. The EA approach is suited to the size and the nature of the optimization at hand though considerable time and computational resources will be required as the dimensionality increases.

3.5 Complementarity and Optimality Conditions

Energy production in many parts of the globe is liberalizing giving rise to a new paradigm of markets featuring predominantly both the old centralized and highly regulated structure and the new, deregulated architecture with many players. Since the deregulated market is still very small in comparison, the competition between regulated and de-regulated markets is still very imperfect. For control and operational reasons, robust market models are needed to assist and guide decision-making with these attendant developmental imperfections. Complementarity models, an increasingly popular framework for formulating and solving bottom-up energy market models find use in this context for energy market modelling, [209]. These models generalize linear, (convex) quadratic, and (convex) nonlinear programs. The link is made possible through the Karush-Kuhn-Tucker optimality conditions for the appropriate problems. Statement of these conditions is a special case of a complementarity problem. Of note is the fact that the link between non-convex optimization and complementarity problems fails due to the lack of meaningful KKT conditions.

Complementarity Problems Generalization

A complementarity problem is an optimization problem. It involves minimizing or maximizing a function of two vector variables subject to certain requirements or constraints. These models can represent the simultaneous optimization problems of one or several interacting consumers or prosumers in the energy market. Fundamental to all complementarity problems are the complementarity conditions, each of which requires the product of two (or more) non-negative quantities to be zero i.e., they should satisfy the orthogonality condition. Mathematically, $\underline{x}$ is complementary to $\underline{y}$ if,

$$\underline{x} \geq 0, \quad \underline{y} \geq 0 \quad \text{and} \quad \underline{x}^T \cdot \underline{y} \geq 0 \tag{3.20}$$

which is typically written in a more compact form as,

$$0 \leq \underline{x} \perp \underline{y} \geq 0 \tag{3.21}$$

The "perp" operator $\perp$ denotes the inner product of two vectors. Given a square matrix $\mathbb{M} \in \mathbb{R}^{n \times n}$ and a column vector $\mathbb{q} \in \mathbb{R}^n$, the linear complementary problem (LCP) is to find $\omega = (\omega_1, \omega_2, \ldots, \omega_{n-1}, \omega_n)^T$ and $\xi = (\xi_1, \xi_2, \ldots, \xi_{n-1}, \xi_n)^T$ satisfying the condition;

$$\omega - \mathbb{M}\xi = \mathbb{q} \tag{3.22}$$
$$\omega \geq 0$$
$$\xi \geq 0$$
$$\omega_i \xi_i = 0, \quad i = 1,2,\dots,n$$

LCPs are very important problems in optimization as the optimality criterion for LP and the necessary optimality conditions for quadratic programming can be formulated as LCPs. LCPs also arise naturally in many applications in engineering science and economic problems.

Karush-Kuhn-Tucker Optimality Conditions

The Karush-Kuhn-Tucker (KKT) optimality conditions play a significant role in optimization theory. KKT are first-order conditions, formulated by applying the first derivative gradient vectors and Jacobian matrices [209]. A wide range of optimization problems should satisfy the KKT optimality conditions [210]. However, they are a category of problems where these conditions cannot be meaningfully formulated to characterize optimality. Additionally, KKT conditions are necessary but not sufficient conditions, but optimal solutions should satisfy them.

It is convenient to formulate the KKT conditions by defining the Lagrangian function of problem (3.20) - (3.23).

$$\mathcal{L} = f(x) + \sum_{i=1}^{m} \lambda_i h_i(x) + \sum_{j=1}^{r} \mu_j g_j(x) \tag{3.23}$$

Stationarity condition, $\partial\mathcal{L} = \partial f(x) + \sum_{i=1}^{m} \lambda_i \partial h_i(x) + \sum_{j=1}^{r} \mu_j \partial g_j(x) = 0$ (3.24)

where $f(x)$, $h_i(x)$ and $g_j(x)$ are continuously differentiable in the region they are defined. The KKT conditions of the problem (3.6) are thus;

Complementary slackness, $\lambda_i \cdot h_i(x) = 0, \ \forall i$ (3.25)

Primal feasibility, $h_i(x) \leq 0, \ g_j(x) = 0, \ \forall i, j$ (3.26)

Dual feasibility, $$\lambda_i \geq 0,\ \forall i \tag{3.27}$$

where $\lambda_i \in \mathbb{R}$ and $\mu_j \in \mathbb{R}$ the equality and inequality Lagrange multipliers, respectively. Constraint (3.24) is a statement of the fact that the gradient of the Lagrangian function at the optimal point is zero. Expressions in (3.26) are the equality and inequality constraints and constraint (3.25) shows that the inner product of the multiplier vector of the inequality constraints and the inequality constraint vector is zero. Lastly (3.27) ensures that the Lagrange multipliers are positive. In summary, if the convexity conditions obtain, the optimal solution $\underline{x}_{opt}^{*}$ of (3.11) should satisfy the KKT conditions.

3.6 Conclusion

For control of SGs, three types of approaches are applicable namely, rule-based optimization-based, classical and hybrid techniques, Fig. 3-5 [193]. With the rule-based technique, an existing situation is used to define I/O scenarios, for example utilizing decision trees. The system is then tuned or trained for application to prevailing conditions by providing feasible solutions. This however does not guarantee the best possible solution[211]. The optimization-based or classical techniques provide local or global solutions. Mathematically, the formulation of an optimization problem is about the maximization or minimization of an objective function while satisfying all constraints in the model [147]. This dissertation uses MILP for the energy management problem with characteristics models of the integrated DEGs. Integer and binary variables represent the operational status of the DEG systems, BESS, EVs and smart appliances in SHs of the MG, [206]. To solve the extended optimization time horizon problem in the SG environment, we use two techniques, the MILP, and the greedy method (constructive algorithm) to obtain a hybrid technique which can reach the global near-optimal solution. The proposed meta-heuristic algorithm generates a locally optimal solution every simulation period to get the global near-optimal solution.

Chapter 4 Modelling MG Elements for Optimization

4.1 Introduction

Microgrids with REGs are increasingly being used to complement energy supply-demand problems. Balancing demand and supply at any time instant in a power system has always been critical, more so when peak load is growing at a fast rate as is the case in most economies. Traditionally control has been unidirectional in the sense that generation had to be adjusted to match load demand. However, as seen in the previous sections, this approach is no longer adequate or even desirable due to certain technical constraints. This chapter presents stochastic models for MG applications. DEGs and loads are simulated in MATLAB and results are compared with experimental as well as analytical results. Power flow scenarios of the modelled network that uses typical operating bounds are applied against factors of wind speed, PV insolence, rated values, and state of charge (SoC) for BESS.

Given the uncertainty in weather-dependent parameters, the representation of solar or wind yields for the development of PV solar models or WT for wind generators is far from trivial. These challenges can be tackled through many statistical and mathematical techniques within the limits of tractable solutions and computational efficiency. Envisaged is an SG with N_{DEG} DEGs of which N_{DG} are diesel generators, N_{PV}, PV generators, N_{WT} wind turbine generators and N_{ES} are energy storage systems integrated through a common bus to a utility grid. The loads are connected to the common bus via different systems as illustrated in Fig. 1-11. Our objective is to model the energy yield or transactions within the overall objective of demonstrating DSM optimization able to meet performance matric such as user satisfaction, PAR etc. in an SG network.

The architecture of an SG can be represented by a directed graph made up of N_{DEG} DEG sources, N_{ES} ESS systems, N_b network buses, and N_H loads. In short, an SG is a generalized flow system along the lines of common networks. Generic flow networks have common components like sources, flow branches or links, nodes, storage elements, and loads or sinks. Available models of MG components are summarized in the following sub-sections.

Section 4.8 presents a simulation case study for a community of microgrid scheduling schemes based on a hybrid DE technique to deal with intermittency. This contribution resonates with the UN agenda for Sustainable Development as intermittency still makes it difficult to secure the economic operation of CMGs in real-time without critical attention to control[169]. Due to these difficulties, the real-time energy management of interconnected MGs, and demand-supply balancing control are very active in microgrids research.

4.2 MG Source elements

MG sources consist of PV, WT, BESS energy generators etc. supplying the energy demanded by the loads within design limits or constraints. The flow sources are constrained with upper and lower bounds as well as rate limited when discharging or discharging or velocities for WT. For any of the DEGs, we can generalize that energy produced at any time t, i.e., $\mathrm{P}(t)$ is limited according to $\lambda^{min} \leq P(t) \leq \lambda^{max}$. First, we present the models for the distributed energy sources i.e., PV, Wind Turbine (WT) gen, battery storage etc.

PV Model

The structure for modelling PV cells is briefly illustrated by one diode model in Fig. 4-1. I_o PV cell rated current, V_d is diode voltage, V_t is the terminal voltage, k_v is constant value, T is the provided temperature, F_{ff} is diode ideality factor and N_{cell} is total count of cells connected in PV module. R_{sh} and R_s are the shunt and series resistors as depicted in. These influence the PV module's maximum power. Typically, $0 \leq R_s \leq 1, \Omega$ and R_{sh} is much larger. Under this scheme, the current-voltage characteristic of Fig. 4-1 model can be expressed as (4.3) and (4.4).

The stochastic model of solar irradiance data is done when included in the PV model through 's' in (4.1). To find the PV cell temperature, a linear relationship between the insolation level, the surrounding temperature, and the nominal temperature for the operation of the PV cell, with respect to the solar irradiance, is applied.

For a practical PV model, various OEP data are required. Weather parameters within a given locality are freely available from various national online weather data for download [12]. The PV generations depend on several factors such as daily irradiance, seasonality, number of PV module cells and temperature. Since irradiance is stochastic, the generation of the PV can be described by a stochastic probability density function(pdf) model. The Beta bimodal distribution function (1) is used [212];

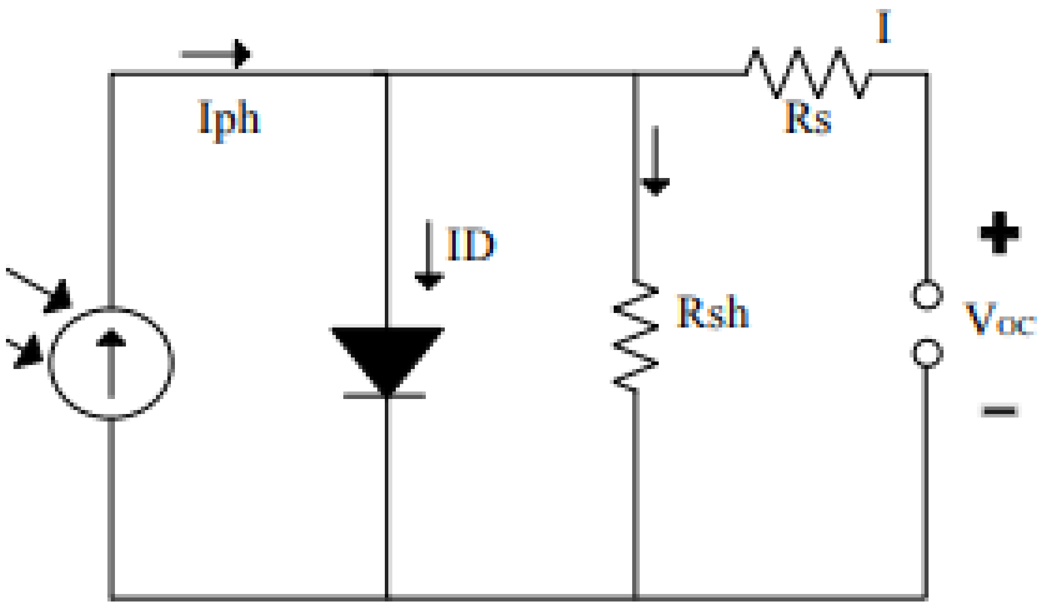


Fig. 4-1. Single diode model of PV cell

$$f_{pv}(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\cdot\Gamma(\beta)} s^{\alpha-1}\cdot(1-s)^{\beta-1}, 0 \le s \le 1, \beta \ge 0 \\ 0 \end{cases} \quad (4.1)$$

Where $\alpha = \frac{\mu\beta}{1-\mu}, \; and \quad \beta = (1-\mu)\left(\frac{\mu(\mu+1)}{\sigma^2} - 1\right)$

The parameters α and β, determine the shape of the Beta distribution function. $f_{pv}(s)$. Solar irradiance is represented by s in kW/m^2. s and σ^2 denote the mean and variance of the solar irradiance. The output power of the PV module is dependent on the solar irradiance and site ambient temperature as well as the characteristics of the PV module. For a given specific site the Beta pdf generates the solar irradiance at a specific time and the output power during the different states is estimated from (4.2).

$$P_{pv} = N_{cell}\, F_{ff} \mathrm{VI} \tag{4.2}$$

Whereby the parameter in (4.2) are defined above. If solar irradiance belongs to the interval s ∈ $[s_1, \quad s_2]$, the probability that irradiance s lies in this interval at a specific time interval is mathematically the cumulative probability function *(pdf)* i.e., cumulative probability function which by integration is;

$$\Theta_{pv}(s) = \int_{s_1}^{s_2} f_{pv}(s)\, ds \tag{4.3}$$

$$F_{ff} = \frac{V_{mpp} I_{mpp}}{V_{OC} I_{sc}} \tag{4.4}$$

$$\mathrm{V} = V_{OC} - k_v T_{cell}$$

$$\mathrm{I} = \mathrm{s}\big(I_{sc} + k_c (T_{cell} - 25^o)\big)$$

$$T_{cell} = T_a + \mathrm{s}\frac{T_N - 20^o}{0.80}$$

Typical output generated by experimental panels at PV Plant at MUT is shown in Fig. 4-2.

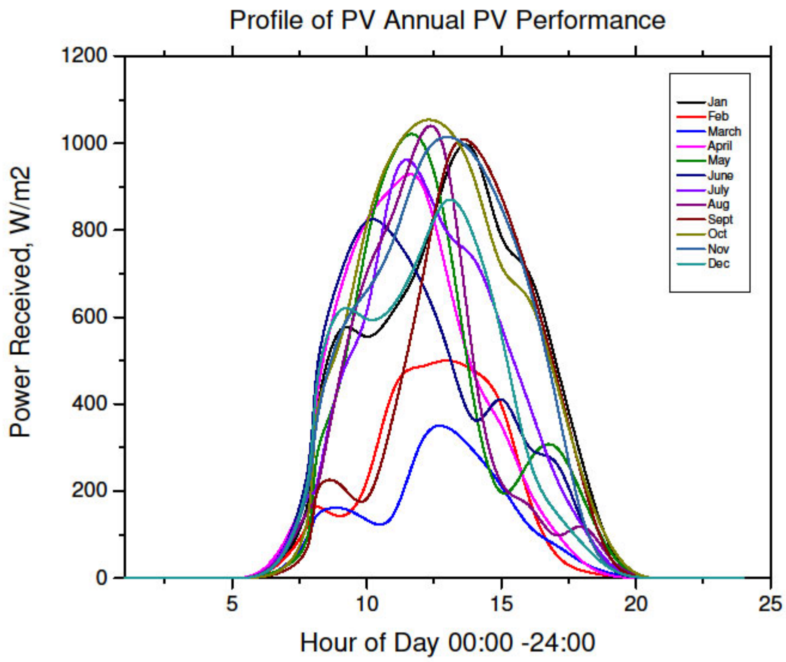


Fig. 4-2. Profile of PV Performance over 24 Hrs for different months

Generally, the aim is to exploit REGs to meet MG load and then store or back feed to the grid all excess energy. In DA markets, the REG is accepted in the day-ahead scheduling phase to the extent grid allows. The storage system is charged over the low tariff time and discharged during the higher tariff time. However, PV and storage systems increase the SCR. The portion of the power produced in the MG to the total power used in the MG as a ratio is called the self-production ratio (SPR). Installation of PV plant increases this ratio and can reduce the kWh cost for prosumers, Fig. 4-3. Clearly during daytime hours, SPR is ratio is high.

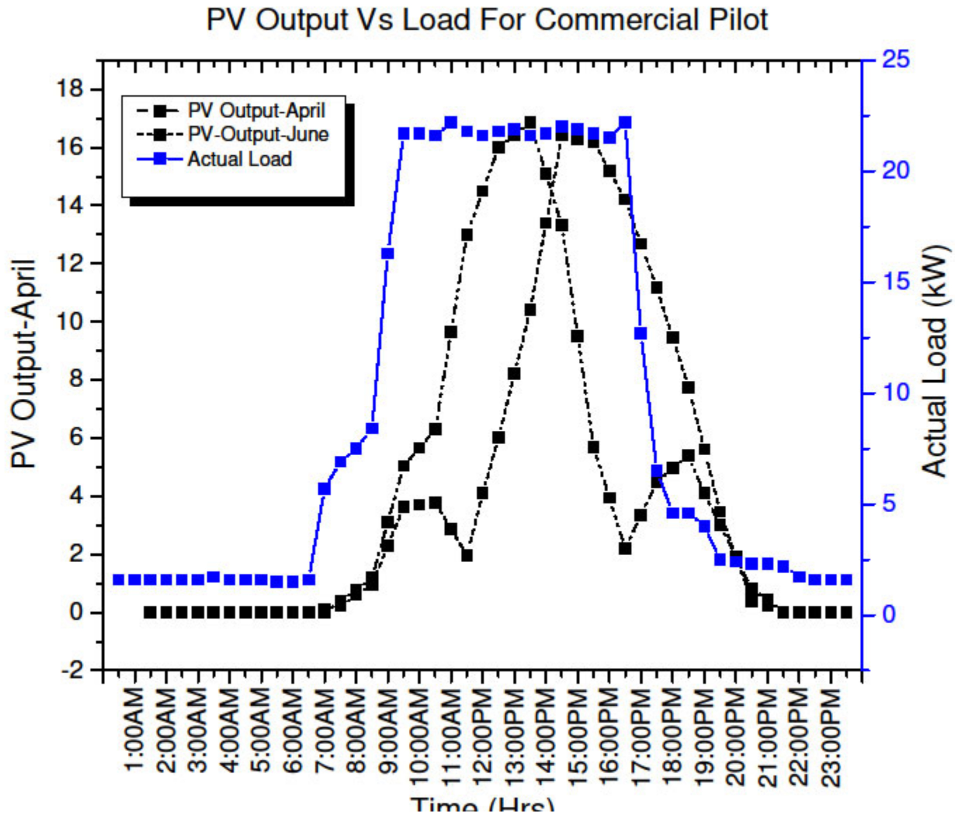


Fig. 4-3. Output of two groups of a PV Pilot scheme

4.3 WT Model

WT output depends on the wind speed profile. The Weibull pdf (4.5) is widely used to represent the wind speed profile [212].

$$f_w(w) = \begin{cases} \frac{v}{\lambda}\left(\frac{w}{\lambda}\right)^{v-1} e^{-\left(\frac{w}{\lambda}\right)^{v}}, \mathrm{w} \geq 0 \\ 0 \end{cases} \tag{4.5}$$

The Weibull distribution interpolates between the exponential and Rayleigh distributions and for certain values of v and λ, the Rayleigh distribution is closer to the wind distribution function. Based on estimated speeds the generated power from the wind can be estimated as follows.

$$P_w(v) = \begin{cases} 0, v < v_{in}, v > v_{out} \\ P_r\left(\frac{v - v_{in}}{v_r - v_{in}}\right), v_{in} < v < v_{out}, \\ P_r \text{ , } otherwise \end{cases} \tag{4.6}$$

The WT power output depends on the site wind speed as well as the OEM power performance curve parameters. Once the Rayleigh pdf is generated for a specific time, the power output at the different states is calculated for that time interval as (4.2). If wind speed belongs to the interval w ∈ $[w_1, \ \ w_2]$, like the PV model in (4.3) the probability that wind speed w lies in this interval at a specific time interval is mathematically the *cpf* i.e., which by integration is;

$$\Theta_{WT}(v) = \int_{w_1}^{w_2} f_w(v)\mathrm{dv} \tag{4.7}$$

Subject to $f_w(s) \geq 0$ and $\int_{w_1}^{w_2} f_w(s)\mathrm{ds} = 1$

The pdf of each DG (4.6) and (4.7) can be divided into periods in which solar irradiance and wind speed range within certain limits. For each such period, there are several states for solar irradiance and wind speed. The joint probability of both irradiance and wind speed to be within the given intervals is given by the convolution assuming events are independent i.e.,

$$\Theta = \Theta_{PV} * \Theta_{WT} \tag{4.8}$$

s_i and v_i, i $= 1,2, \ldots$ are respective irradiance and wind speed limits in a particular state. At any given time, the total power P_{re} from both RES is governed by the probability (4.8) and subject to an upper limit, $\mathrm{P}_{re,max}$.

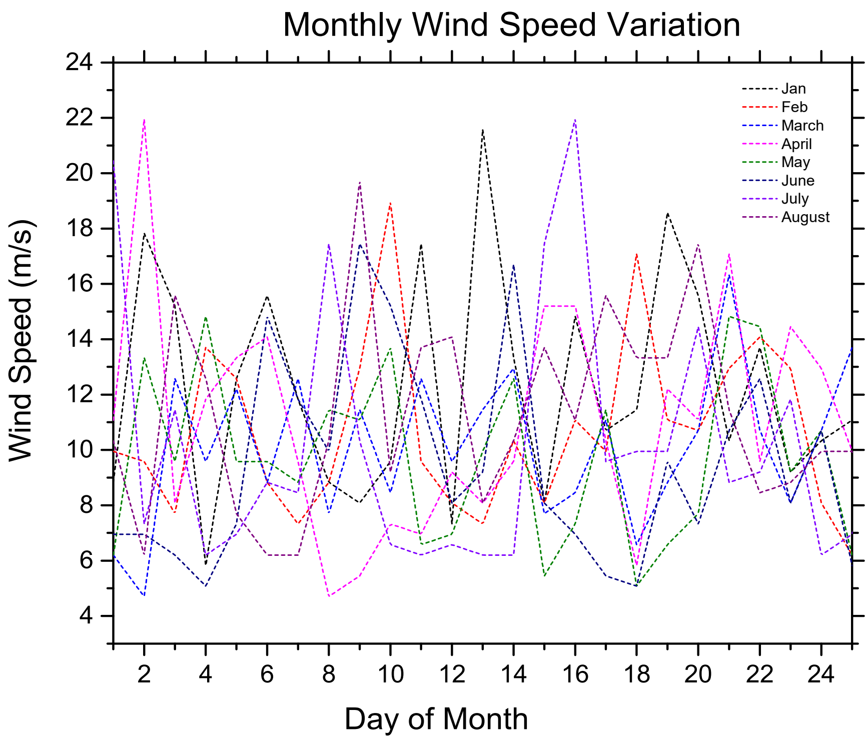


Fig. 4-4. Eight months daily average wind speed

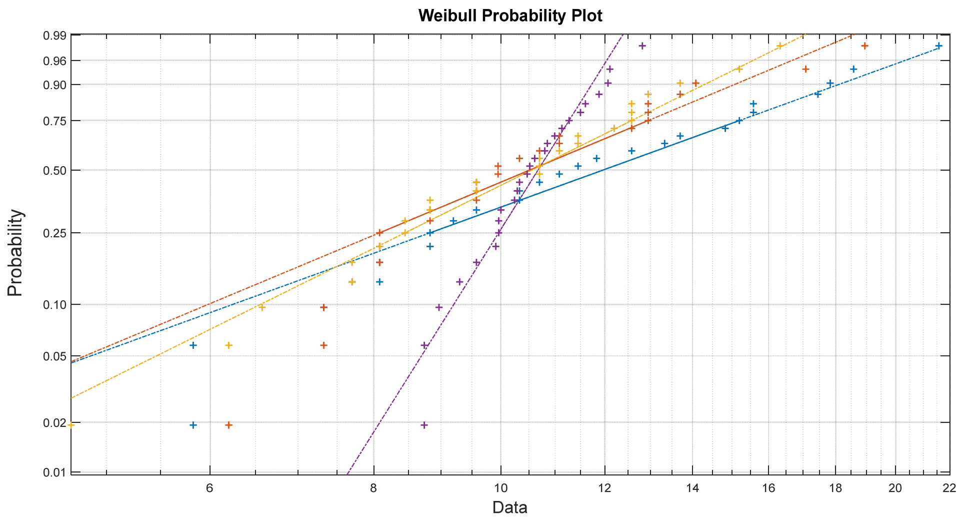


Fig. 4-5. Probability plot for checking conformance of data to Weibull distribution fit

The first three months' data and the 8 months average are plotted on the Weibull probability. The Weibull plots are linear which implies the wind data fit the Weibull distribution for power estimation.

4.4 ESS Battery Model

The ESS seeks to utilize PV systems and grid electricity effectively. They store energy from the grid or REGs during low tariffs. The parameters used to model the ESS are listed below. Effectively the ESS sources energy to the load or acts as sinks for excess grid or REGs output. During any time interval $t: 0 \leq t \leq h$ [213].

$$E_{BESS,disc} = \left(E_{BESS,load} + E_{BESS,sold}\right)\left(1 - \delta(t)\right) \tag{4.9}$$

$$E_{BESS,charg} = \left(E_{GRID,charg} + E_{REG,charg}\right)\delta(t) \tag{4.10}$$

The function $\delta(t) = 1$ when the BESS is charging and 0 otherwise. In expressions (4.9) and (4.10) state of energy of the BESS when discharging to the load or selling to grid and, charging from the Grid or REGs sources. ESS takes the form of batteries, fuel cells, flywheels, Liquid Air Energy Storage (LAES) systems, etc. They store the energy for later use. The ESS state of charge $\mathrm{SOC}(t)$ at any time instant $t,\ is\ also$ limited according to; $\mathrm{SOC}^{min} \leq \mathrm{SOC}(t) \leq \mathrm{SOC}^{max}$. Dynamics of discharging and charging can be defined by the recursive equation relationship.

$$SOC(h+1) = SOC(h) + \Delta t \cdot \left(P_{in}(h) - P_{out}(h)\right) \tag{4.11}$$

The model for $\mathrm{SOC(t)}$ will depend on the specific ESS. With $E_{BESS,t}$ as the energy level of the BESS, we may formulate the relationship for energy levels at any time $0 \leq t \leq h\ as,$

$$E_{BESS,l}(t) = E_{BESS,l}(t-1) + \eta_{BESS} E_{BESS,charg}(t) - \frac{1}{\eta_{BESS,disc}} E_{BESS,disc} \tag{4.12}$$

η_{BESS} is the efficiency of the energy storage system. The BESS is subject to energy capacity and discharge constraints as well as rates of charge and discharge constraints.

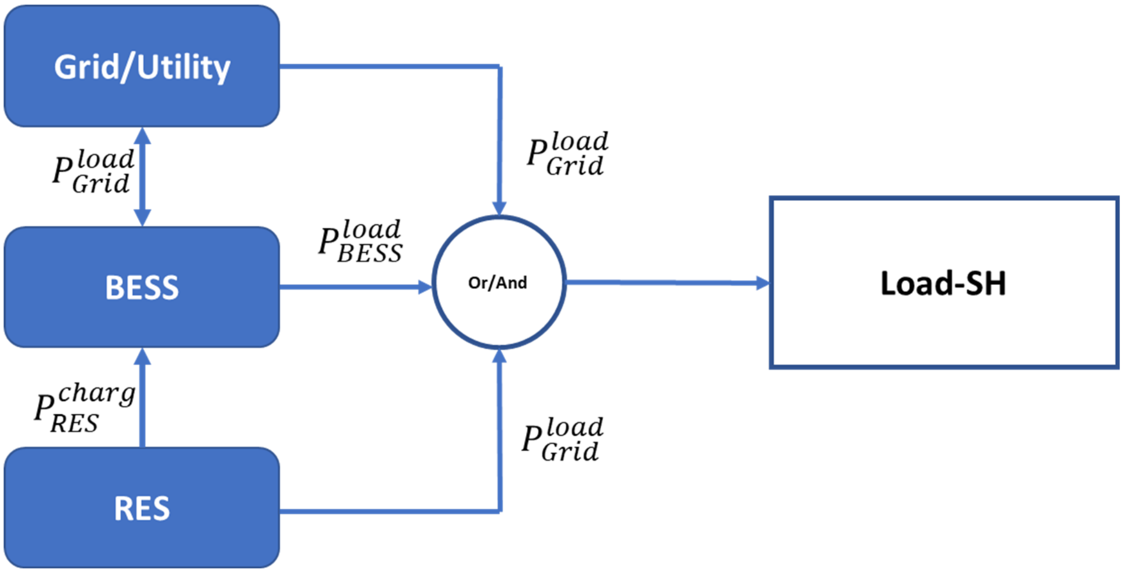


Fig. 4-6. Power flow in Smart Home(SH)

4.5 Flow Processing Components

These are inverters or converters depending on the configuration of the MG. Their incorporation depends on the nature of the source resulting in either an AC or DC coupled bus system. Inverters modify the nature of an input/output hence, they are power flow conditioning elements. They are subject to the same maximum and minimum power handling limits, $\lambda^{min} \leq P(t) \leq \lambda^{max}$. Sometimes these can be taken as "*active nodes"* that can change the form of flowing power such as current.

Links are power electronics drives that connect the DEGs to the AC or DC Bus. Unlike inverters, converters do not alter the nature of the power input. They can be regarded as "*Passive nodes*". They are subject to the same maximum and minimum power handling limits, $\lambda^{min} \leq P(t) \leq \lambda^{max}$ *such as happens in power lines*.

Nodes are buses or network transformers. They are an interface between the generation subsystems and the loads. By comparison to the city road network, nodes are junctions or compared to river systems a confluence where two or more rivers merge. At a bus, energy flows merge or are directed to other downstream sub-systems. The basis of modelling in such flow systems is 'flow balance' i.e.,

$$\sum_{i=1}^{H} P_{in}(i) = \sum_{i=1}^{H} P_{out}(i) \tag{4.13}$$

The sinks in a network are the loads that consume the power flowing in it. At any given time, system integrity sinks cannot consume above what is produced which means,

$$P_{Load}(h) \leq P_{in,max}(h) \tag{4.14}$$

where $P_{Load}(h)$ is the load demand, and $P_{in,max}(h)$ is the total energy flow at time h.

4.6 Integrated SG Model

For any of the DEGs or their totality, we can generalize that energy produced at any time t, $\mathrm{P}(t)$ is limited according to $\lambda_{\mathrm{DEG}_i}^{min} \leq P(t) \leq \lambda_{\mathrm{DEG}_i}^{max}$. The total energy demand of consumers in a day, the per hour energy consumption is already given from the summation of all appliances. In Fig. 4-7, the load demand varies between 2 kW to 14.1 kW. The available power from the PV and the Wind generators especially over the mid-morning to mid-afternoon hours is first used and access is available to charge batteries.

$$P(t) = E_{BESS,l}(t) + P_w(v) + P_{pv} \tag{4.15}$$

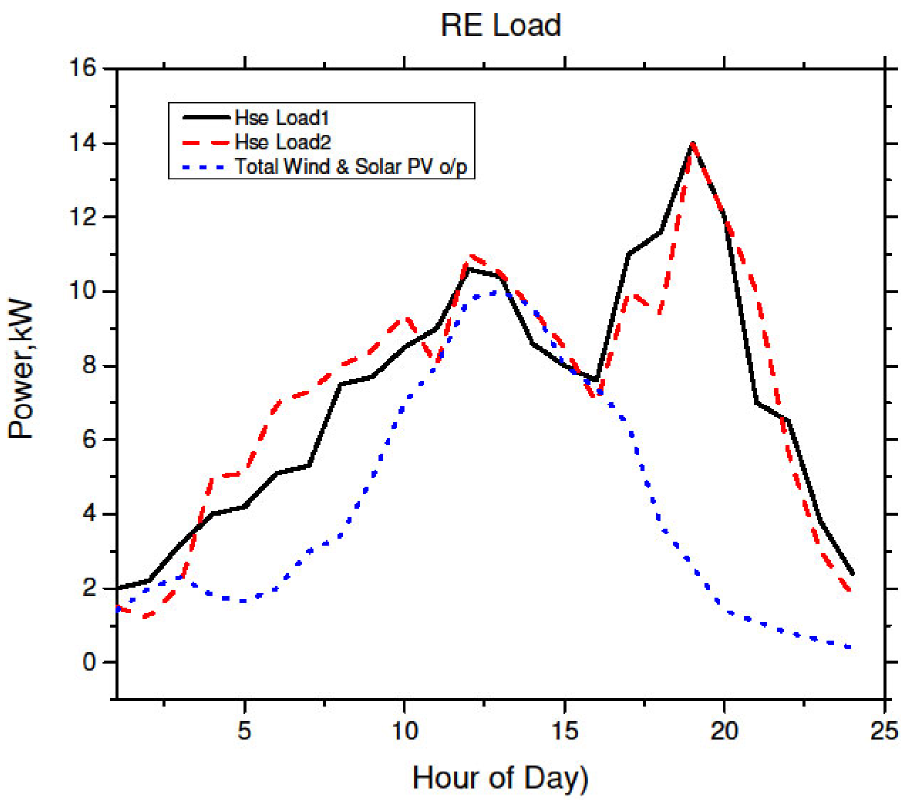


Fig. 4-7 Matlab hourly load and RE PV+WT output without DG and FC

4.7 Case Study: RT scheduling of CMG

REGs and ESS systems are increasing rapidly in imaging smart grids. When several of these REGs and loads interconnect, they form a community of MGs (CMG) and corresponding(equivalent) VPP which need proper scheduling. This optimal scheduling is difficult due to a combination of non-linearities, time variability, and other random phenomenon. This section proposes and simulates a real-time scheduling scheme for CMGs based on a hybrid DE technique. The contribution to the scheme is in line with UN Agenda for Sustainable Development but a major hurdle with REGs is intermittency. This alone makes it difficult to secure the economic operation of CMGs in real-time without critical attention to control [12]. Due to these difficulties, the real-time energy management of interconnected MGs, and demand-supply balancing control are still being actively researched.

To deal with these problems, research has focused on system modelling under uncertainties and load dispatch in the context of DSM. Akin to multiloop cascade feedback control, multiple layered scheduling schemes for MG energy management are reported in the literature. From outer to inner loops, the timescale for scheduling horizon decreases so that inner loops are faster. In [214] is devised a 2-stage scheduling technique for optimizing grid-tied MG. The 1st stage implements DA forecast. Optimal dispatch problem is controlled using intra-day data in the 2nd stage. Hence from this second stage's view, the 1st stage DA is modified in real-time. Further refinements to the multi-stage (wherein intermediate prediction stages are interlaced in between) scheme have been proposed to improve sub-optimal results. In simple terms, these schemes operate like multiloop feed cascade control.

By employing multi-stage schemes, stages having larger prediction horizons produce improved results which are refined in the 'inner' multi-time scale stages for optimal results. When real-time feedback is introduced to track decisions on scheduling, better results accrue. Solving energy management requires a variety of tool techniques reviewed in Chapter 3. Meta-heuristic techniques have been satisfactorily used giving sub-optimal results due to complex hard constraints. This section borrows from[215], a real-time 3-stage scheduling scheme and an evolutionary stochastic optimization algorithm for improved operation of MGs. The technique is applied to real-time aggregate domestic consumption data.

The innovative scheduling scheme is in two stages. First, a 3-stage real-time stage with an internal or 'inner-loop feedback' is introduced. This internal feedback corrects intra-day output fluctuations in the outer scheduling layer. As mentioned, this layer can arrive at optimal set points as it has a shorter operational cycle time. In this way, the schemes can improve optimal real-time results even in the presence of a substantial difference between the inner intra-day and the outer DA scheduling layers. To handle real-time scheduling, a heuristics-based differential evolution technique is employed though it's known that equality constraints are difficult to attain using evolutionary population-based stochastic algorithms. The advantage of fusing heuristics schemes with other search techniques is to enable the speedy convergence to feasible solutions, so-called solution repair Simulations are used on real data to investigate the performance of the 3-layer scheduling method. Results obtained are compared with those from existing scheduling approaches and attest to possible improvements.

Current RT MGs scheduling uses 2-stage schemes. In 2-stage and multi-stage schemes, the DA-schedular and real-time dispatch stages are present. Given DA load prediction, the schedular produces the operational schedule of the REGs whiles command set points for REGs are determined by the dispatch in real-time within a few minutes to an hour horizon. During this dispatch horizon, the DA schedular cannot be re-set as its prediction horizon is much larger plus other constraints such as on/off time or ramping limits. To correct this difficulty, an intra-day schedular is used as a 3rd layer. The intra-day scheduler's prediction horizon, T_{intra} is larger than the 24-Hours for the DA-schedular but smaller when compared to the horizon time for the dispatcher. Corrected dispatch command set points of the REGs are used. Schedules from the top stages or inner have priority in the outer corrective layers. The internal dispatch horizon progresses till the end of the DA prediction interval, $T_{DA} = 24$ Hours. In (4.18) $\delta t_{DA} =$ h, δt_{intra}, δt_{disp} represents the time interval between scheduling points in hours, the time interval between intra-day scheduling points in fractions of an hour and the time interval between dispatch layer points in minutes, respectively. Lack of feedback from the intra-day predictor to the scheduler can give sub-optimal results. The 3-stage schedular overcomes this limitation by feeding back to the scheduler updated intra-day data. Through the feedback mechanism, the average values of intra-day predictions in each hour are updated in the outer scheduling stage. This process advances according to the repeat cycle time. In this fashion, the real-time schedules are corrected closer to optimal schedules from the 'outer loops' via feedback. Consequently, schedule deviation (4.18) between intra-day and RT data in the MG decrements.

4.8 Problem Statement

The 3-stage scheduling scheme is outlined. The REGs are taken as having zero OPEX costs and take preference in utilization to minimize costs. Decision variables are the outputs of REGs, ESS and utility power exchange. DA scheduling has the objective of producing switching schedules of the REGs that minimize OPEX cost. The total cost objective function can be written as,

$$Min\ C_{k}^{CMG} = \sum_{h=1}^{T_{DA}} C^{h} \tag{4.16}$$

In (4.16) C_{k}^{CMG} is total cost over the prediction interval and C^{h} is the cost at h^{th} $(or\ t^{th})$ hour. When electricity flows from CMG to the utility grid, the cost is regarded as negative otherwise cost is taken as positive when the flow is from the utility grid. CMGs are constrained by the power limits of individual N_{MG_i}as well as links, nodes/buses etc. Dispatchable DEGs have minima or maxima ratings. BESS have charging or discharging limits. When BESS is charging the power is regarded as negative and when discharging its positive. Another constraint is expressed as the squared norm of the deviations of the energy profile as measured by summing the squared difference between the DA schedule compared to the intra-hour target for each CMG. Equality constraint demands that power consumed and generated must always be balanced. Outputs of the intra-day stage are corrected in the dispatch stage to keep this supply-demand stability.

$$\sum_{h=1}^{N_{DG}} P_{DG_i} + \sum_{h=1}^{N_{REG}} P_{REG_i} + \sum_{h=1}^{N_{Grid}} P_{Grid_i} + \sum_{h=1}^{N_{BESS}} P_{BESS_i} = \sum_{h=1}^{N_{load}} P_{Load_i} \tag{4.17}$$

$$Deviation_{k,intr}^{2} = \left(\sum_{h=1}^{T_{DA}} \delta t_{DA} P_{DG,i} - \sum_{h=1}^{T_{intr}} \delta t_{intra} P_{DG,i}\right)^{2} + \left(\sum_{h=1}^{T_{DA}} \delta t_{DA} P_{Grid,i} - \sum_{h=1}^{T_{intr}} \delta t_{intra} P_{Grid,i}\right)^{2} + \left(\sum_{h=1}^{T_{DA}} \delta t_{DA} P_{BESS,i} - \sum_{h=1}^{T_{intr}} \delta t_{intra} P_{BESS,i}\right)^{2} \tag{4.18}$$

The technique to solve the proposed 3-layer scheduling scheme is the enhanced Differential Evolution (DE) algorithm[215] whose flowchart is depicted in Fig. 4-8. DE is superior in solving optimization problems and its performance is enhanced by incorporating heuristics which help in convergence.

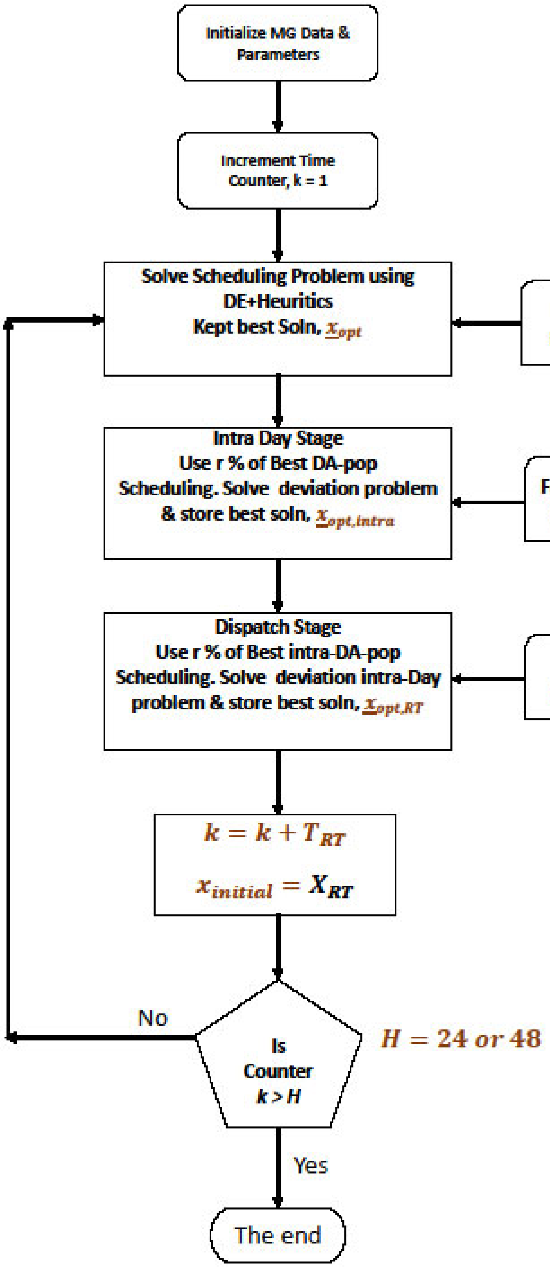


Fig. 4-8. 3-Stage prediction for energy optimization

Initially, data and states at $t = 0$ of the CMG resources are initialized then the optimization problem presented in (4.16) is solved following Fig. 4-8 and the best solutions are fed to the second layer. In the second layer, the optimization problem is solved using the same flowchart but with intra-day samples available. To speed the solution process 17% of the member of the initial population are selected from the best DA solutions.

The best solutions obtained at this stage are passed to the next stage. During the third and final stage, the deviation (4.18) is solved. The resultant best schedule is then implemented, and initial states are updated for the subsequent optimization cycle.

DE initialization of generation set points

The initial optimization step is setting the reference points of the decision variables or chromosomes of the DE problem. Variables that need optimization are the set points of REGs for $t = 1,2,\ldots,H$. A DE chromosome is formulated from all decision variables over $\{h\}\epsilon H$ (2)[215].

$$\underline{\boldsymbol{x}} = \left[\left\{P_{\mathrm{DG}_1,}^{i}\right\}_{i=1}^{H}, \left\{P_{\mathrm{DG}_2,}^{i}\right\}_{i=1}^{H}, \ldots, \left\{P_{\mathrm{DG}_N,}^{i}\right\}_{i=1}^{H}\right], \tag{4.19}$$

$$\underline{\boldsymbol{x}}_{\boldsymbol{i}} = \underline{\boldsymbol{x}}_{\boldsymbol{l}} + \left(\underline{\boldsymbol{x}}_{\boldsymbol{u}} - \underline{\boldsymbol{x}}_{\boldsymbol{l}}\right)\boldsymbol{LHS}\left(\mathbf{N}_{\boldsymbol{p}}\right), \forall \mathbf{N}_{\boldsymbol{p}} \tag{4.20}$$

$\underline{\boldsymbol{x}}_{\boldsymbol{l}}$ and $\underline{\boldsymbol{x}}_{\boldsymbol{u}}$ are the minima and maxima limits of the optimization variables. $\mathbf{N}_{\boldsymbol{p}}$ is the population size and LHS stands for hypercube sampling used for generating a near-random sample of parameter values from a multidimensional distribution.

Outline of Heuristic Technique

CMG Scheduling involves a combination of EAs optimization and heuristic to speed up the convergence to feasible solutions. The heuristic first attempts to meet equality constraints that are elusive in the presence of uncertain REGs. Deviation in power balance is found and if this deviation is positive, power from expensive distributed generators is reduced until it’s minimal. Power is increased from economic distributed generators if the deviation is negative. The algorithm of [215] is adopted with modification of including user utility.

Stage A: If Power imbalance > 0; sort the REGs in the descending order of per unit energy cost from most costly to cheaper and most favourable user utility.

Step 1: Start with the 1st generator and reduce the generation by the amount that makes imbalance zero or minimal and optimizes user utility.

Step 2: Test required power reduction for constraints violation as well as utility.

Step 3: If constraints are not violated then the decision variables are used to update the value in (2) otherwise proceed to the next REG and repeat the steps.

Stage B: If Power imbalance $<$ 0 sort REGs in increasing per unit energy cost. Then increase generation by the amount that makes zero imbalance as much as possible whiles maximizing consumer utility.

Stage C: Completion of the above processes repairs the solution vector.

Simulation Results

The performance of the adopted scheduling scheme is assessed using a simulated radial community CMG consisting of PV, WT, MT, FC, and BESS. Forecast DA data is used with DEGs parameters in Table 1. The charging/discharging efficiency of FC and BESS is taken as 30% and 89%. The sample forecasted generation from RES of CMG is given in Fig. 4-9. The cost of grid electricity in the simulation is scaled from [215].

Table 4-1. Simulation Cost Parameters

	Min, kW	Max, kW	Running cost R/kWh	Maintenance R/kWh	Ramping rate kW/h
FC	3	13	0.00287	0.00271	2.25
MT	3	18	0.00442	0.00142	6.0
PV	0	5		0.00107	
BESS	-3	10		0.0018	0.5
WT	0	10	0.0041	0.0013	

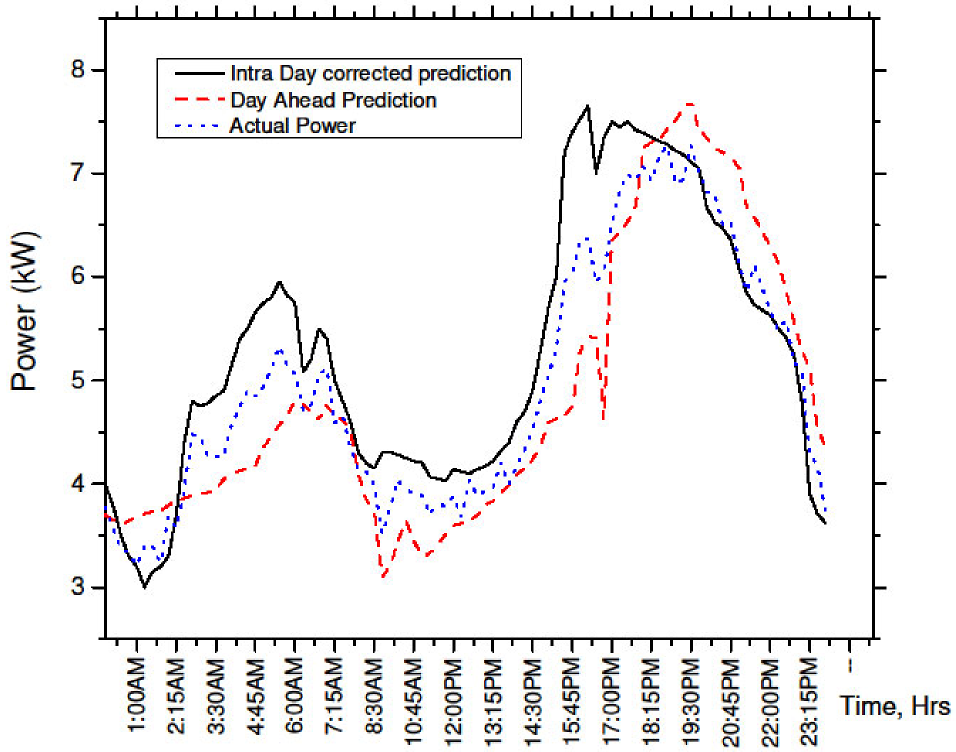


Fig. 4-9. Simulated, predicted and actual demand

Standard day-ahead energy management problems[216] were simulated wherein the energy resources were scheduled using Hybrid Differential Evolution. Comparative results were yielded in Table 4-2. The second scheduling scenario[217] includes distributed energy sources of an MG for both islanded and grid-connected modes using GA. Furthermore, the DA scheduling of the CMG in the scheduling layer considered in this work was solved using Hybrid DE. Results in the third row of Table 4-2 depict better performance of the hybrid technique. Peak price occurs at prime hours of morning and evening respectively.

Table 4-2. Operating metrics comparison for normal & the 3 -stage scheduling methods

Technique	Best, R	Median, R	Mean, R	Worst, R	SDV
Normal scheduling	14.99	15.96	15.99	16.31	0.173
New Scheduling Technique	13.44	13.49	14.49	14.92	0.183
% Improvement	10.4	15.5	9.4	8.6	-5.8

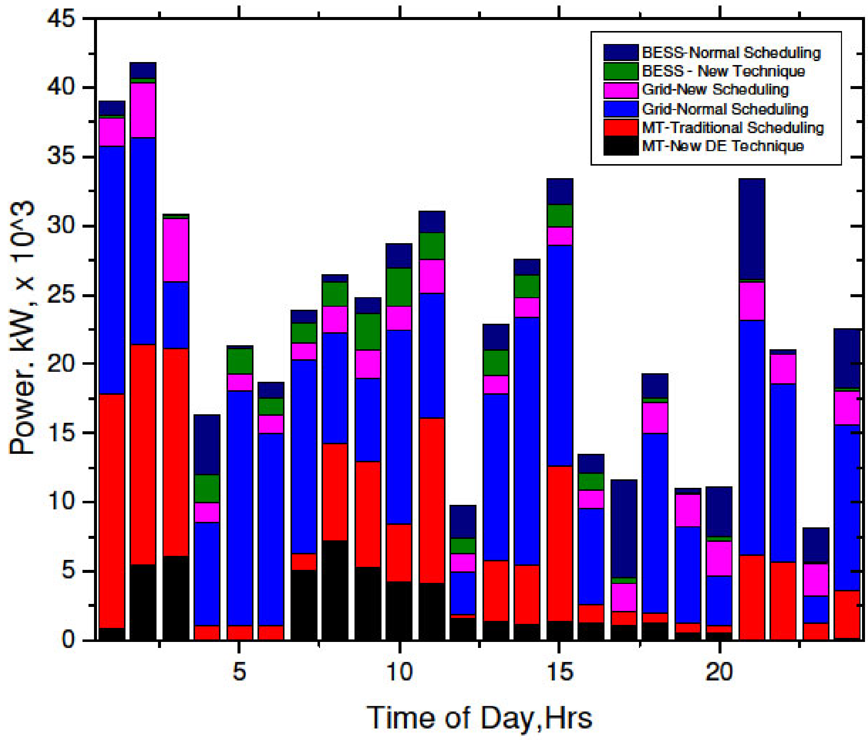


Fig. 4-10. Comparative scheduling results with different strategies

In the stacked scheduling results in Fig. 4-10, the performance of the micro-turbine, grid and BESS performance is compared. At each time interval across the scheduling horizon, the incidence of normal scheduling and the relative width of each source is indicative of its active state and hence the eventual cost to the consumer. Evidently, in all three cases, better performance is given by the reduced relative width in each stack or reduction of grid activity.

4.9 Conclusions

This Chapter has outlined a 3-layer RT scheduling scheme with internal 'minor loop feedback' for energy management in MG. The scheme points to better handling of variations in REGs generations/demand and finding optimal schedule points. A hybrid heuristic-DE technique was demonstrated to offer better scheduling. Simulation results show that the hybrid heuristic-differential evolution technique performs better compared to normal scheduling. Applied in real-time the 3-layer energy management scheduling scheme has the potential to decrease OPEX costs by at least 8% compared to traditional techniques. The minor loop feedback reduces the error between predicted and actual demand. However, the simulation could be refined through the incorporation of random behaviour of REGs and other power flow network constraints optimization problems.

This section discussed optimization in the context of economic DEGs dispatch in SGs under uncertain load demands. The REGs components models are used to develop a Matlab MG system tied to an electrical power grid. The overall objective of this section is to design an SH energy schedular based on economic optimization strategies, that tackle uncertainty and ensure reliability, minimize consumer costs and maximize utility at the user level. This layer is necessary to be able to coordinate DSM from the load side more effectively. A hybrid PV/WT/electrical grid-connected energy system, including a FC and a battery-based ESS, was simulated. Minimum operating cost is achieved by proper scheduling of different energy resources, using a hybrid differential evolution optimization algorithm, for the system's scheduling. Additionally, a BESS is optimally dispatched decreasing the grid Electricity costs. Real load demand is used in the simulation.

Optimization is vital for secure and reliable energy management in MG with REGs. However, this task is difficult given the uncertainty and intermittency of REGs and users' behaviour. A strong optimization model with intermittent, stochastic, and non-linear properties is needed. Hence, a novel energy optimization model can optimize the CMG by reducing OPEX costs and maximizing the use of cheap REGs energy. PV and Wind pdf and cdf are used for prediction. For the developed cost model, an energy optimization strategy based on DE heuristic technique is devised. Simulation results are considered in two cases: consumption using normal 2-stage prediction and operating using a new 3-stage prediction technique. Simulation results illustrate that the proposed energy optimization model optimizes the cost of operating a CMG.

Chapter 5 Optimal Energy Management

1.9 Introduction

Energy used in the residential sector accounts for anything in the range of $30 - 40\ \text{percent}$ [218] of total generation. If energy management infrastructure is in place, unlike the industrial or commercial sectors, residential load offers more flexibility for implementing DSM. Potential serving of the order of 17% or more on energy costs using DEGs and ESS or BESS in the SG have been reported [219]. The operational classification of SH appliances is dealt with in this Section. Some appliances are highly intolerant to long turn-on delays and in some, LOT determines service satisfaction. Turn-on delay-tolerant appliances are flexible as they can start at different times. Each of the categories has peculiar constraints. In this chapter, we outline the basic framework for modelling an SH for energy management purposes.

The concept of DSM has been discussed in Chapter 2. As noted, both prosumer or consumer and grid utility can benefit from cost reduction and enhanced grid stability. From an overall system view, the primary goal is optimally utilising energy such that electricity peak demand is reduced in both residential and commercial settings. This has a positive reductive impact on both CAPEX for expanding generation and OPEX for peaking power plants. Our optimization objectives are minimization of home energy costs and reduction of PAR. Lower PAR enhances system stability and reduces system losses. There is a growing body of SH concepts, techniques, and technologies for energy management [220].

DSM techniques reshape the load profiles. The efficacy of the optimization techniques is validated using home appliances load curves. The work considers electricity supply from both the DEGs, utility and BESS or ESS. Mathematical techniques discussed in Chapter 2 can be used to solve the problem. Analytical methods cannot tackle stochasticity and nonlinearity. On the other hand, stochastic models tend to be complex, with long execution times and may result in sub-optimal solutions. Game theoretic techniques are also highly complicated and contain impractical assumptions about players i.e., consumers. Heuristic methodologies fail to converge to optimal solutions in scheduling problems or converge prematurely.

From the literature, DSM has looked at various combinations of optimization criteria such as electricity cost reduction, carbon emission minimization, user comfort maximization or appliance waiting time minimization, PAR reduction[219], MG sizing etc. In this work, the hybrid technique of [219] is modified to a hybrid Genetic Algorithm plus the newly developed metaheuristic technique called Atom Search Optimization(ASO)[221]. A hybrid combination of GA and ASO or HGAASO algorithm for energy management is expanded to solve the multi-objective DSM optimization problem that seeks to optimize multiple criteria. The novelty and major contribution of this work are as follows.

- Solution of the DSM in an MG or CMG optimal energy management problem with multiple REGs sources consisting of PV, BESS, WT, MT, and grid power.
- Improved energy management framework proposed in[219] to HGAASO technique for scheduling SH appliances.
- A DR program's RTP scheme pertinent to the local context is formulated and then simulated for DSM scenario planning.
- Electricity cost, PAR, and user utility are simultaneously considered, and an objective function is formulated to reduce power cost and PAR and minimize consumer discomfort.
- The superiority of the proposed HGAASO or optimal energy management is demonstrated through simulations by comparing it with results obtained elsewhere using techniques such as GA, BFO and ACO.

The rest of this Chapter is organized as follows: The system model is described in Sections 5.2 and 5.3 together with the classification of appliances. Section 5.4 introduces typical operational profiles of appliances and the basic formulation of cost optimization criteria. Section 6 discusses mathematical ways to model user comfort and some simulation on load shifting using MATLAB optimization.

1.10 System Model

A conceptual schematic of the proposed model is shown in Fig. 5-1. In the MG, the set of consumers is represented by K≜1, 2,...,k,k+1,...,K. The cardinality of this set is K, i.e., they are K households in the MG. Each home is equipped with a HEMS and the 24-hour optimization period is divided into H time slots, such that $\mathcal{H} \in \{1,2,\dots,H\}$. H the total number of time slots can be 24 or 48 in which case the interval is either one hour or half an hour respectively. In the k^{th} household, the set of energy consuming appliances is represented as $\mathcal{A}_{k} \in \{a_{k,i}\}_{i=1,2,\dots,n}$ with n appliances such that the i^{th}appliance, $a_{k,i}$ for k^{th} consumer, at the h^{th} hour consumes x_{ki}^{h} power. Over the 24-hour scheduling horizon the energy consumption vector for the k^{th}consumer's i^{th}appliance is;

$$x_{k,a_i} = \{x_{k,a_i}^{1}, x_{k,a_i}^{2}, \dots, x_{k,a_i}^{H}\}, \quad \mathrm{i} = 1,2,\dots,\mathrm{n} \tag{5.1}$$

Each smart appliance has a starting and ending time of its operation, represented by $\mathcal{T}_{start,i}$ and $\mathcal{T}_{end,i}$. The length of such an appliance's operating time is expressed by (5.2).

$$\mathcal{T}_i = \mathcal{T}_{end,i} - \mathcal{T}_{start,i} \tag{5.2}$$

The i^{th} the appliance can be scheduled according to the time constraints which are expressed as;

$$0 < \mathrm{h} < \mathrm{H} \tag{5.3}$$

$$x_{k,i}^{h} = \begin{cases} 0 & if \;\; h \geq \mathcal{T}_{end,i} \\ 0 & if \;\; h \leq \mathcal{T}_{start,i} \end{cases} \tag{5.4}$$

Depending on the type of appliance as discussed in the previous sections, there is a general delay of Δt_d which is a multiple of the optimization operational time slots, h.

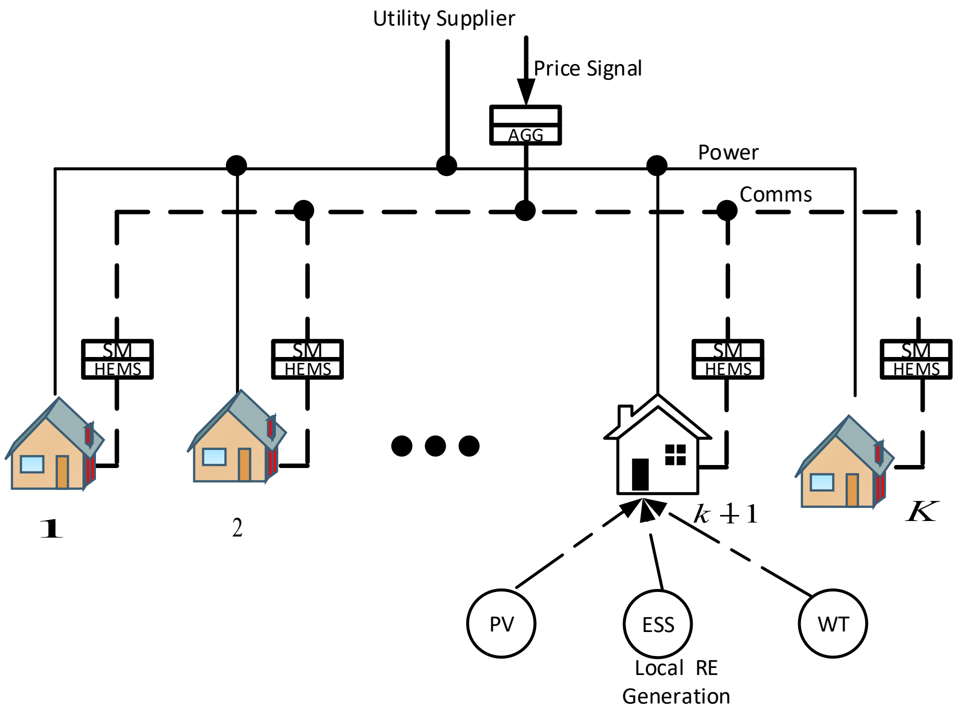


Fig. 5-1. Schematic diagram of the proposed scheme

Constraints (5.3) and (5.4) simply state that no energy is consumed outside the scheduling interval of the respective load. Each appliance has a lower and upper limit to its power consumption according to (5.5).

$$\lambda_{ki}^{min} < x_{ki}^{h} < \lambda_{ki}^{max}, \ \ \mathrm{i} = 1,2,\dots,\mathrm{n}; \ \ \mathrm{h} \in [\mathcal{T}_{start,i} \quad \mathcal{T}_{end,i}] \tag{5.5}$$

Each k^{th} consumer's i^{th} appliance, $a_{k,i}$ has a scheduling horizon between the time interval $[\mathcal{T}_{end,i} \quad \mathcal{T}_{start,i}]$. However, the actual scheduling interval of each appliance depends on its LOT. We can denote the scheduling horizon of any of the appliances by (5.4). ToU tariff is applicable in this model. The cost of a unit of energy consumed in each time interval $\mathrm{h} - 1 < \mathrm{t} < \mathrm{h}$ changes but it is known ahead of time to the HEMS. If $e^{\hbar}$ represents this unit cost, $\mathrm{Rands/kWhr}$ of energy for the $\mathrm{k^{th}}$ household, then the total hourly load is (5.6), and the total daily load is (5.7). The corresponding hourly and daily costs of energy consumption of all appliances are given by (5.8) and (5.9) respectively.

Hourly load l_k^h, for all n-appliances, $l_k^h = \sum_i^n a_{ik}^h$ (5.6)

The total daily load $\mathcal{L}_{\mathcal{k}}$, for the $\mathrm{k^{th}}$ household is;

$$\mathcal{L}_{\mathcal{k}} = \sum_{h=1}^{H} \sum_i^n a_{ik}^h \tag{5.7}$$

The corresponding hourly $\mathcal{C}_k^h$, and daily costs $\mathcal{C}_{\mathcal{k}}$, for the $\mathrm{k^{th}}$ consumer are;

The hourly cost for all n-appliances, $\mathcal{C}_k^h = \sum_i^n e^{\hbar} \cdot a_{ik}^h$ (5.8)

$$\mathcal{C}_{\mathcal{k}} = \sum_{h=1}^{H} \sum_i^n e^{\hbar} \cdot a_{ik}^h \tag{5.9}$$

Classification of household loads to model different groups of appliances is proposed in [222]. In this work, we propose three operational categories or sets, $\mathbb{C}_k$, $\mathbb{Q}_k$, and $\mathbb{R}_k$ illustrated in Fig. 5-2. The following sections expand on the different types of loads according to how flexible their operating times can be shifted. In each household, we assume they is $n_{s1,k}, n_{s2,k}$ and $n_{s3,k}$ appliances of each of three categories as expounded in the next section according to load shifting flexibility [81]. For the $\mathrm{k^{th}}$ smart home with smart appliances $\boldsymbol{a}_{\mathcal{k}} \in \{a_{ik}\}_{i=1,2,\ldots,n}$, $\mathcal{T}_i$'s flexibility and operating time constraints can also be used to divide these appliances into operational regimes for better scheduling and energy management, [11].

$$|a_k| = n_{s1,k} + n_{s2,k} + n_{s3,k} \tag{5.10}$$

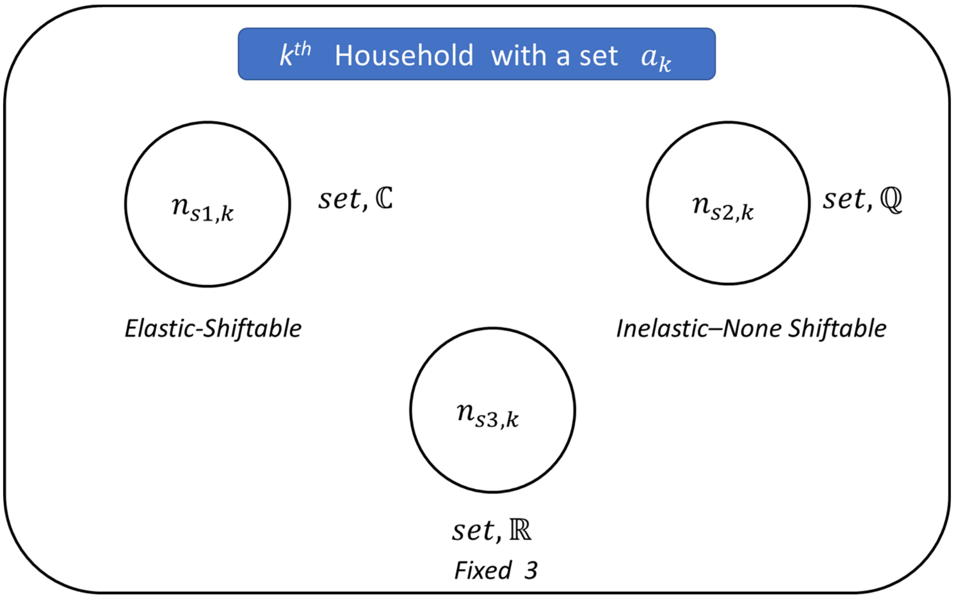


Fig. 5-2 Classes of household appliances

$$\boldsymbol{a}_k = \mathbb{C}_k \cup \mathbb{Q}_k \cup \mathbb{R}_k \tag{5.11}$$

$$\mathbb{C}_k \in \left[\mathcal{T}_{end,i} - \mathcal{T}_{start,i} + 1\right], \quad \forall t = \left\{\mathcal{T}_{start,i} \leq t \leq \mathcal{T}_{end,i} + 1\right\} \tag{5.12}$$

Over the optimization interval H, the set of elastic appliances $\mathbb{C}_k$ has as many load curves as they are appliances. These load curves can be aggregated at a time $t = h$. By choice, we impose the condition that appliances in this class have specific flexibility in terms of admissible scheduling delay. Specific load curves can be optimized, [91].

Elastic or Shiftable Appliances, Δt_d =h, 2h, …

Load elasticity means the flexibility to change or interrupt the power consumption pattern of an appliance [223]. Elastic loads have flexible finishing times set by the user within certain consumption periods and power ratings. Proactive scheduling is possible for these appliances. Dishwashers, irons, washing machines, electric stoves etc. are examples of flexible appliances [222]. This appliance set is represented by $\mathbb{C}_k$ for the k^{th} consumer and the cardinality is $n_{s1,k}$. The start and stop times of shiftable appliance are confined to the window (5.16), and the total hourly $\mathcal{L}^h_{\mathscr{k},\mathbb{C}_k}$ and daily $\mathcal{L}_{\mathscr{k},\mathbb{C}_k}$) power of all shiftable appliances for the k^{th} consumer is according to (5.13) and (5.14) respectively.

$$\mathcal{L}_{\hbar,\mathbb{C}_k}^{h} = \sum_{i}^{n_{s1,k}} a_{ik}^{h} \tag{5.13}$$

$$\mathcal{L}_{\hbar,\mathbb{C}_k} = \sum_{h=1}^{H} \sum_{i}^{n_{s1,k}} a_{ik}^{h} \tag{5.14}$$

The objective function $\mathcal{J}_{\mathbb{C}_k}$, to minimize cost for this class of appliances can be formulated as;

$$\min_{a_{ik}^{h}} \mathcal{J}_{\mathbb{C}_k} = \sum_{h=1}^{H} \sum_{i=1}^{n_{s1,k}} e^{\hbar} \cdot a_{ik}^{h} \tag{5.15}$$

$$\text{St.} \quad t \in \{\mathcal{T}_{start,i} \leq t \leq \mathcal{T}_{end,i} + 1\}\text{, for set } \mathbb{C}_k \tag{5.16}$$

$$\text{and} \quad \lambda_{ki}^{min,\mathbb{C}_k} < x_{ki}^{h} < \lambda_{ki}^{max,\mathbb{C}_k}, \;\; \mathrm{i} = 1,2, \dots, n_{s1,k} \tag{5.17}$$

The unit price for power in each time interval is taken to be the same for all appliances. Constraints (5.16) to (5.17) relate to limits imposed on the respective set of appliances.

Inelastic or Fixed Appliances, $\Delta t_d = 0$.

Luminaries, TV, fridge, lighting etc. are examples of nonshiftable loads. The energy consumption of these loads is fixed. Once switched on they should start and there is no elasticity in starting times. This inflexibility means these appliances cannot be shifted to other time slots or $\Delta t_d = 0$. Once on, they must run to their LOT to completion barring any prize or energy limits. The start and stop times of none-shiftable appliance is confined to the times, $\mathcal{H} \triangleq \{1,2, \dots h, h+1, \dots, H\}$ according to their specific LOT and start/end times. The total hourly and daily power of all none-shiftable appliances for the k^{th} consumer are;

$$\mathcal{L}_{\hbar,\mathbb{Q}_k}^{h} = \sum_{i}^{n_{s2,k}} a_{ik}^{h} \tag{5.18}$$

$$\mathcal{L}_{\hbar,\mathbb{Q}_k} = \sum_{h=1}^{H} \sum_{i}^{n_{s2,k}} a_{ik}^{h} \tag{5.19}$$

The cost minimization objective function $\mathcal{J}_{\mathbb{Q}_k}$ for inelastic appliances is given as;

$$\mathcal{J}_{\mathbb{Q}_k} = \sum_{h=1}^{H} \sum_{i=1}^{n_{s2,k}} e^{\hbar} \cdot a_{ik}^{h} \tag{5.20}$$

$$\text{s.t.} \quad t \in \{\mathcal{T}_{start,i} \leq t \leq \mathcal{T}_{end,i}\}\text{, for set } \mathbb{Q}_k \tag{5.21}$$

$$\text{and} \quad \lambda_{ki}^{min,\mathbb{Q}_k} < x_{ki}^{h} < \lambda_{ki}^{max,\mathbb{Q}_k}, \ \text{i} = 1,2,\dots,n_{s2,k} \tag{5.22}$$

Again, the unit price for electricity for each appliance in the respective set is the same throughout the time interval. The constraint (5.22) specifies the consumption energy limits.

1.11 General flexibility & inflexible Appliances

Certain home appliances such as tea makers, dryers, washing machines, toasters, etc., can be scheduled with more flexibility and very limited discomfort to the user. These belong to set $\mathbb{R}_k$. The appliances do not need to be immediately turned on when demanded i.e., $\Delta t_d > 1$ but once on, they should run to finish. For this class of appliances, it is more instructive that they activate during off-peak hours as far as possible to save electricity and hence cost. The waiting times Δt_d, are therefore much longer than the previous class.

$$\Delta t_k \in \left[\mathcal{T}_{end,i} - \mathcal{T}_{start,i} + \Delta t_d\right], \quad \forall t = \left\{\mathcal{T}_{start,i} \le t \le \mathcal{T}_{end,i} + \Delta t_d\right\} \tag{5.23}$$

$$\text{s.t.} \quad t \in \left\{\mathcal{T}_{start,i} \le t \le \mathcal{T}_{end,i}\right\}, \text{ for set } \mathbb{R}_k \tag{5.24}$$

Cost minimization objective function $\mathcal{J}_{\mathbb{R}_k}$ for this class of appliances is given as;

$$\mathcal{J}_{\mathbb{R}_k} = \sum_{h=1}^{H} \sum_{i=1}^{n_{s3,k}} e^{\hbar} \cdot a_{ik}^{h} \tag{5.25}$$

$$\text{s.t.} \quad t \in \left\{\mathcal{T}_{start,i} \le t \le \mathcal{T}_{end,i}\right\}, \text{ for set } \mathbb{R}_k \tag{5.26}$$

$$\text{and} \quad \lambda_{ki}^{min,\mathbb{R}_k} < x_{ki}^{h} < \lambda_{ki}^{max,\mathbb{R}_k}, \ \text{i} = 1,2,\dots,n_{s2,k} \tag{5.27}$$

The expression (5.26) specifies the constraint on operating time and (5.27) is the energy consumption bounds for each appliance.

1.12 Scheduling and Optimization

We assume a ToU pricing signal is received from the utility. The objective is to optimize the electricity bill so that overall, a utility PAR is reduced. The range of appliances considered belong to the $\mathbb{C}_k, \mathbb{Q}_k,$ and $\mathbb{R}_k$ i.e., elastic, shiftable to within $\Delta t_d =$ h, 2h, …, and shiftable with $\Delta t_d = 2h,$ sets wherein $h = 1\ Hour$. Consumers can specify Δt_d to suit self-energy needs. To avoid new peaking during low grid pricing time intervals, consumers are limited to a specified upper bound in the total amount of energy they can utilize. Hence overall, the optimization is carried out within the limits of each respective LOT, Δt_d delay flexibility and the consumption bounds $\lambda_{ki}^{min}, \lambda_{ki}^{max}$. The objective function is;

$$\mathcal{J}_k = \mathcal{J}_{\mathbb{C}_k} + \mathcal{J}_{\mathbb{R}_k} + \mathcal{J}_{\mathbb{Q}_k} \tag{5.28}$$

$$\min_{a_{ik}} \mathcal{J}_k = \sum_{h=1}^{H} \sum_{i=1}^{n_{s1,k}} e^{\hbar} \cdot a_{ik}^{h} + \sum_{h=1}^{H} \sum_{i=1}^{n_{s2,k}} e^{\hbar} \cdot a_{ik}^{h} + \sum_{h=1}^{H} \sum_{i=1}^{n_{s3,k}} e^{\hbar} \cdot a_{ik}^{h} \tag{5.29}$$

Each of the three components in (5.29) is subject to the constraints defined in earlier expressions above. This objective function (5.29), can be solved by first solving partial problems in (5.15), (5.20) and (5.24). Since these sub-problems are convex, they are solvable by standard optimization techniques while minimizing energy consumption and considering all constraints.

1.13 Simulation Methodology

The problem outlined above is simulated for an SH with appliance loading parameters of Table 5-1. The initial energy vector is initially randomly distributed between all appliances. The simulation is done for scheduled and unscheduled scenarios. For the unscheduled case, the appliance that is ON runs its full LOT to completion disregarding energy consumption constraints and time flexibility. For the scheduled case, optimized scheduling happens. Simulation parameters $\mathcal{T}_{end,i}$, $\mathcal{T}_{start,i}$ and $\mathcal{T}_i$ applied in the simulation are selected randomly. To evaluate the proposed algorithm, the performance of unscheduled appliances is compared with that of scheduled cases.

Table 5-1. SH Appliances Loading parameters

						Power In Each Hour, Watts																							
Hour	Rating, W	***t_ON***	***t_OFF***	***LOT***	***Diversity***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Lighting: Single x 20	800			**5**	**1.00**	35	12.5	10	8	5	12.5	25	40	30	30	30	28	31	24	13	45	55	75	97	125	135	145	144	94
Fridges	700			**12**	**1.00**	62.5	62.5	62.5	62.5	62.5	62.5	62.5	75	75	75	75	62.5	62.5	62.5	62.5	62.5	75	79.2	78.3	79.1	75	71	75	75
Stove:Large Plates	2100			**3**	**0.83**	2.5	2.5	4.2	4.2	4.2	12.5	17	18	30	30	30	42	50	42	26	25	84	118	118	68	50	50	17	8.2
Oven:Bake Element	1500			**0.5**	**0.67**																								
Oven:Grill Element	1500			**0.5**	**0.50**																								
Oven:Warmer	400			**0.8**	**0.83**																								
Kettel	2000			**0.5**	**1.00**																								
Dishwasher	1500			**2**	**0.83**	5	0	0	0	0	0	0	4.2	8.4	12.4	12.5	16.8	8	6	3	6	8	9.5	18	18	22	25	25	8
Microwave	1000			**1**	**0.67**																								
Washing Dryer	5400			**2**	**0.13**	9.2	0	0	0	0	0	3.3	3.4	3.4	12.5	15	20	20	20	16	15	22	22	22	22	25	13	8	4
Washing Machine	2300			**4**	**0.33**																								
Audio Sets	450			**5**	**1.00**	0	0	0	0	0	0	0	3.3	3.3	3.3	3.3	3.5	3.5	3.5	3.5	3.5	3.5	4	4	4	4	4	4	4
TV	100			**6**	**1.00**	16	8	8	5	3.2	3.2	5	14	16	17	17	17	17	17	17	17	17	19	25	30	45	50	40	18
PC's	300			**8**	**0.83**	30	25	25	25	25	25	25	30	30	32	37	37	37	37	37	37	37	37	44	45	45	46	43	40
Cell Phone Chargers	84			**5**	**0.17**																								
Heater	1000			**5**	**0.33**																								
Geysor	3000			**6**	**1.00**																								
Ironing	1500			**4**	**0.20**																								
Hoover	1400			**3**	**0.17**																								
Pool Pump	750			**8**	**1.00**																								
Tooster	800			**0.5**	**0.53**	0	0	0	0	0	0	50	50	0	0	50	50	0	0	0	0	0	50	50	50	0	0	0	0
Air Con	2500			**12**	**0.67**	0	0	0	0	0	0	0	650	650	650	3500	3500	3500	3500	0	0	0	750	750	750	750	750	0	0
Others	250			**8**	**1.00**	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	20	20	20	12.5	12.5	12.5

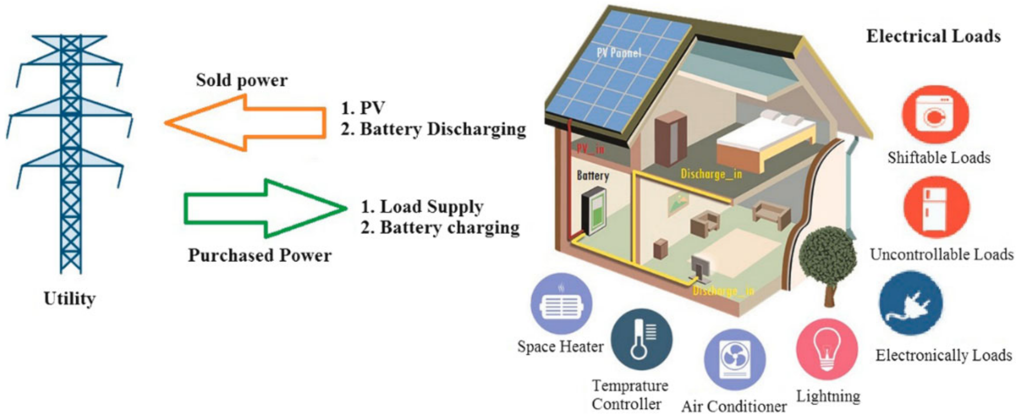


Fig. 5-3. Model schematic of smart home [79]

Fig. 5-3 depicts further loading details of a smart home model based on which we develop the subsequent optimization algorithm. The SHs in each area are serviced by an MG. The utility grid and RES are connected to SH via SMs. Multiple homes share a PCC or bus bar as such form a common node of the multiple homes/loads in a radial connection configuration. The SM connects to the HEMS responsible for scheduling residential appliances according to some optimization algorithm. Consider three types of N appliances which use electrical energy over a set of $\mathcal{H}$ time slots in 24 hours. The 24-hour scheduling horizon is divided into 24 equal slots h of one-hour duration. Under scheduling, the HEMS calculates the starting $\mathcal{T}_{start,i}$ and finishing $\mathcal{T}_{end,i}$ time intervals as well as the energy consumption of each appliance in each time interval without exceeding stipulated power capacity. The energy consumption during the h interval is defined in (5.13) - (5.25).

Each entity model comprises HEMS, ICT networks and utility tariff signal as shown in Fig. 5-3. Appliances for each SH have specified consumption ratings, LOT and time window within which they can be scheduled, $\mathcal{T}_i$ as depicted in Table 5-1. With K households and each having N smart appliances, they are a total of $K \times N$ controllable appliances for an area. Each of the KN appliances has a specific energy consumption profile and operational time as set out in (5.30). DR in the residential sector achieves more savings as its more tolerable to switch-on delays times, Δt_d when compared to commercial sectors. Elastic or shiftable appliances work their full LOT within the allowable delay, constraints placed by the utility, comfort requirements and optimization interval $\mathrm{h} = 1$ hour. This is depicted in Fig. 5-4. Table 5-2 illustrates a typical classification and power ratings of the SH appliances.

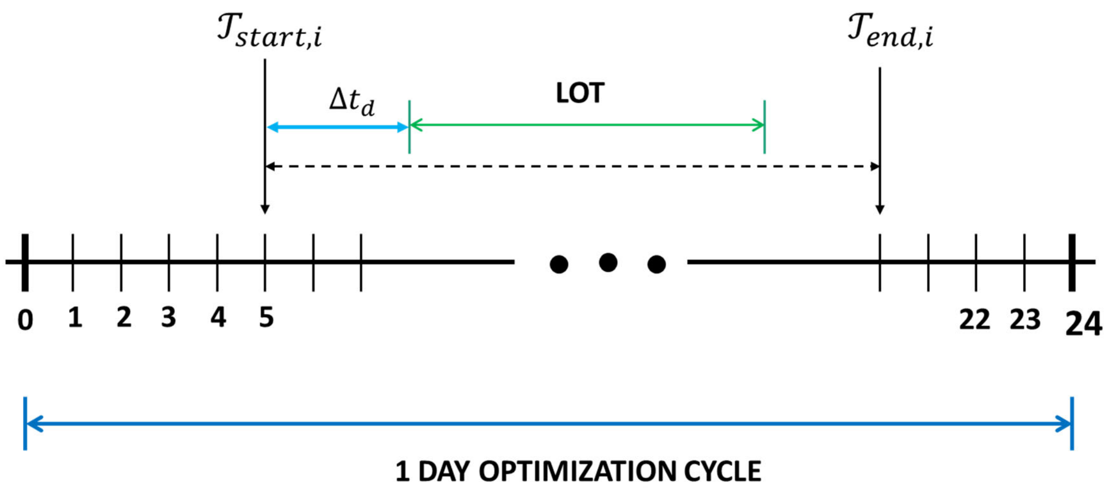


Fig. 5-4 Load time shifting cycle times

Table 5-2. Load classification

			Op Interval			
CLASS OF APPLIANCE	**Hour**	Rating, kW	***t_ON***	***t_OFF***	***LOT***	***Diversity***
None Interuptable Appliances	Lighting: Single x 20	0.8	18:00	6:00	**5**	**1.00**
	Fridges	0.7	1:00	0:00	**12**	**1.00**
	PC's	0.3	1:00	24:00:00	**8**	**0.83**
	Stove:Large Plates	2.1	6:00	22:00	**3**	**0.83**
	Washing Machine	2.3	1:00	22:00	**2.5**	**0.33**
	Audio Sets	0.45	1:00	24:00:00	**5**	**1.00**
	TV	0.1	1:00	24:00:00	**6**	**1.00**
	Microwave	1	6:00	22	**1**	**0.67**
	Dishwasher	1.5	15:00	22:00:00	**2.5**	**0.83**
Interruptable Appliances, <= 1 Hour.	Oven:Bake Element	1.5	14:00	16:00	**0.5**	**0.67**
	Oven:Grill Element	1.5	14:00	16:00	**0.5**	**0.50**
	Oven:Warmer	0.4	16:00	22:00	**0.8**	**0.83**
	Kettel	2	6:00	23:00	**0.5**	**1.00**
	Tooster	0.8	6:00	18:00	**1**	**0.53**
	Cell Phone Chargers	0.084	1:00	24:00:00	**5**	**0.17**
Flexible Appliances, =>2 Hr Interruption	Washing Dryer	1.2	18:00	6:00	**4**	**0.13**
	Heater	1	18:00	23:00	**5**	**0.33**
	Geysor	3	5:00	20:00	**6**	**1.00**
	Ironing	1.5	6:00	16:00	**3**	**0.20**
	Vacuum Cleaner	2	6:00	15:00	**2**	**0.17**
	Pool Pump	0.75	1:00	12:00	**8**	**1.00**
	Air Con	2.5	10:00	23:00	**12**	**0.67**
	Others	0.25	1:00	24:00:00	**8**	**1.00**

The utility connects via the HEMS which allows dual-direction information flow. It receives utility real-time price information and performs the DSM based on load shifting as well as load monitoring to achieve optimal utilization of energy in terms of cost, energy, consumer utility function or a combination thereof. Power flow can also be bi-directional. The HEMS can store consumption patterns and serve as gateways between the utility and other households in the MG. Configured appropriately, the HEMSs can process large numbers of household appliances with reference point information from the consumers. Each of the household appliances requests their respective HEMS for switch-on at appropriate time slots, Fig. 5-4. These switch-on requests are processed according to a specified optimal criterion which relies on the availability of day ahead rates.

This work assumes that communication networks WANs, NANs and HANs are in place. Immediately, households' devices link to the SM via HANs. From the SM, information is channelled to the HEMSs. Multiple SMs of different consumers connect to the NANs from which all the consumption signals and information are sent to a central aggregator. The central aggregator communicates its information to the utility through WANs. Finally, the WANs communicate DR and the price information between the power utility and the main EMS. This uses DA and CPP pricing schemes to analyse the performance of the proposed model.

Day-ahead prizing provided through SM enables households to appropriately schedule their appliances. This secures flexibility in keeping with the comfort demands of specific households and objectives to decrease electricity costs. The price signal adopted for this study is a combination of Fig. 5-5 (Eskom Tariff) and Fig. 5-6. The tariff regimes for each of these signals are discussed briefly below. In Fig. 5-5, they are three main regimes namely on-peak, off-peak and shoulder-peak hours. The load can be adjusted by observing the pricing signal sent from the utility.

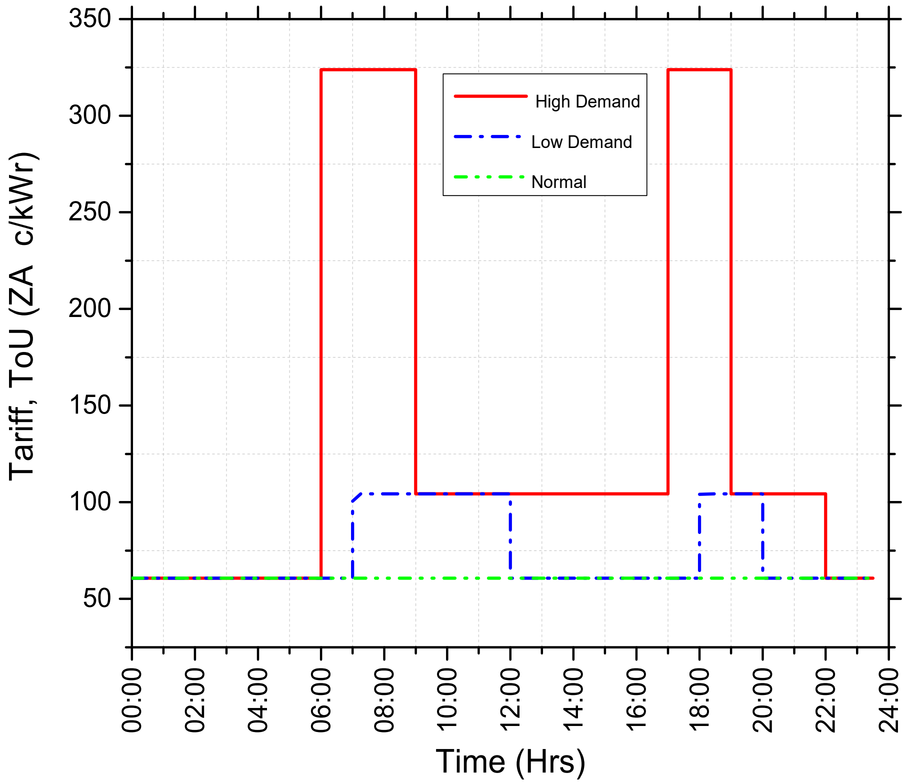


Fig. 5-5 Typical ToU tariffs for utility electricity

Mathematically the high demand pricing regime can be represented by peace wise stepped function, Fig. 5-5**.** The proposed SH energy management technique is based on CPP scheduling. Electricity tariffs are higher during critical peak hours. In the South African context, critical peaks are seasonal and diurnal. Concerning seasons, the tariff regime recognizes low and high-demand seasons. In respect of daily variations, they are three categories of periods namely peak time, standard and off-peak time [224], Fig. 5-5**.** Depending on the utility, during very hot summer days or very cold winter days, critical peak tariffs can be double or more as high as at other times.

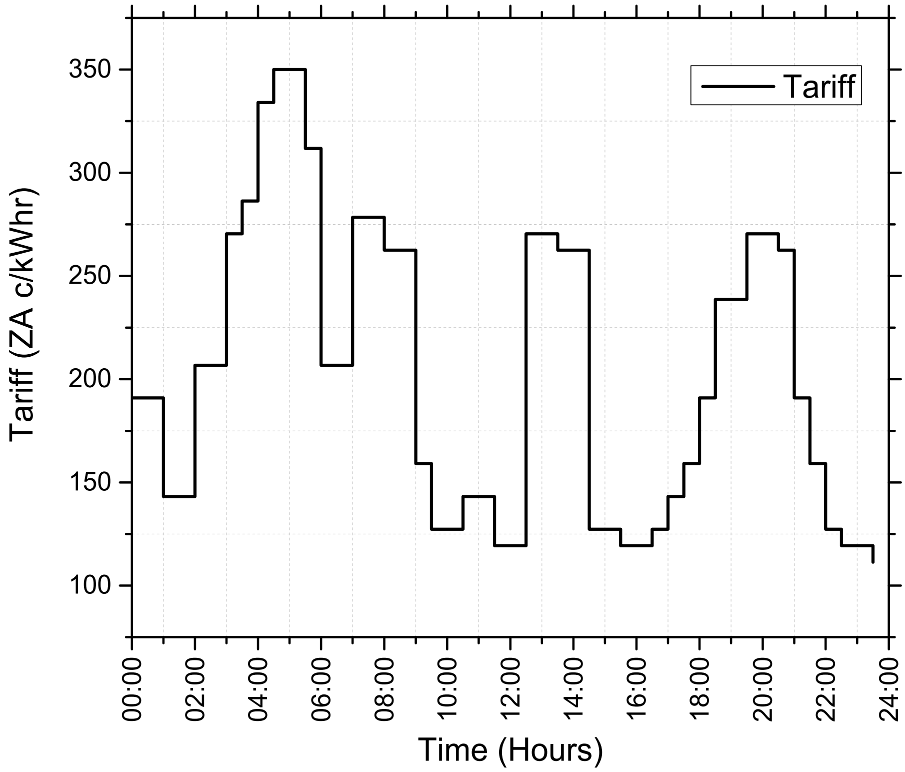


Fig. 5-6. Electricity day-ahead price signal, ZA c/kWhr

1.14 Load Shifting Model

The DSM energy consumption control reduces cost and improves efficiency and reliability. DSM optimally adjusts load. The key to its success is an accurate forecast consumer load profile. Domestic power consumption fluctuates and is dependent on occupancy and controllable appliance usage patterns. The presence of random REGs renders the forecasting of energy balance difficult. The most practical method for home DSM is load shifting (LS) through 'on-off' appliance control. Classification of these appliances has been dealt with in earlier sections. DSM can be achieved through SH load shifting automation or indirect load control via incentivized tariffs with user preference participation.

LS schemes work in tandem with some optimization routines where the single or multiple objectives could be minimizing energy cost or PAR using various techniques reviewed previously. Incorporation of REGs DSM creates additional optimization objectives in LS i.e., maximization of REG out consumption. If both forecastings of the REGs yield and load consumption are improved the efficiency of LS is equally improved. This synchronization of demand and supply from REGs is being intensively researched. This section outlines the DSM LS algorithm model of an MG with REGs. The LS scheme is adopted from [225]. It is based on the energy balance of the MG. The objective is to increase REGs and decrease utility energy consumption, from (4.17). The model is based on the energy balance between generation and consumption in CMG with K households supplied from the utility grid and REGs.

$$\sum_{h=1}^{N_{DG}} P_{DG_i} + \sum_{h=1}^{N_{REG}} P_{REG_i} + \sum_{h=1}^{N_{Grid}} P_{Grid_i} + \sum_{h=1}^{N_{BESS}} P_{BESS_i} = \tag{5.31}$$
$$= \sum_{l=1}^{K} \{ (\mathcal{L}_{l,\mathbb{C}_l} + \mathcal{L}_{l,\mathbb{Q}_l} + \mathcal{L}_{l,\mathbb{R}_l}) + \mathcal{L}_{k,Base} \}$$

$\mathcal{L}_{k,Base}$ is the base load for the k^{th} household. $\mathcal{L}_{l,\mathbb{C}_l}$, $\mathcal{L}_{l,\mathbb{Q}_l}$ and $\mathcal{L}_{l,\mathbb{R}_l}$ are total daily loads for the respective l^{th} household as defined in the classification of Fig. 5-2. The energy consumed by the categories of these appliances plus the base load for the k^{th} household is,

$$\mathcal{L}_{Controllable,k} = (d_{k,1}\mathcal{L}_{k,\mathbb{C}_l} + d_{k,2}\mathcal{L}_{k,\mathbb{Q}_l} + d_{k,3}\mathcal{L}_{k,\mathbb{R}_l}) + \mathcal{L}_{k,Base} \tag{5.32}$$

$d_{k,1}$ are coefficients indicating the presence of a respective class of appliance in k^{th} household. If categories $\mathbb{C}, \mathbb{Q}$ and $\mathbb{R}$ are present all the coefficients are one otherwise it is zero. The energy consumption (5.32) can be formulated as a matrix of matrices.

$$\boldsymbol{\mathcal{L}}_{Controllable} = [\mathbf{D}]_{\boldsymbol{K\cdot n}} \cdot [\mathbf{E}]_{\boldsymbol{n\cdot 1}} + [\mathcal{L}_{k,Base}]_{\boldsymbol{K\cdot 1}} \tag{5.33}$$

The consumption over the simulation H time intervals is expressed in (5.9), (5.15) and (5.18). Outside the scheduled time this power in the specific interval is zero.

1.15 MKP Optimization Approach

To minimize consumption and users' discomfort the energy scheduling problem can be formulated as a constrained Multiple Knapsack optimization problem (MKP). The concept of the knapsack is that a backpack can only maximally hold a specific amount of weight. The challenge is to pack the right set of items into it in terms of value and weight. The objective is to maximize the value of items so that the total weight is minimal and below maximum capacity. In essence, this is what is referred to as the MKP. It's a combinatorial dynamic programming optimization wherein the problem is divided into subproblems the results of which are used to solve the larger problems. Summarizing, the scenario is;

- A knapsack holds a maximum weight of, W. This is like the maximum energy demand $\mathcal{L}_{k,max}^{h}$, a user can draw from the grid at a time instant, h.
- They are a collection of n items to choose from to load the backpack.
- Each of the n items weights w_i and they are an array of weights, $[w_1 \quad w_2 \quad , \ldots, \quad w_{n-1} \quad w_n]$ to choose from, analogous to the energy consumed by appliance i of the k^{th} household x_{ki}^{h} .
- Each of the n items has a value $v_i \in [v_1 \quad v_2 \quad , \ldots, \quad v_{n-1} \quad v_n]$ that can be selected, this talks to the number of household appliances to be switched optimally. e^h cost of energy consumed by appliance i at time instant h.
- m knapsacks to be packed are like H optimization time intervals in the energy management scenario.

The target is that an optimal set of items that maximize the value but minimize the weight to within knapsack capacity, W be selected. This typifies a resource allocation combinatorial problem. Every resource has a capacity constraint. Applied to household energy management, the question is to find an optimal combination of appliances' operation modes while observing the total capacity of available power from the REG sources and /or the grid. The MKP formulation results in a practical simple Integer Linear Programming (ILP) scheduling problem which naturally is a subproblem of an otherwise complex optimization task. This can be used to schedule SH appliances.

Optimization formulation

In this section, the constrained objective function is formulated together with the performance indices being the cost of electricity consumption, user discomfort, aggregate energy consumed, and PAR. Based on these the residential load optimization is derived.

The parameter h_{ut} is the user preferred switch-on time, h_{st} scheduler defined switch-on time. The energy consumed by a single residential device over a 24-hour time horizon can be expressed as,

$$\mathcal{L}_{k,i} = \sum_{h=1}^{H} a_{ik}^{h} \cdot \delta_{i,h} \quad , \quad \delta_{i,h} = \begin{cases} 1, when\ appliance\ i\ is\ ON \\ 0, when\ appliance\ i\ is\ OFF \end{cases} \tag{5.34}$$

where $\delta_{i,h}$ represents the on/off status of appliance i at time slot h. This function is defined as (5.35)The total household energy consumed by the total of n smart appliances is given by,

$$\mathcal{L}_{k} = \sum_{h=1}^{H} \sum_{i}^{n} a_{ik}^{h} \cdot \delta_{i,h} \tag{5.35}$$

The cost of energy consumed by all the devices is given by;

$$\mathcal{C}_{k} = \sum_{h=1}^{H} \sum_{i}^{n} e^{k} \cdot a_{ik}^{h} \cdot \delta_{i,k} \tag{5.36}$$

Maximization of consumer utility is the same as minimization of consumer disutility or discomfort. This implies that the optimization problem can be cast as a "minimization" of both cost and discomfort. Time-flexible appliances may delay switch times by Δt_d to another time slot $\Delta t_d + h$. This delay is accompanied by consumer discomfort. In the same way, appliances whose power is curtailed to operate at reduced levels to minimize the energy bill also result in discomfort. Various formulations are adopted in the literature to express this discomfort Υ due to time-flexible appliances such as;

$$\Upsilon = \sum_{i=n}^{N} \xi \left(t_{start,a_i}^{h} - t_{end,a_i}^{h} \right)^{\mu}, \quad 0 < \xi < 1, \ \mu \geq 1 \tag{5.37}$$

t_{start,a_i}^{h} and t_{end,a_i}^{h} are the appliances' actual start and end operational times in the possible operational interval $[\mathcal{T}_{end,i} \quad \mathcal{T}_{start,i}]$. ξ and μ are real numbers so limited to minimize dis-utility due to delayed operation. If these limits are violated, the consumer suffers on-delay discomfort, the utility function decreases, or the dis-utility increases. Discomfort caused by power-flexible or curtailable appliances is also formulated using the Toguchi loss function [226]. This quality loss Loss^{fn}, function is a U-shaped parabolic curve, determined by a quadratic function of the form.

$$\text{Loss}^{fn}(x) = \text{Constant} \times \left(x - \text{Target}^2 \right) \tag{5.38}$$

x is the value of the observed quality characteristic. Target is the nominal value of the quality characteristic and Constant is a proportionality constant. In instances of appliances with rated power, dis-utility can be formulated as;

$$\upsilon = \omega_x \left(x_{k,a_i}^h - x'^h_{k,a_i} \right)^2. \tag{5.39}$$

The parameter, ω_x depends on the type of appliance. x_{k,a_i}^h is the nominal power consumption, and x'^h_{k,a_i} curtailed power from nominal during the h^{th} time interval? This function has a minimum of zero when they are no deviation. The combined discomfort due to delays and power curtailment becomes.

$$\text{Discomfort} = \upsilon + \Upsilon \tag{5.40}$$

In [227] the comfort function due to an appliance on delays at $\mathrm{t} = \mathrm{h}$ is formulated as;

$$\upsilon = \left| t_{start,a_i}^h - t_{end,a_i}^h \right| \tag{5.41}$$

For all the appliances in each interval, this can be re-formulated as;

$$\Upsilon = \sum_{i=n}^{N} \xi \left| t_{start,a_i}^h - t_{end,a_i}^h \right|^{\mu} \tag{5.42}$$

Another formulation [228] expresses the user comfort as a function of delay which is computed according to;

$$\Upsilon = \frac{\sum_{i=n}^{N} \xi \left| t_{unscheduled\,start,a_i}^h - t_{scheduled\,start,a_i}^h \right|^{\mu}}{\sum_{i=1}^{N} t_{scheduled\,start,a_i}^h}, \quad \mu = 1, \quad \xi = 1 \tag{5.43}$$

Load curves for shiftable appliances are modified by adjusting and shifting their energy consumption profile in time to reduce electricity costs and PAR through a mechanism enunciated in Section 5.5. These appliances are subdivided into three classes, which are fully elastic (in time and power level), non-interruptible and fixed devices. Various other utility function formulations exist in the literature. The PAR can be formulated as;

$$\text{PAR} = max_{h \in \mathcal{H}} \left(\sum_{i}^{n} e^{\hbar} \cdot a_{ik}^h \cdot \delta_{i,k} \right) \left(\frac{1}{H} \sum_{h=1}^{H} \sum_{i}^{n} e^{\hbar} \cdot a_{ik}^h \cdot \delta_{i,k} \right)^{-1} \tag{5.44}$$

Here we have two objectives i.e., minimization of cost (5.40) and minimization of alternate comfort functions (5.37) - (5.43). Scalarization is applied to combine the two objectives into a single objective optimization problem. User-specified trade-off weights ξ_1 and ξ_2 are such that $|\xi_1| \leq 1$, $|\xi_2| \leq 1$ and $\xi_1 + \xi_2 = 1$. ξ_1 and ξ_2 are associated with the importance attached to cost and discomfort objectives respectively. The objective function and constraints can thus be summarized as;

$$min_{\mathcal{C}_{k},\Upsilon} \ \mathbb{J}(k,h) = \xi_1 \mathcal{C}_{k} + \xi_2 \Upsilon \tag{5.45}$$

$$\text{s.t.} \quad \mathcal{L}_{k^h} = \sum_i^n a_{ik}^h \cdot \delta_{i,h} \leq \lambda_{max}^k \text{ for all time.}$$

$$\text{PAR} \leq \text{PAR}_{max}^k$$

$$\sum_{i=1}^{H} \delta_{k,h} \leq \text{T}_i^k, \forall\, i = 1,2,\dots,H$$

$$\mathcal{T}_{start,i} \leq \text{h} \leq \mathcal{T}_{end,i}$$

$$\mathcal{C}_{k} \leq \mathcal{C}_{k}^{max}, \text{ Costs ceiling}$$

$\delta_{i,h}$ means the on/off state of a given smart appliance. The constrained objective function to be minimized consists of cost and dis-utility components (5.45). PAR is addressed included to arrest peaking at any time again securing grid stability. The LOT of each appliance is completed to ensure consumer satisfaction and finally, the total consumption cost with HEMS should be lower than the total cost without HEMS.

Inclusion of RES in the model & Simulation Results

A typical SH has RES such as PV, DG or WT and the utility grid. The RES feed the SH or BESS during peak price times of grid electricity. The HEMS coordinates the RESs with the utility grid as needed. At time $t = h$, the power generated by the PV source is $P(t)$. Over the time interval, $[T_{v_1}, T_{v_2}]$. Total energy from the PV RES can be expressed as;

$$\text{P}(t) = \sum_{T_{v_1}=ah}^{T_{v_2}=bh} a_{ik}^h \cdot \delta_{i,k} \tag{5.46}$$

Connection to SH is subject to generation being above a certain threshold. The total energy consumption model is given in (5.29).

Simulation

The optimization problem formulated in section 5.6 is considered with $N = 23$ smart appliances each consuming a_{ik}^{h} when running under scheduled and unscheduled conditions. These two operational modes allow for a comparison of the optimization techniques. In the unscheduled scenario, each appliance runs to completion without regard to energy limits whereas the scheduled scenario incorporates DSM optimization. The random simulation parameters used are set out in Table 5-1 and a typical ToU praise signal is shown in Fig. 5-6.

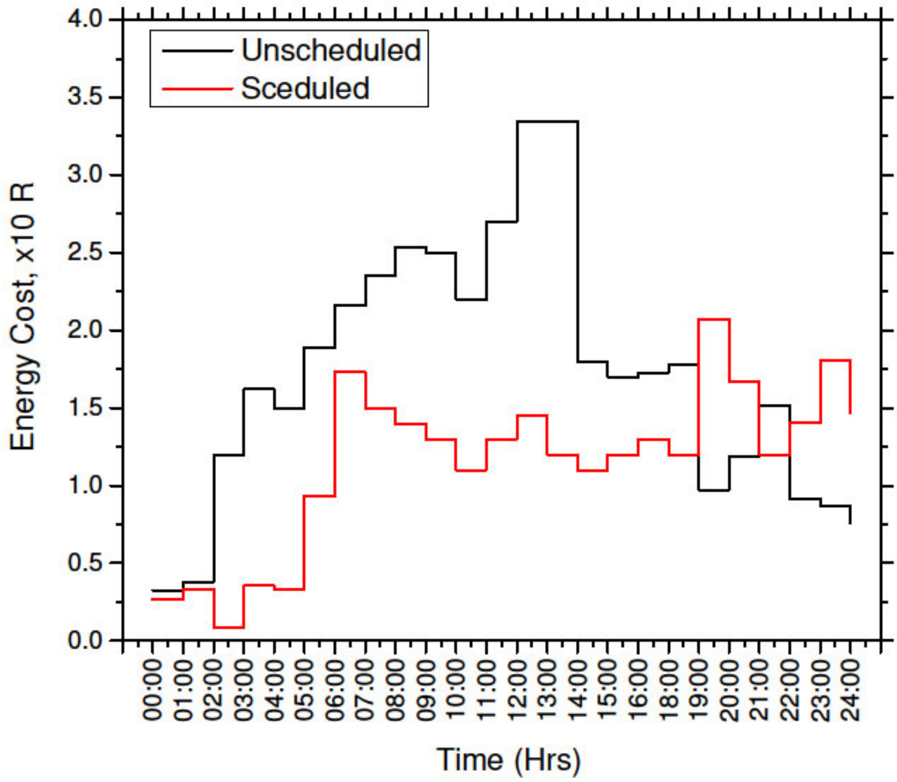


Fig. 5-7. Comparison of unscheduled energy costs and Scheduled costs

Early morning hours, midday and evening cost of power is relatively high. As expected, this is due to more power usage probability. The gap between scheduled and unscheduled power consumption is clear. Unscheduled consumption is high during high pricing hours, while scheduling tries to bring this cost down. The proposed algorithms optimally adjust the on-time of smart appliances to bring about a reduction in the peak load. Comfort is ignored.

Power consumption of scheduled, unscheduled as well price signals is depicted in Fig. 5-7. It is clear from the figure when we compared the unscheduled case with the proposed algorithm which consumes more power when the price during times (4 AM-7 AM) is low and less power when the price during (10 AM-6 PM) is relatively high.

1.16 Chapter Conclusion

In this chapter, we studied a residential electricity load management problem for a smart home in a ToU pricing environment. Different appliances are used based on their *LOT* and energy consumption cycle. An SH mathematical model and an optimization algorithm to reduce the overall electricity bill, as well as peaks during low-price hours, were developed. User comfort was not included. The proposed algorithm will be useful when practically implemented. Future work will enhance this model by inclusion of variable scheduling flexibility, RTP models, user comfort etc. Although this chapter demonstrates that a significant reduction of energy cost is possible, limitations exist due to user-specific LOT which determines acceptable levels of comfort or discomfort.

This section focused on the residential SH consumer since the residential energy management with SG holds the most promise of MG energy management initiatives to reduce electricity consumption. By integrating the SG and DSM in this sector, overall energy reduction is quite achievable. The two most promising REG technologies in this sector are PV systems and WT. Two methods of resolution have been proposed, first proposed a robust MILP model to optimize the energy production and consumption systems. Then, an algorithm based on a mate-heuristic technique to minimize the electricity cost of the consumer. Two case studies have been simulated showing significant energy cost savings. The next chapter aims to propose an optimized energy management model based on a new heuristic technique called Atom Search Optimization (ATOM) search optimization. This chapter provides comprehensive work on load scheduling using such heuristic algorithms.

Chapter 6 Non-Convex MG Dispatch Optimization

1.17 Introduction

A convex optimization problem has one global optimal solution or no feasible solution. On the other hand, a nonconvex optimization problem is multi-modal and generally takes long to identify if a global solution exists. Hence, convex optimization problems are easier whereas non-convex problems require greater effort if solvable. Strides have been made in the integration of DSM in the planning of Isolated or Islanded Microgrids (IMGs). However, there are few works of literature on non-convex cost function optimization for DGs. Not much has been covered regarding algorithms for microgrid optimal load-dispatch either.

In this section, we formulate a day-ahead dispatch problem of microgrids with DGs subject to the non-convex cost function. An operational framework to address the DGs 'valve-point' loading effect as well as optimise its performance is proposed. The valve-point effect induces a ripple in a 'fuel-cost' curve. The impact of DSM on convex and non-convex EMS problems with different load participation levels is investigated. Further, the DA scheduling horizon of a fifteen-minute resolution time is considered to examine the effect of load dynamics in the MG. The new optimization algorithm, Quantum Particle Swarm Optimization (QPSO) is employed for the solution of the non-convex DGs cost optimization problem. It is demonstrated that the algorithm solves the energy management system (EMS) problem efficiently. Simulation results point to a 5% reduction in OPEX costs with a minimal penalty on customer satisfaction or utility.

MGs integrate and interconnect a variety of stochastic as well as nonstochastic renewable sources at LV or MV distribution network levels. Their EMS executes several operations e.g. interchange of power and market parameters at the bulk utility-scale, dispatch, and control of DER plants at the consumer level. Most microgrid scheduling techniques perform optimization of DGs from the supply side. The continual increase in energy consumption is edging grids towards their loading capacity. DSM techniques are a way to accommodate increasing load by promoting local DGs and influencing clusters of controllable loads. These strategies reshape consumers' consumption patterns and with proper management of consumer demand storage investment is reduced [229]. Several DSM strategies have already been introduced and the application of these strategies for solving DA optimal scheduling problems in microgrids is gaining importance. Intermittency and uncertainty concerning load demand are other problems that need circumventing.

Unlike the standard DA scheduling problems with a time step of 1 hour, specific MG configurations will have a non-integer parameter in the energy transition period. This intra-hour optimized model for dispatch which is based on a centralized EMS framework is considered in [230]. However, such variable time step models result in a heavy processing computer processing load, more so when many REGs are used such as Rolling Time Horizon method in [230]. Other techniques, such as the Adaptive Neuro-Fuzzy system energy management have reported superior computational results[218].

In this section, an EMS model is synthesized for different depths of DSM on controllable loads,[245]. Smaller MGs can be connected to form larger microgrids. The interconnectivity of MGs enhances smart distribution networks' security, reliability, and resiliency [230]. Most microgrid EMS problems aim to reduce operating costs. The assimilation of DSM into the EMS problem is increasingly being reported in many research articles. A flexible load re-shaping technique is introduced in [231] to improve inter-energy trading costs between utility and MGs.

Overall OPEX of the grid-tied MGs are substantially decreased when DSM is implemented. Bidding models of DGs in the MG are treated as usual quadratic convex functions. Throttling, akin to traditional generators refers to 'steam' power output adjustments in tandem with load demand. When these adjustments occur, power losses also happen. This phenomenon also occurs in DG units but often such losses are generally not accounted for in the literature [231]. This throttling effect resulting from power adjustments in response to loading demand is described as the "Valve-Point Effect" (VPE). Including the VPE in MGs with DGs, makes their cost function non-convex, discontinuous, and not differentiable. The day-ahead dispatch problem of microgrids with DGs subject to a non-convex cost function to address the research gap discussed earlier, [245] is formulated and the effect of load dynamics with DSM participation is also incorporated and investigated. Traditional algorithms fail to solve the non-convex optimization problem due to trapping in localised optimal points [231]. This is where a novel Quantum Particle Swarm Optimization (QPSO) algorithm is introduced to resolve the EMS DA optimized scheduling in MGs with a non-convex cost function.

1.18 Islanded Microgrid Model & Scheduling

A generic model of microgrid comprising of DERs that can be dispatched and those that cannot be dispatched is adopted, [232]. As shown in Fig. 6-1, three MG feeders namely residential, commercial, and industrial are connected to the utility at the PCC. PV, WT, DG, MT, and FC supply power to adjustable and non-adjustable appliances. An MGCC determines the power set point to the various local controllers (LC) to turn on or off or adjust the scheduled loads. Generation profiles for the non-dispatchable sources like PV and WT can be forecasted 24 hours for scheduling purposes. The system data on generation, forecasted load, market unit costs, and DER offers and the model nonconvex coefficients are borrowed from [233].

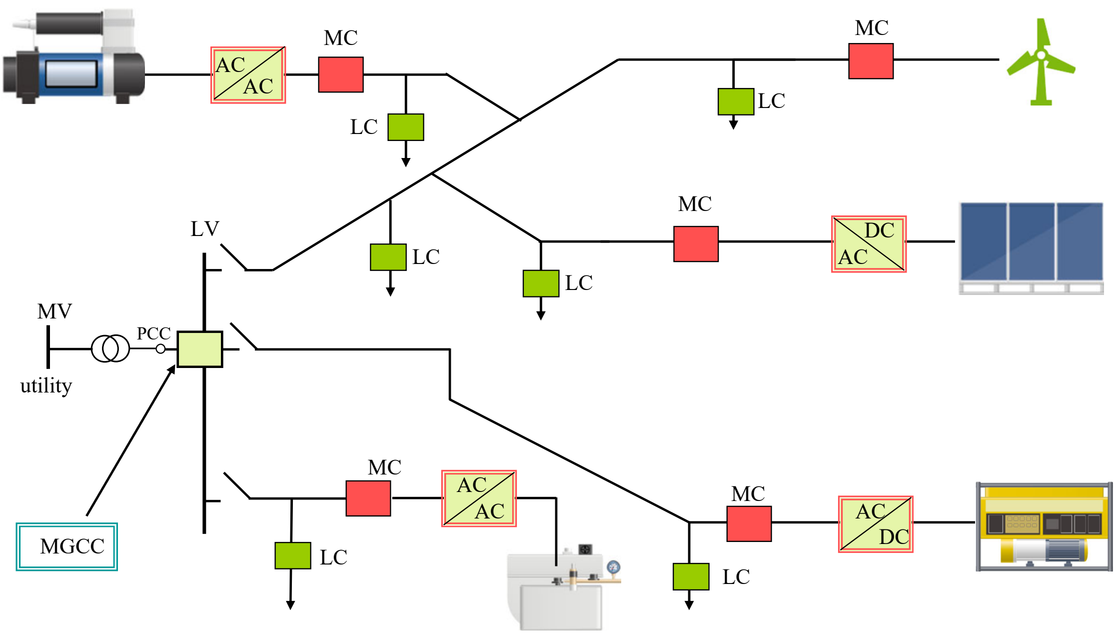


Fig. 6-1. Islanded MG Model

The PV and WT generator models are outlined in Chapter 4. DG units comprise fossil fuel engines coupled to a synchronous generator to produce electrical energy. Air is blown into the generator until it is compressed. Under high pressure, it is directed towards the turbine's blades whence its kinetic energy produces a turning effect. The DG's fuel consumption $F_{DE}$is normally characterized by its kW power rating according to a quadratic convex function [233]. This quadratic cost function can be modified to a non-convex function by the inclusion of its valve–point loading effect (VPE) as follows, [234]:

$$F_{DE} = a_{DE}P_{DE}^{min} + b_{DE}P_{DE}^{2} + \mathrm{c} + \mathrm{d}\cdot \mathrm{Sin}\left|eP_{DE} - eP_{DE}^{min}\right| \tag{6.1}$$

Where, a, b, c, d and e are none convex quadratic coefficients of the DG, P_{DE}^{min} and P_{DE} represent the minimum and nominal power outputs from the diesel generator respectively. The sine term mimics the valve throttling effect.

An FC, via an electrochemical redox reaction, converts e.g., H_2 chemical energy and an oxidizing agent, O_2 into electricity. FCs require a continuous flow of fuel and O_2 /air to sustain the reaction. They can continuously produce electricity for as long as H_2 and O_2 are supplied. Like DG, the cost function of an FC is taken as quadratic non-convex to account for the VPE; It can be expressed as (6.2), [234].

$$F_{FC} = aP_{FC}^{min} + \mathrm{b}P_{FC}^{2} + \mathrm{c} + \mathrm{d}\cdot Sin\left|eP_{FC} - eP_{FC}^{min}\right| \tag{6.2}$$

Where, P_{MT}, P_{FC} are *MT* and *FC* power outputs, P_{MT}^{min} is the lowest power obtained from *MT*. In general cost function of DG unit, *i* is given in (6.5). The cost of power from the FC is normally estimated according to the bid relationship (6.3):

$$B_{FC} = C_f \frac{P_{FC}}{\eta_{FC}} + C_{inv},\ Rands \tag{6.3}$$

Such that, C_f is the fuel cost to operate the FC, η_{FC} is the efficiency of the fuel cell, and C_{inv} is its annual investment cost. The objective is to find the optimal set points for the DGs to minimize the total cost due to load demand imposed on the MG. This cost covers the fuel consumption of DGs, unit start-up costs, and market rates attributed to power grid-MG interchange. Mathematically, this can be modelled as;

$$Min\,E(\alpha) = \sum_{t=1}^{H} OC \tag{6.4}$$

$$= \sum_{t=1}^{H} \left\{ \sum_{i=1}^{N} \left[u_i^t B_{DG_i}^t P_{DG_i}^t + S_{DG_i} \left| u_i^t - u_i^{t-1} \right| \right] + \sum_{i=1}^{N_{BESS}} \left[u_j^t B_{BESS_j}^t P_{BESS_j}^t + S_{BESSj} \left| u_j^t - u_j^{t-1} \right| \right] + p_u^t B_{grid}^t \right\}$$

$$B_{\mathrm{DG}_i}^t = a_i p_{G_i}^2 + b_i p_{G_i} + c_i \tag{6.5}$$

$$p_{\mathrm{DG}_i}^t = \alpha_i p_{G_i}^2 + b_i p_{G_i} + c_i + d_i \mathrm{Sin} \left| e_i p_{G_i} - e_i p_{G_i}^{min} \right| \tag{6.6}$$

$$\boldsymbol{\alpha} = \left[p_{G_1}^t, p_{G_2}^t, \dots, p_{G_N}^t, p_{BESS_1}^t, \dots, p_{BESS_{N_{BESS}}}^t, p_{ut}^1, u_1^t, u_2^t, \dots, u_{G_N+N_{BESS}}^t \right] \tag{6.7}$$

The decision variables to be determined $\boldsymbol{\alpha}$, are expressed in (6.7) and the bids of DGs are represented by quadratic cost function (6.5) with coefficients a_i, b_i and c_i . The ripple VPE for DGs is modelled with modified trigonometric sine term whose cost coefficients $d_i$and e_i are as expressed by (6.6). The i^{th} DG unit and j^{th} BESS output, utility power exchange, and the ON or OFF state of DG units will have their respective decision variable, $\boldsymbol{\alpha}$**.**

Traditionally optimal DGs scheduling problem is based on the standard convex quadratic cost function. As outlined before, with the involvement of VPE, the DG cost function becomes non-convex [235]. In this section, the objective is to find the *MG* optimal schedule considering a non-convex quadratic cost function such as the optimal generation command set points of each DG unit such that OPEX subjected to demand response is minimized. Further, the EMS utilizes the DSM strategy as a tool to shape the energy exchange optimally and dynamically between utility and MG and load demand changes. The MG's OPEX cost includes fuel of DGs, start-up/shutting down costs, and the utility's market bid price as illustrated in (6.4). The mathematical representation of the MG-EMS is formulated in the following sections:

Active Power Balance and Limits

At any time t, hours, given N_L loading levels, the power generation from all DG($P_{\mathrm{DG}_i}^t$) and utilities (P_{ut}^t) should supply the total load demand P_i^t. This active power balance is effectively an equality constraint in the problem of minimizing effective MG generation costs, (6.8).

$$\sum_{i=1}^{N_{DG}} P_{\mathrm{DG}_i}^t + P_{ut}^t = \sum_{l=1}^{N_L} P_l^t \tag{6.8}$$

All DGs and utilities are limited to their respective active power output to the maxima $P_{\mathrm{DG}_{i,max}}^t$, $P_{\mathrm{ut}_{i,max}}^t$ and minima $P_{\mathrm{DG}_{i,min}}^t$,$P_{u_{i,min}}^t$respectively. These limits are specified in (6.9). The upper bounds are imposed by the limits of the DGs while lower bounds are directly linked to the consideration required to maintain the minimum output power.

$$\begin{cases} P_{\mathrm{DG}_{i,min}}^t \leq P_{\mathrm{DG}_i}^t \leq P_{\mathrm{DG}_{i,max}}^t \\ \quad P_{u_{i,min}}^t \leq P_{u_i}^t \leq P_{u_{i,max}}^t \end{cases} \tag{6.9}$$

Out of all DGs considered in the MG network, the non-convex cost coefficients are assigned to MT and DGs set to address the VPE.

Table 6-1. DG power limits with none-convex quadratic coefficients

type	$P_{G_{\min}}^t$	$P_{G_{\max}}^t$	a_i	b_i	c_i	d_i	e_i
MT	90	300	0.062	21.15	819	252.73	0.043
FC	30	300	0.006	1.62	2204	0	0
DE	0	80	0.049	18.16	869.7	335.45	0.034
WT	0	600	0	6.5	0	0	0
PV	0	250	0	43.57	0	0	
UTILITY	**2000**	**2000**	**-**	**-**	**-**	**-**	

The DGs bid information and minimal and maximal generation limits are illustrated in Table 6-1[236][237]. The load forecast data and utility market price information are shown in Fig. 6-2.

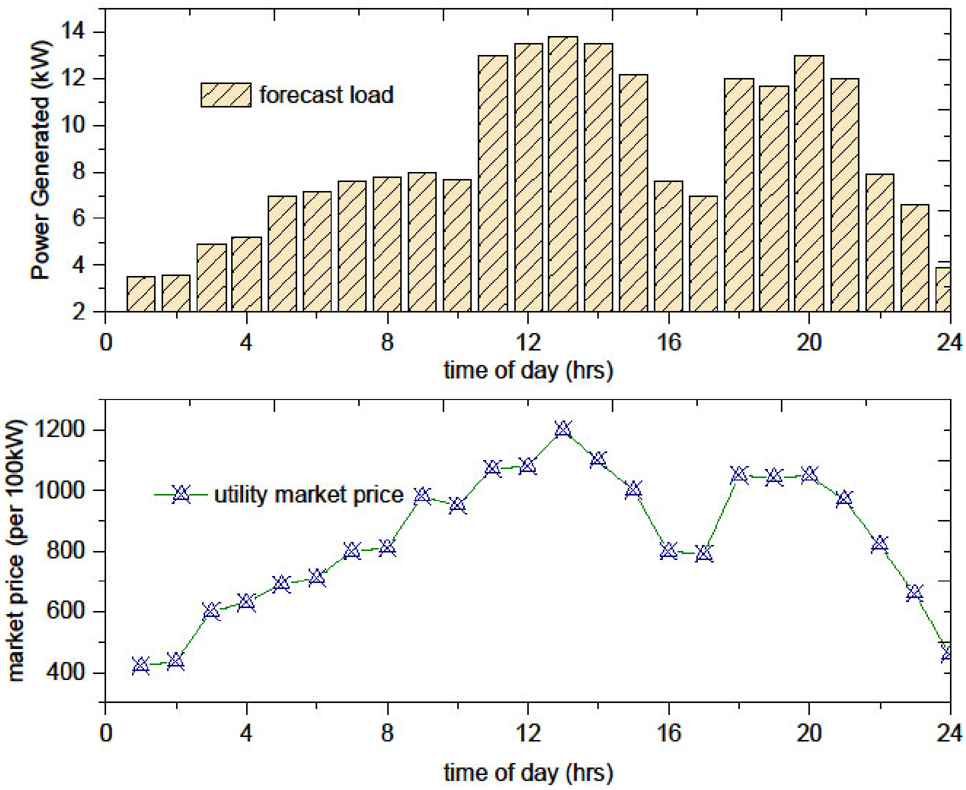


Fig. 6-2. Forecast Load and Utility market price

When the VPE factor, $d_i = 0$ in (6.6), MATLAB quadratic programming approach is applicable. This objective function (6.4) is formulated into an equation is converted into the following form.

$$Min\ E(\alpha) = \sum_{t=1}^{H}\left\{\sum_{i=1}^{N} u_i^t B_{DG_i}^t P_{DG_i}^t + \sum_{i=1}^{N_{BESS}}\left[u_j^t B_{BESS_j}^t P_{BESS_j}^t + S_{BESSj}\right] + p_u^t B_{grid}^t\right\} \tag{6.10}$$

The incremental cost of the battery depends on the state of charge,

$$d_t = \frac{\mathrm{SOC}_{h-1}\sigma_{h-1} + (\mathrm{SOC}_h - \mathrm{SOC}_{h-1})F_{h-1}}{\mathrm{SOC}_h} \tag{6.11}$$

The quadratic cost function (6.4) is now formulated as;

$$\mathrm{F}(\underline{x}) = \mathrm{Min}(C^T\underline{\boldsymbol{\alpha}} + 0.5\underline{\boldsymbol{\alpha}}^T h\underline{\boldsymbol{\alpha}}) \tag{6.12}$$

Where $\underline{\boldsymbol{\alpha}}$ is the vector of decision variables defined in (6.7) and the reformulated objective function is subject to equality constraints in (6.8), expressed, $A\underline{\boldsymbol{\alpha}} = \underline{\boldsymbol{b}}$. The lower and upper limits are the sets of $P^t_{\mathrm{DG}_{i,min}}$ and $P^t_{\mathrm{DG}_{i,max}}$ given in (6.11). The requirement is to find the optimal dispatch of the DEG in each hour according to the load demand. This problem is solved using the optimization toolbox MATLAB Algorithm of interior-point-convex, quadprog through the recursive process illustrated in

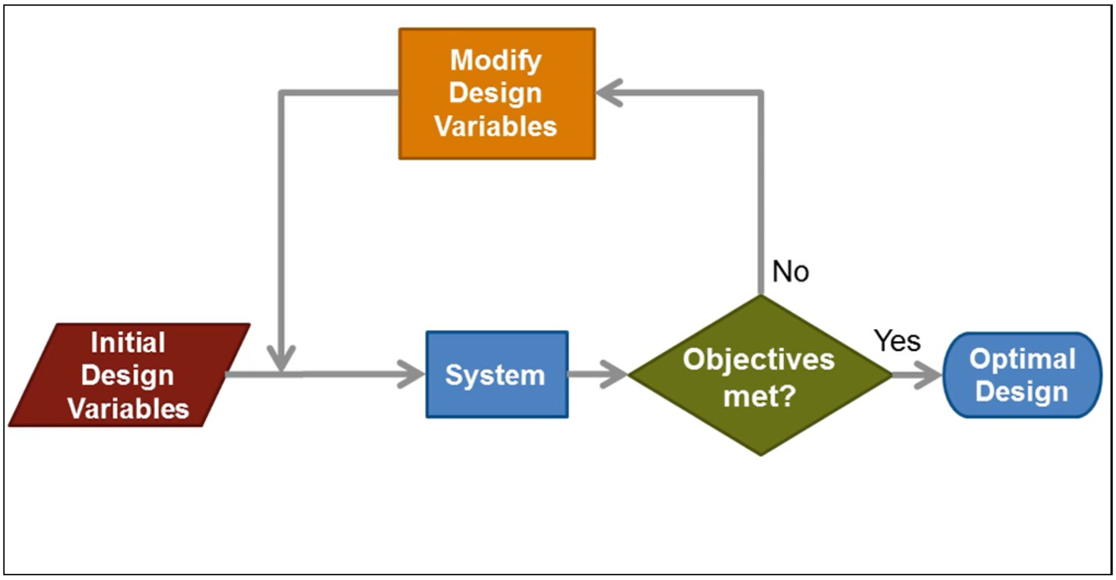


Fig. 6-3. Recursive design process

1.19 Methodology to integrate DSM

This section looks at the modelling for implementing a utility-driven DSM program and its infusion into the EMS framework. An outline for solving non-convex MG scheduling problems is presented.

A distribution supply operator (DSO) facilitates consumers or prosumers to contribute to DSM programs for financial gain and improvement of the overall system load profile. The strategies fall into two categories i.e., utility and customer driven. The DA optimal scheduling problem is incorporated with an adjustable load shifting technique [237] at 10% and 20% DSM participation. Initially, the DSM controller is supplied with DA or 24 Hours demand forecast, and then it implements requisite control to achieve the required load shaping. Loads that can be controlled will either turn ON or OFF at specific operation times. Incorporating the DSM program into the proposed non-convex EMS problem is to bring the controllable load consumption profile to be like the desired load profile [237] such that,

$$\text{Min} \sum_{t=1}^{H} \left(P_{target}(t) - P_{desired}(t)\right)^2 \quad (14) \tag{6.13}$$

$$P_{target}(t) = \varphi(t) + \phi(t) - \Delta\phi(t) \quad (15) \tag{6.14}$$

The parameters related to targeted load $P_{target}(t)$ are supplied to the DSM controller to achieve the desired loading profile $P_{desired}(t)$ at a given time interval t. Three input variables influence the target load. These are the predicted $P_{pred}(t)$, connected $P_{con}(t)$, and disconnected loads $P_{disc}(t)$.

$$P_{con}(t) = \sum_{i=1}^{t-1} \sum_{l=1}^{N} \mathbb{N}_{l,i,t} \cdot P_{1,l} + \sum_{j=1}^{k-1} \sum_{i=1}^{t-1} \sum_{l=1}^{N} \mathbb{N}_{l,i(t-1)} \cdot P_{(1+j),l} \tag{6.15}$$

The increase in connected load $P_{con}(t)$ is obtained by shifting l-type the number of controllable appliances to time t and those appliance connections that were scheduled before time t. N stands for l-type controllable or adjustable appliances transferred from $t = 1$ to $t = l$. $\mathbb{N}$ is the totality of controllable appliances. $P_{1,l}$ and $P_{(1+j),i}$ denote the l-type appliances' total load at time step $t = 1$ and $t = i$. This is taken over the total period of lk.

$$P_{disc}(t) = \sum_{q=t+1}^{t+m} \sum_{l=1}^{N} \mathbb{N}_{l,t,q} \cdot P_{1,l} + \sum_{j=1}^{k-1} \sum_{q=t+1}^{t+m} \sum_{l=1}^{N} \mathbb{N}_{l,(t-1),q} \cdot P_{(1+j)l} \tag{6.16}$$

Similarly, the disconnected load $P_{disc}(t)$ is dependent on decrement in loads delayed connection because of shifting l-type adjustable appliances from time step t to q as well as connection delay of N number of l-type appliances that are expected to be consuming power before time t. The allowable time delay, denoted with m is such that;

$$\sum_{t=1}^{H} \mathbb{N}_{l,i,t} \leq \mathbb{N}(i) \quad (18) \tag{6.17}$$

$$P_{(1+j),l} = 0, \forall (1+j), l > T_D \quad (19) \tag{6.18}$$

$$\mathbb{N}_{l,i,t} = 0, \forall (t-1) > m \quad (20) \tag{6.19}$$

Equation (6.18) represents the inequality constraint where the number of shifted devices at a given time t cannot exceed the maximum available number of controllable devices $N(i)$ and the delayed characteristic of the DSM approach is shown in (6.8) and (6.9) [237][237].

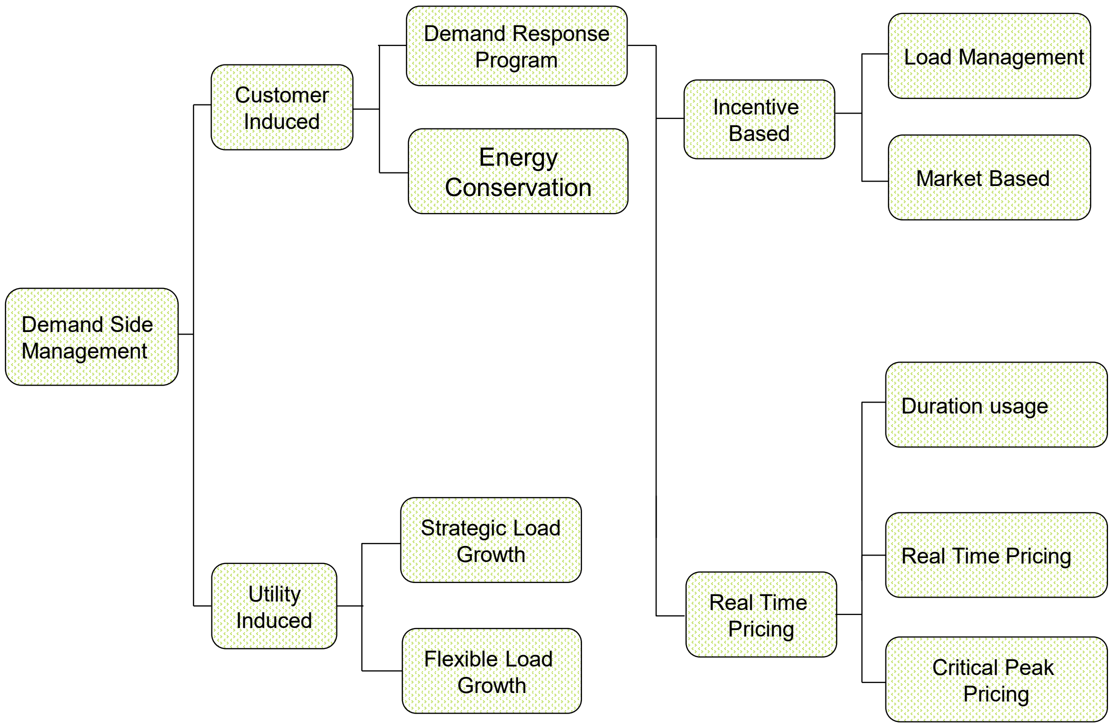


Fig. 6-4. Classification of demand side management programs

Proposed Solution Framework

The general framework to solve the proposed MG EMS problem is depicted in Fig. 6-5. Initially, the non-convex function cost coefficients of the DG units are configured according to Table 6-1. Then, the MG system information related to the market unit costs forecasted yields of REGs, and loads are provided for DA scheduling. Commercial and residential consumers are potential participants in emerging DSM initiatives. The optimized ON/OFF load state data is channelled to the LC to either turn On or OFF non-critical appliances. The impact of this load shaping technique for energy management is investigated by applying the QPSO method which as reported can handle NL, none-smooth and convex optimization problems.

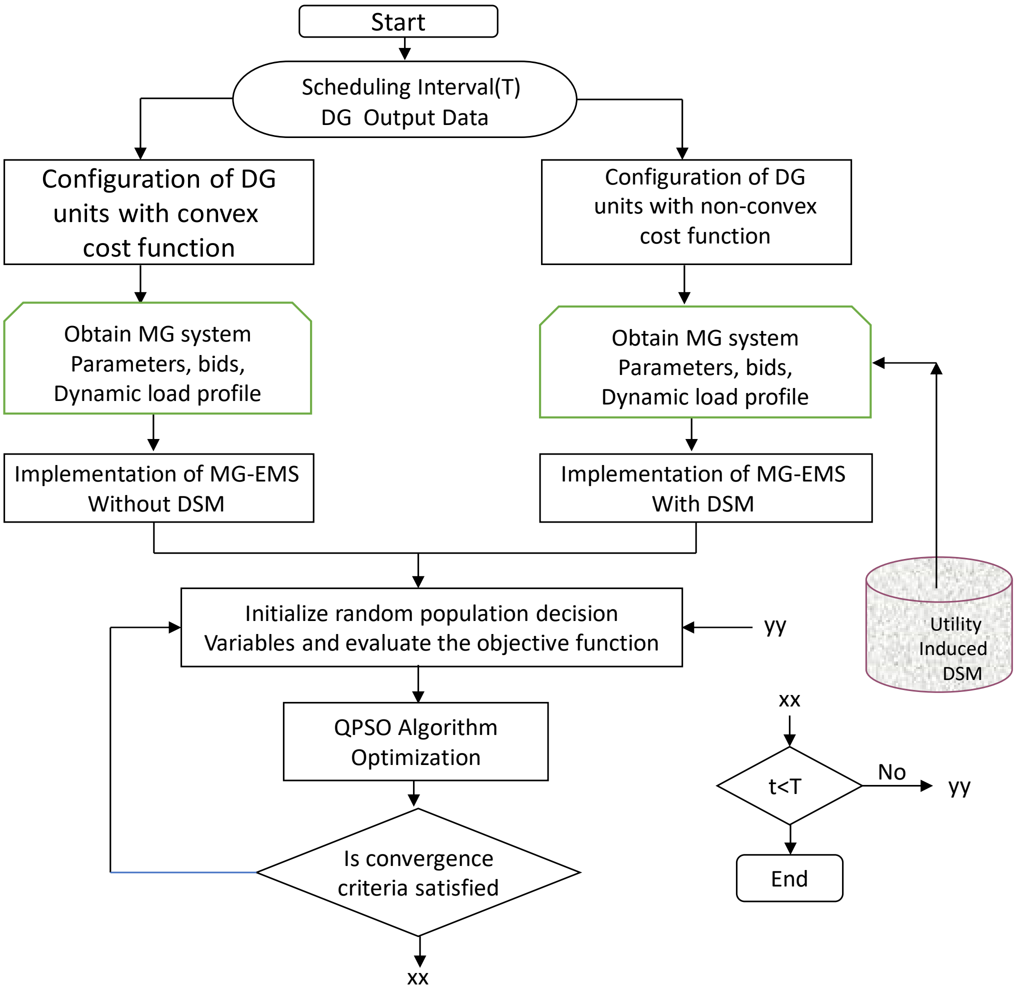


Fig. 6-5. QPSP Flowchart for solving non-convex EMS problem

A PSO has the drawback of getting easily trapped in local minima causing premature convergence. In [105] the classical PSO algorithm is merged with quantum mechanics resulting Quantum PSO algorithm or QPSO. This improved version of PSO improves searching by introducing a new point called global mean best position m_{best}. m_{best} is the mean of all feasible solutions of all particles. In QPSO, particles depend on each other to converge to the global best. Particles close to the global best solution can globally explore the area around m_{best}. In this way, QPSO maintains exploration and exploitation balance in a trial. This avoids premature convergence. The position of a particle is influenced by two terms; attraction and the gap between the current position and m_{best}. Position during the $(1+i)^{th}$ iteration is updated according to (6.20);

$$x_{ij}^{t+1} = p_{ij}^{t} \pm \beta \left| m_{best,j}^{t} - x_{ij}^{t} \right| \cdot \mathrm{In}\left(\frac{1}{u_{ij}^{t}}\right) \quad \text{where } u_{ij}^{t} = rand(0,1) \tag{6.20}$$

p_{ij}^{t} is a local attractor evaluated by;

$$p_{ij}^{t} = \varphi_{ij}^{t} s_{best,j}^{t} + \left(1 - \varphi_{ij}^{t}\right) \cdot g_{best,j}^{t}\ , \ \text{with } \varphi_{ij}^{t} = rand(1,0) \tag{6.21}$$

β is an adjustable contraction/expansion parameter. It influences the QPSO's algorithm convergence speed. m_{best} is evaluated according to;

$$m_{best}^{t} = \frac{1}{N}\sum_{i=1}^{\Upsilon} s_{best,i} = \left(\frac{1}{N}\sum_{i=1}^{\Upsilon} s_{best,i1}, \frac{1}{N}\sum_{i=1}^{\Upsilon} s_{best,i2}, \dots, \frac{1}{N}\sum_{i=1}^{\Upsilon} s_{best,iD},\right) \tag{6.22}$$

Such that Υ is the population size and D is the search dimension. The pseudo-code for QPSO is;

QPSO Pseudo Code[238]

```
Initialise swarm i.e., the random population of MG.
Initialise best particles, (6.7).
Locate the global best particle, m_best.
Initialise the contraction-expansion parameter
While (not termination-condition) do
        Compute m_best position, (6.22)
        for Each particle do
                Update position, (6.20)
                Evaluate position
                Update self-best particle, s_best
        end for
        Update g_best position
        Decrease contraction-expansion parameter linearly.
End while
```

1.20 Simulation Evaluation and Results

Renewable power generation, utility market price, and load information were sourced from [237], and the values are tabulated in Table 6-2. The EMS problem is simulated in MATLAB using the QPSO algorithm with 40 simulation trials. The results are compared with the normal PSO to prove the efficacy of QPSO. The population size and the maximum iterations for both algorithms are 40 and 200, respectively. Two (2) are used as cognitive and social parameters for PSO; the upper and lower limits of the inertia constants used are 0.92 and 0.38 respectively. Several assumptions were made before implementing the algorithm as follows.

- PV and WT outputs are kept at the upper bound $\forall t$.
- All the DG units in the MG will provide active power at the unity power factor.
- Loads are segregated into classes and load curves are manipulated for DSM purposes over peak periods.

With these assumptions, four scenarios were looked at;

Case 1 looks at convex and non-convex DG cost functions. The implementation of the DSM program in the base case is neglected.
Case 2, the DSM participation of $\sim 10\%$ is evaluated with both convex and non-convex DG costs.
Case 3 deals with the DSM participation of $\sim 20\%$ with both convex and non-convex DG costs.
Case 4, 24 Hour dynamic loading at $1/_4$ hour interval is considered, and the results are evaluated with DSM participation of 15%.

A discussion of simulation results for each of the scenarios is given in the following subsections.

Table 6-2. Day-ahead forecast data of RE generation, load and Marketing Price(MP)

time	PV(kW)	WT(kW)	Load(kW)	MP(kWh)
1	0	2.516	4.79	3.4
2	0	2.473	4.79	3.4
3	0	2.801	5.99	3.4
4	0	2.583	5.99	3.4
5	25	2.905	7.19	6.9
6	5.535	2.970	7.19	6.9
7	6.533	2.459	8.39	6.9
8	1.125	2.565	8.39	6.9
9	1.602	2.148	9.59	6.9

10	1.655	2.299	9.59	6.9
11	1.873	2.463	10.79	11.9
12	1.955	2.971	10.79	11.9
13	1.859	2.959	11.99	11.9
14	1.893	3.141	8.39	11.9
15	1.401	2.899	8.39	11.9
16	1.389	2.801	9.60	6.9
17	6.059	2.891	10.79	6.9
18	5.019	3.001	10.97	6.9
19	3.698	3.319	9.59	11.99
20	1.805	3.009	8.39	11.99
21	1.176	2.910	7.19	6.9
22	0	2.801	5.99	6.8
23	0	2.800	7.19	6.9
24	0	2.800	6.19	3.4

The following part explores the simulation and analysis of the typical microgrid shown in Fig. 6-1 and the analysis of DSM effects. The QPSO was implemented in MATLAB R2021b on a modified downloadable version of the algorithm. The simulation parameters for the various techniques used as set out in Table 6-3 population size and an iteration count of QPSO are considered as 50 and 200, respectively.

Table 6-3. Simulation parameters of various algorithms

Algo-rithm	Population/Swarm size	Iteration Count	Cognitive Factor, c_1	Social Factor, c_2	Max inertia Factor	Min inertia Factor	Cross over Proba-bility	Mutation Factor	Scaling Factor	Distribution Index for cross over	Distribution index for mutation	Contraction Expan-sion coefficient
PSO	40	200	1.4	1.4	0.9	0.38						
QPSO	40	200										0.76
DE	40	200					0.68	0-2	0.7			
EDE	40	200							0.5	4/0.75	4/0.18	

To check the efficiency of the algorithm, QPSO is compared with popular state-of-the-art algorithms like Differential Evolution (DE), Enhanced Differential Evolution (EDE), and the standard counterpart of QPSO, i.e., PSO. The algorithm-specific parameters for DE are taken as a crossover probability of 0.78, and a scaling factor of 0.6. For EDE the contraction expansion coefficient is taken as 0.78. The cognitive and social attributes of PSO are taken as 1.4 and 1.4, respectively with a maximum inertia factor of 0.92 and the minimum inertia factor of 0.38. Like QPSO, the population size and iteration count of DE, EDE and PSO were 40 and 200, respectively. Four case studies were deployed in four scenarios to evaluate the DSM framework.

Scenario 1: No DSM. Convex cost minimization targeting minimizing utility imports in preference to local REG. The results are depicted in Fig. 6-6. The MT and FC supply are at maximum limits. This reduces the consumption of diesel-generated power most of the time. The MG's total OPEX with convex and non-convex DG costs are R2,630 and R2,636 respectively. The costs of this base case is highest compared to cases 2 and 3 below because the DSM participation is not considered. The MG uses DG to a large extent. During the peak demand, the FC gets utilized thus saving on the high utility market price.

Case 2: Comparison of the convex and non-convex problem with ~10% DSM participation, Fig. 6-7 depicts the optimal generation of DGs with non-convex cost. OPEX costs are minimized to R2,582 with a drop of 1.86 % in price compared to the baseline case without DSM participation. Similarly, a 2.09% reduction in cost while considering convex cost function with ~10% DSM participation occurs. The flexible load shaping strategy helps the MG operator export more energy to the utility by reducing peaks, especially during the late morning to mid-afternoon hours.

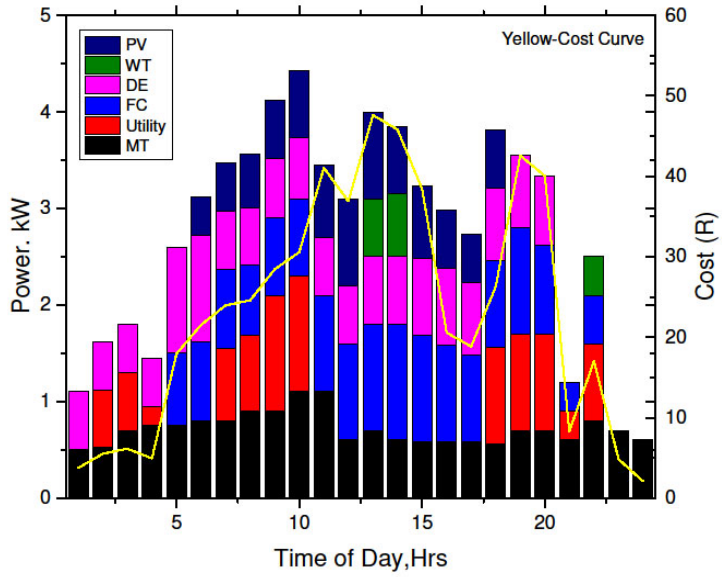


Fig. 6-6. Case 1:(a) Convex Cost (b) Non-convex cost

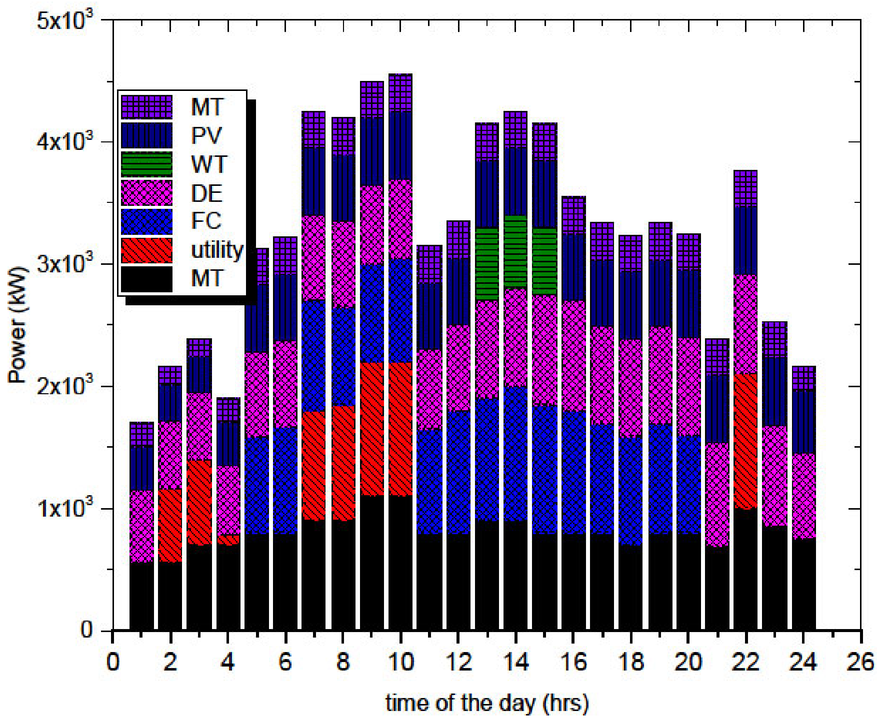


Fig. 6-7. Case II, Non-convex cost (b) convex cost

Case 3: Comparison of the convex and non-convex problem with ~20% DSM participation. DGs' daily operating costs with non-convex and convex cost functions are R2,526 and 2,522 respectively. In contrast with the case without DSM participation, there is a cost reduction of 4.354 % and 4.28% for non-convex and convex cost functions of DGs. The extent of peak shaving and savings are better given the highest DSM participation. Fig. 6-11 shows that the utility's energy import is significantly reduced during late mornings to about 21st hours with utility-induced flexible shaping.

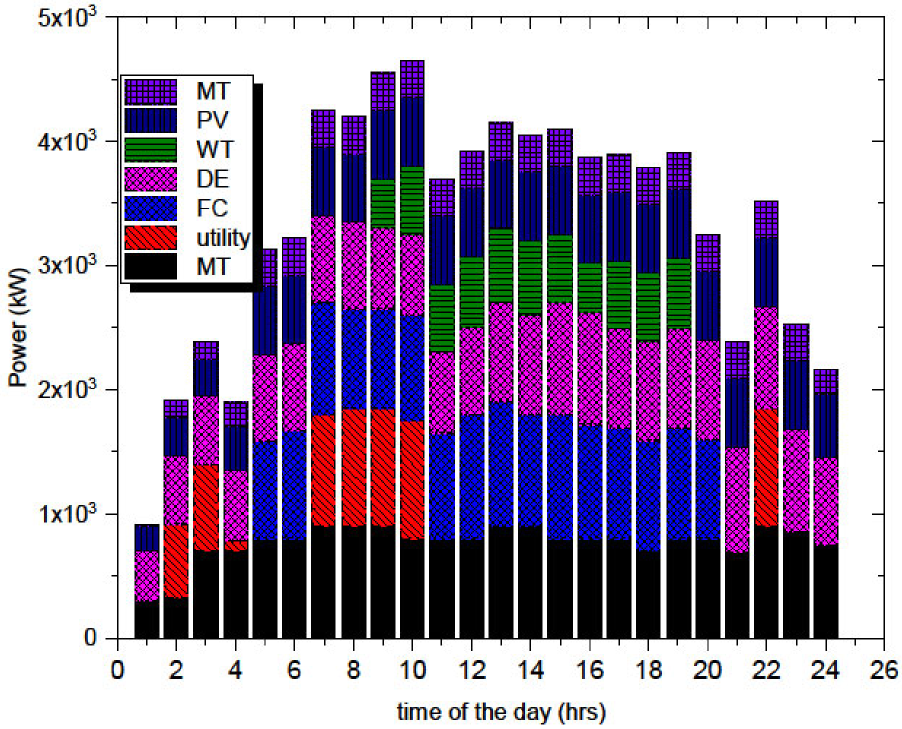


Fig. 6-8. Case II, Non-Convex costs (b) Convex cost

Case 4: Dynamic loads with ~15% DSM penetration. Previous scenarios use 1-hrs time frame for the DA MG scheduling problem. However, the dynamic dispatch of loads with $^1/_4$ hour time frame is considered in this case with $24 \times 4 = 96$ intervals daily. The curtailable loads of MG are controlled the from DSM controller either to turn ON or OFF scheduled devices during peak times. Before energy market trading, demand was taken as the fixed and economic dispatch of generators was the central problem to secure the critical power balance. With schedulable DGs, the need to commit expensive generators fell away. Diversification in the expensive plant for peak loads is replaceable with coordinated and careful investment in RESs. In this way, DSM with RESs becomes significant dealing with demand peaks.

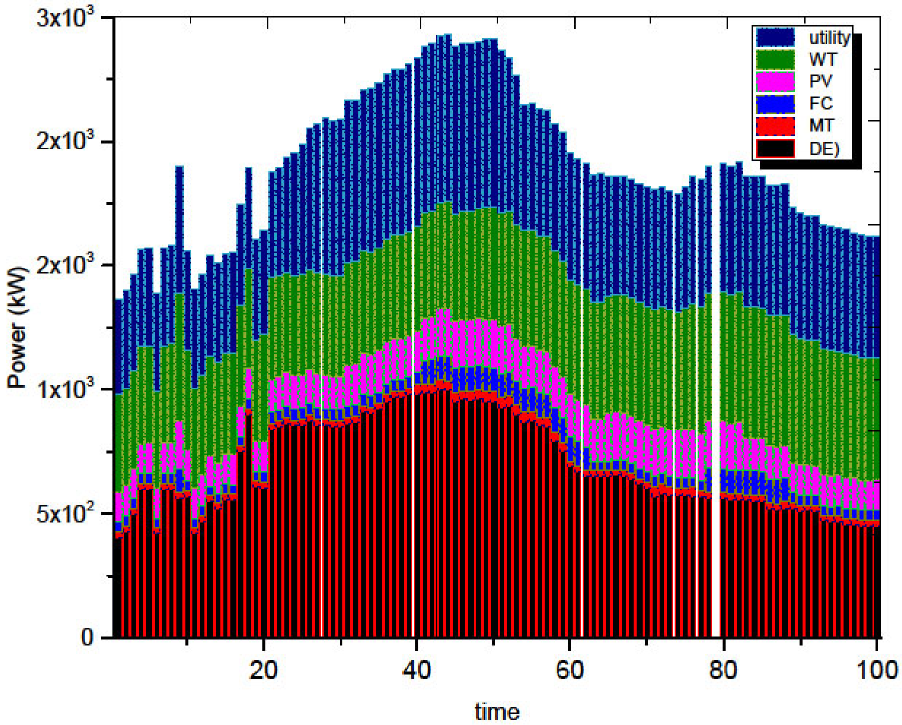


Fig. 6-9. Simulated results of Case 4

In this regard, the dynamic appliances dispatch at ~15% DSM participation is evaluated. The total OPEX cost over the ninety-six scheduled intervals is R3,350. Since the diesel generator set has the highest bid cost, its consumption is restricted to the minimum value.

From the simulation results, the QPSO optimization algorithms yield better results in handling the non-convex EMS problem. A comparison of best, mean, and worst values of costs with the PSO algorithm is given in Table 6-4 to prove its efficacy.

Table 6-4. Performance of QPSO and PSO

PSO				
	best	worst	mean	Time(s)
convex	2588.3	2590.1	2292.3	59.7
Non-convex	2627.3	2629.1	2930.1	73.1
QPSO				
convex	2589.1	2590.7	2592.1	49.7
Non-convex	2629.1	2630.7	2632.1	51.2

The daily optimal costs for the MG network given convex and non-convex functions are tabulated in Table 6-5.

Table 6-5. Optimized costs with different DSM participation levels

	Level	Convex	Non-convex
Case I	-	2589.1	2592.0
Case II	9%	2595.2	2598.1
Case III	19%	2561.7	2568.1
Case IV	16%	-	3319.1

With increasing participation levels of DSM, results show that the optimal load shaping method efficiently decreases costs in all cases in comparison to the baseline case with convex cost but without DSM.

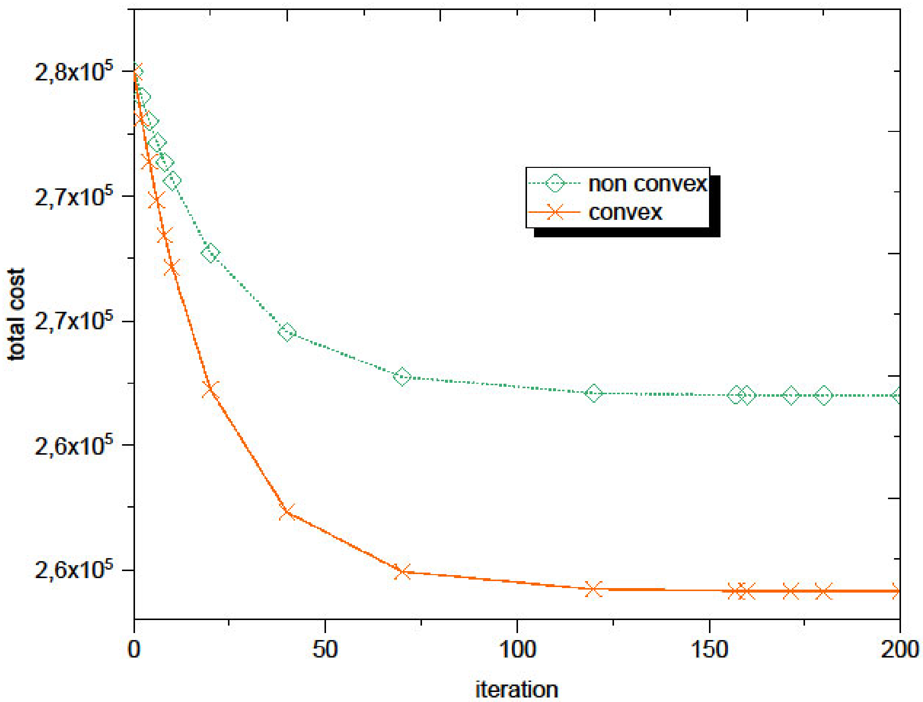


Fig. 6-10. Convergence characteristics for the base case

And further, due to the VPE of DGs, costs accrued from the non-convex scenario are greater than those arising from the convex case in relative terms.

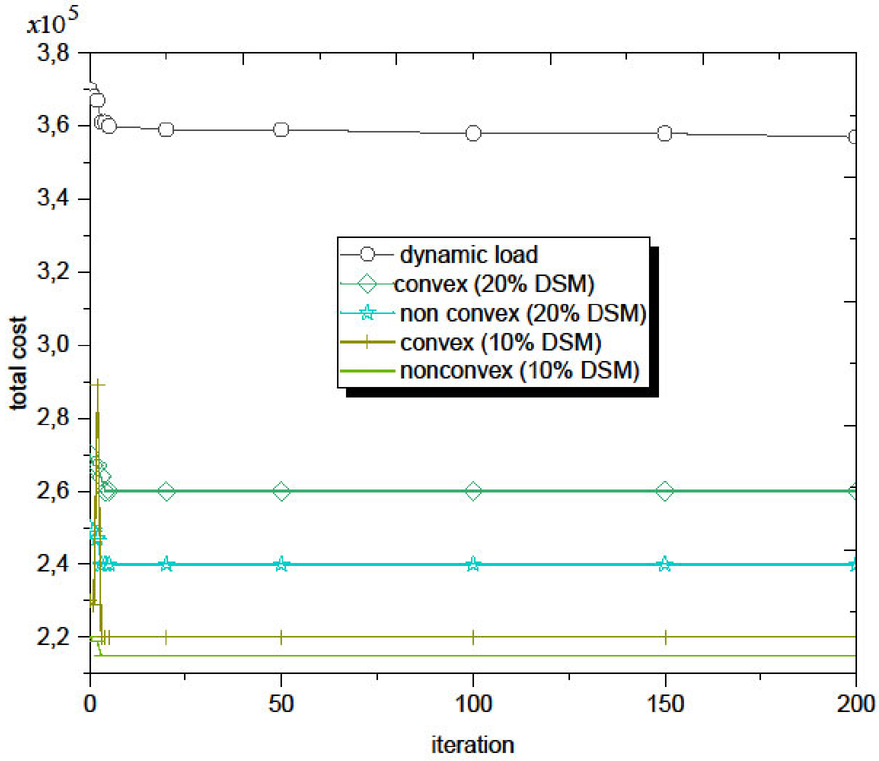


Fig. 6-11. Convergence characteristics of QPSO with DSM participation

As discussed earlier, the QPSO performs better than the classical PSO counterpart in terms of efficiency and time taken to do the computation. Figures 10 and 11 represent the convergence behaviour of the QPSO algorithm without and with DSM participation, respectively. It is observed that the QPSO algorithm gives near optimal better results with fewer iterative steps.

1.21 Molecular Atomic Dynamics Preliminaries

ASO derives from dynamic behaviour constituents of matter i.e., molecules. Molecules are the smallest particle of chemical compounds. Atoms held together by ionic or covalent bonds make up the molecules. These bonds differ in complexity depending on the complexity and nature of the compound. So, all matter is made up of atoms that have mass and volume. Fig. 6-12 shows the composition of the Carbon Dioxide molecule, CO_2, made up of one carbon and two oxygen atoms.

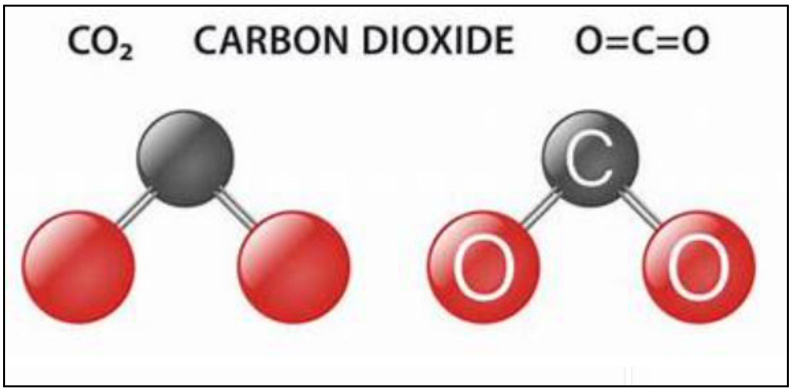


Fig. 6-12. Carbon dioxide molecular interactions

Atoms interact and are in perpetual motion irrespective of the physical state of matter. In the modern study of molecular dynamics, computer simulations are used to study atomic or molecular motion which behaves per classical Newtonian mechanics [81]. Atomic interaction exhibit repulsion forces at close range, and attraction forces that bind atoms together as in solidus and liquidus matter. Atoms attract each after a certain range of separation. These observed interactions result from the potential energy of atoms and a variety of dipole models used to model the potential energy [239]exist in the literature such as the Lennard-Jones (L-J) potential [221], [239]. This is a simple mathematical formula that expresses the force between a pair of atoms. The L-J potential between the i^{th} and the j^{th} atoms is simply expressed as;

$$U(r_{ij}) = 4\varepsilon\left[\sigma^{12} r_{ij}^{-12} - \sigma^{6} r_{ij}^{-6}\right] \tag{6.23}$$

$$\sigma(t) = \left\| \underline{x}_{ij}(t) \quad , \quad \frac{\sum_{j\in\varphi_{best}} \underline{x}_{ij}(t)}{\varphi(t)} \right\| \tag{6.24}$$

The variable ε represents the depth of the potential well i.e., the strength of the interaction, σ is the length scale denoting the collision diameter, $r_{ij} = \left\|\underline{x}_i - \underline{x}_j\right\|$, and $\underline{x}_i = \left(\underline{x}_{i1}, \underline{x}_{i2}, \underline{x}_{i3}\right)$ is the position of the i^{th} atom in $\mathbb{R}^3$space, and r_{ij} in the norm or Euclidian distance between the i^{th} and j^{th} atoms. φ_{best} is a subset of atoms made up of the first φ atoms with the best fitness function values.

In (6.23) the first and second terms model the repulsive and attractive forces respectively and the corresponding L-J potential curve is depicted in Fig. 6-13. In the LHS of the potential minimum (Blue curve) atomic repulsive forces increase rapidly as the intermolecular or inter-atomic distances between two atoms decrease. To the RHS of the potential minimum, as the intermolecular or interatomic distance increases, the attractive force rapidly then gradually drops to nearly zero. At the potential minimum, the atoms or molecules are at an equilibrium distance. The radial equilibrium distance corresponds to $r_{ij,equilibrium} \approx 1.2\sigma$. At this point minimum bonding potential energy is reached and the interatomic interaction forces become zero. From the PE function (6.23), the interaction force that the i^{th} atom exerts on the j^{th} atom is, obtained by taking the gradient of the potential.

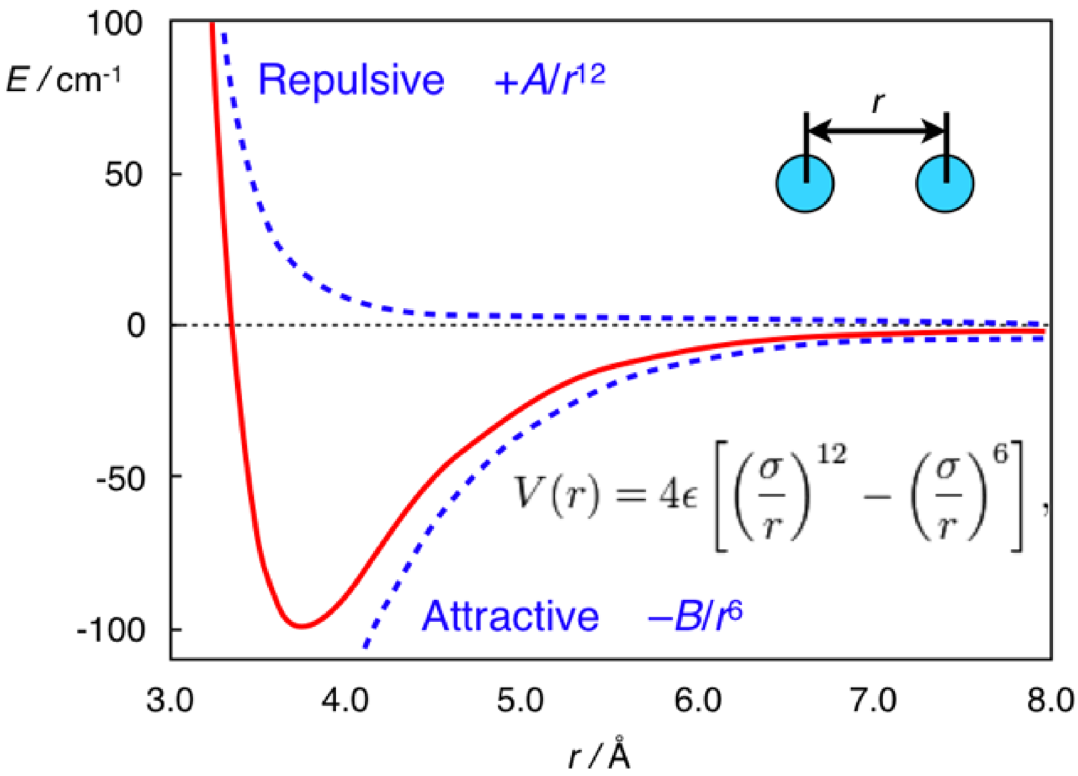


Fig. 6-13. L-J Potential Energy/ Interaction Atomic forces[240]

$$U(r_{ij}) = 4\varepsilon[\sigma^{12}r_{ij}^{-12} - \sigma^{6}r_{ij}^{-6}] \tag{6.25}$$

Graphically, this means that if we have potential energy vs. position, the force is the negative of the slope of the function at some point.

$$F_{ij}(r_{ij})\Big|_{j\,=\,1} = -\nabla U(r_{i1}) = -24\varepsilon[2\sigma^{12}r_{i1}^{-13} - \sigma^{6}r_{i1}^{-7}], j \neq i \tag{6.26}$$

The total force acting on atom i in the presence of a total number of N is,

$$F_i(\quad) = \sum_{j=1}^{N} \frac{\partial U}{\partial r_{ij}} = \frac{\partial U}{\partial r_{i1}} + \frac{\partial U}{\partial r_{i2}} + \ldots + \frac{\partial U}{\partial r_{iN}}, j \neq i \tag{6.27}$$

$$F_i(\quad) = -\nabla U(r_{ij}) = \sum_{j=1}^{N} \frac{\partial U}{\partial r_{ij}} = F_{I1} + F_{I2} + \cdots + F_{IN}\ ,\ j \neq i \tag{6.28}$$

For complex molecular structures, geometric constraints can be imposed on such several rigid bonds meaning fixed radial separation. In such a case, the fixed intermolecular separation means the norm in

$$r_{ij} = \|\underline{x}_i - \underline{x}_j\| = \sqrt{(\underline{x}_{i1} - \underline{x}_{i2})^2 + (\underline{x}_{i1} - \underline{x}_{i3})^2 + (\underline{x}_{i2} - \underline{x}_{i3})^2} = \sqrt{r_{o,ij}^2} \tag{6.29}$$

Where $r_{o,ij}$ is a constant bond radius between the i^{th} and j^{th} atom. If they are ℓ such constraints on a specific molecule or atom, and if the k^{th}constraint for a bond works between the $i^{th}$and j^{th}atoms, then the k^{th}constraint is,

$$\xi_k = \|\underline{x}_i - \underline{x}_j\|^2 - r_{o,ij}^2 = 0 \text{ for } k = 1,2,3,\ldots,\ell \tag{6.30}$$

Hence the constraint force from the stretch of a covalent bond between two atoms acted on the i^{th}atom can be written as;

$$\mathcal{F}_k = \sum_{k=1}^{\ell} -\lambda(\nabla_i \xi_k) = \sum_{k=1}^{\ell} 2\lambda_k(-\underline{x}_{ik} + \underline{x}_{ki}) = 0 \text{ for } k = 1,2,3,\ldots,\ell \tag{6.31}$$

λ_k is the k^{th}Lagrangian multiplier for ξ_k thereby resulting in the Newtonian molecular equation of motion as a constraint that can be modified as;

$$\mathcal{F}_i + F_i = m_i a_i \text{ for } k = 1,2,3,\ldots,\ell \tag{6.32}$$

Expression (6.32) includes non-constraint interaction and constraint atomic force(s). This model captures the essential features of molecular movement and the geometric constraints. The physics of this model presents itself to be used for optimization problems as illustrated in the next section.

1.22 Atom search Optimization (ASO)

The molecular dynamics-inspired atom search optimization is introduced and applied to DSM optimization for the first time in this section. This technique has been successfully used for hydrogeologic parameter estimation problems [239]. In ASO, the position of an atom in the search space represents a solution measured by its mass. A better solution has a heavier mass and vice versa. All atoms in the population will attract or repel each other according to the distance among them, encouraging the lighter atoms to move towards the heavier ones. Heavier atoms have smaller acceleration, which makes them seek intensively better solutions in neighbourhood spaces. Lighter atoms have greater acceleration, which makes them search extensively to find new promising regions in the entire search space. In the context of DSM, the atom is a possible scheduling power vector, (5.1) or (6.7) whereby the general constrained optimization problem is defined by (3.2) or (3.11) which when unconstrained formulates to,

$$\min_{\underline{x} \in \mathrm{R}} f(x), \quad f(x): \mathbb{R}^n \to \mathbb{R} \tag{6.33}$$

$$x_{j,LB} \leq x_j \leq x_{j,UB}, \quad \mathrm{j} = 1,2, \dots, n \tag{6.34}$$

where x_i is the i^{th}component of the search $\mathbb{R}^n$space. To solve this unconstrained optimization, suppose an atom population with *N* atoms or possible scheduling vectors. The position of the i^{th} atom is expressed as (5.1) or (6.7). At the beginning of the iterative process of ASO, each atom attracts or repels neighbourhood atoms. Repulsion prevents the crowding of atoms and hence premature convergence of the algorithm. As the iterations succeed, repulsion progressively fades, and attractive ‘force’ dominate. In such a situation, the exploratory phase decreases, and the exploitative phase increases. Finally, the atomic interactions become purely attractive hence the edge towards convergence with good exploitation capability.

1.23 Modelling of interaction force

The atomic interaction force F_i given rise by the L-J potential is the major driving power behind the atomic motion. The force exerted on the i^{th}atom from the j^{th} at the iteration in (6.28) can be rewritten as,

$$F_{ij}(t) = \frac{12\varepsilon(t)}{\sigma(t)}\left[4\sigma(t)^{13}r_{ij}^{-13}(t) - \sigma(t)^{7}r_{ij}^{-7}(t)\right]\frac{r_{ij}\,(t)}{r_{o,ij}(t)} \tag{6.35}$$

And;

$$F'_{ij}(t) = \frac{12\varepsilon(t)}{\sigma(t)}\left[4\sigma(t)^{13}r_{ij}^{-13}(t) - \sigma(t)^{7}r_{ij}^{-7}(t)\right] \tag{6.36}$$

Atoms are continually within a distance of each other oscillating between repulsion and attraction. Displacement from the neutral distance is much greater for repulsion than attraction. Due to this point, this model cannot be applied directly to optimization problems, as more positive attraction and less negative repulsion is needed as iterations increase, as depicted in Fig. 6-13, (6.36) cannot satisfy this requirement. Accordingly, the force model (6.36) is adjusted to;

$$F'_{ij}(t) = -\nu(t)\,[4\varrho^{13}(t) - \varrho^{7}(t)],\ \varrho = \left(\sigma(t)^{7}r_{ij}^{-7}(t)\ \right)^{1/7} \text{ such that} \tag{6.37}$$

$$\nu(t) = \alpha\left(1 - \frac{t-1}{\tau}\right)^{2n-1} e^{\frac{20}{\tau}t}, n = 1,2,3, \ldots \tag{6.38}$$

$\nu(t)$ is a potential depth function, a general polynomial in t which adjusts the extent of repulsion or attraction and α is the smoothness weighting factor,

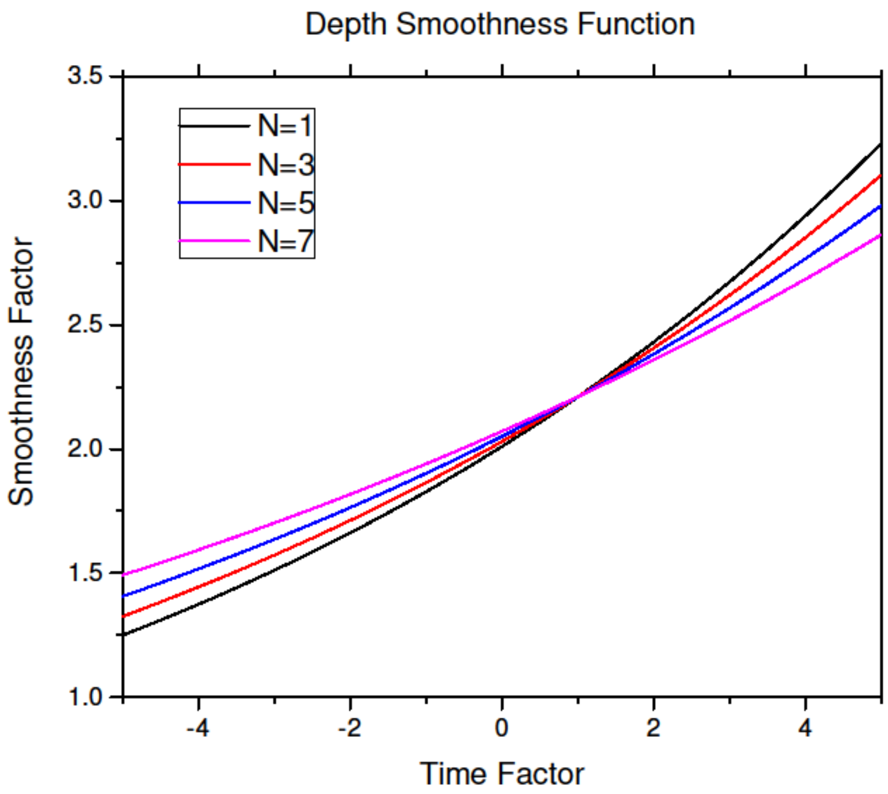


Fig. 6-14. Depth scaling or smoothness function

The function (6.38) for h $\in [0.9 \quad 2]$ is illustrated in Fig. 6-14**.** 4. Repulsion is over $0.9 \leq h \leq 1.12$, and attraction happens when $1.12 < h \leq 1.24$. Equilibration happens at $h = 1.12$. Attraction is almost zero from $h = 2$. In the ASO $h_{LL}^{repulsion} = 1.11$ and $h_{UL}^{attraction} = 1.25$.

1.24 Geometric constraints inclusion

The constraints for the ASO are formulated from (6.30). By analogy, each atom/consumption power vector is 'bonded covalently' with the best neighbour atom. Each such atom is acted upon by a constraint force from the best atom, so the constraint of the i^{th} atom can be rewritten as,

$$\xi_k = \left\| \underline{x}_i(t) - \underline{x}_{best}(t) \right\|^2 - r_{o,best}^2 \tag{6.39}$$

$\underline{x}_{best}(t)$ defines the position of the best atom at the i^{th} iteration, and $r^2_{o,best}$ is the best-fixed bond length between the i^{th} atom and the best atom. Hence the constraint force can be obtained as

$$\xi_i^d(t) = -\lambda(t)\nabla\xi_i^d(t) = -2\lambda(t)\left(-\underline{x}_i^d(t) - \underline{x}_{best}^d(t)\right):\ \lambda(t)$$
$$= \kappa \cdot Exp\left(-\frac{20t}{\tau}\right) \tag{6.40}$$

Given (6.37) and (6.40), acceleration measure at time t of the i^{th} atom can be formulated as;

$$a_i^d(t) = \frac{\mathcal{F}_i^d(t) + F_i^d(t)}{m_i^d(t)} \qquad \text{or}$$

$$= \nu(t) \sum_{j=K_{best}} \frac{Rand_{\ i}\{2h_{ij}^{13}(t) - h_{ij}^{7}(t)\}}{m_i(t)} \frac{\underline{x}_j^d(t) - \underline{x}_i^d(t)}{\left\|\underline{x}_i(t),\ \underline{x}_j(t)\right\|_2}$$
$$+ \lambda(t)\frac{\underline{x}_{best}^d(t) - \underline{x}_i^d(t)}{m_i(t)} \tag{6.41}$$

$m_i(t)$ is the mass of the i^{th} atom at the i^{th} iteration, which is interpreted as the value of the fitness function. $m_i(t)$ can be calculated as

$$m_i(t) = \frac{Exp\left(-(\gamma_i - 1)(\gamma_2 - 1)^{-1}\right)}{\sum_{j=1}^{N} Exp(-(\gamma_i - 1)(\gamma_2 - 1)^{-1})}, \quad \text{where } \gamma_i = \frac{Fit_i(t)}{Fit_{best}(t)}, \quad \gamma_2 = \frac{Fit_{worst}(t)}{Fit_{best}(t)} \tag{6.42}$$

$\text{Fit}_*(t)$, $\text{Fit}_{worst}(t)$, and $\text{Fit}_{best}(t)$, is the i^{th} $atom$ fitness, best i.e. minimum value and worst i.e., maximum value as appropriately indicated. The position and speed of the ATOM are given by;

$$x_i^d(t) = Rand_i^d \cdot \vartheta_i^d(t) + a_i^d(t) \tag{6.43}$$

$$x_i^d(t+1) = \vartheta_i^d(t+1) + x_i^d(t) \tag{6.44}$$

The initial exploration stage is improved by having each atom interact with many atoms with better fitness values. To improve the final exploitation of each atom, need to interact with fewer candidate solutions. ASO initiates the optimization from a randomly generated. Positions and velocities are then updated at each iteration stage, and then the position of the best atom is discovered is also updated. The pseudo-code for ASO is illustrated in Fig. 6-15.

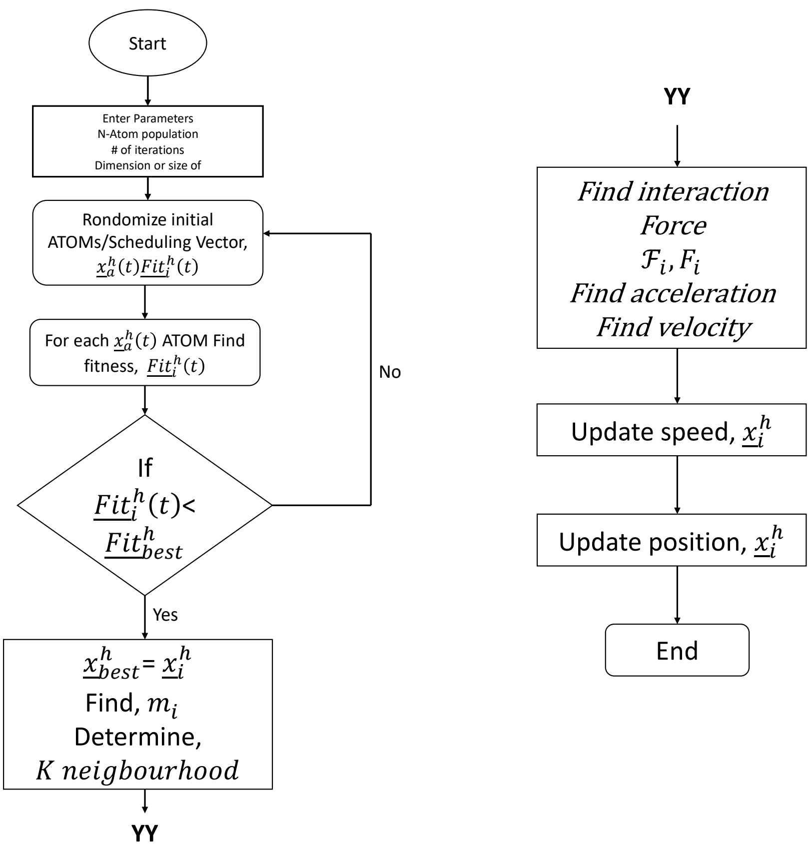


Fig. 6-15 ASO Pseudo code flowchart.

1.25 ASO DSM Simulations

The optimization problem is evaluated based on a scenario with N number of smart appliances with a load energy vector $\{\boldsymbol{a}_{ik}^h\}$ randomly distributed between the appliances in the various classes. Optimization is done for scheduled and unscheduled situations. For unscheduled cases, ON appliances run their full LOT without regard to consumption limits. For the scheduled case, optimization runs to attempt to find optimal schedules. To evaluate and validate the working of the proposed algorithm, the performance of unscheduled appliances is compared with that of the scheduled case using different optimization algorithms together with ASO for convex and none-convex cost functions. Initial results are depicted in Fig. 6-16. The prize signal, in this case, is shown in Fig. 5-6.

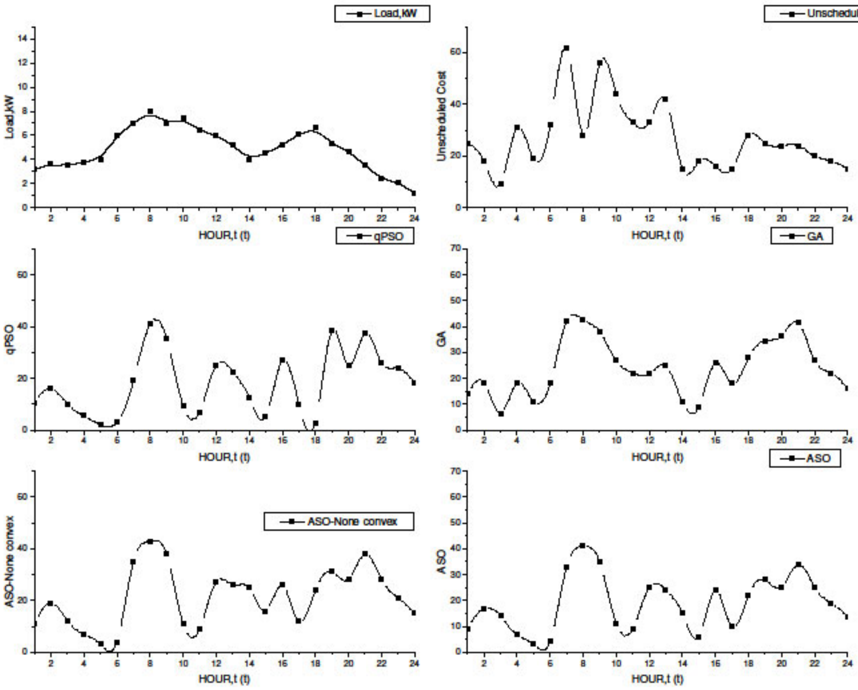


Fig. 6-16 Comparison of simulated results using different optimization techniques

For the unscheduled case, simulations are conducted for *N* appliances using the ToU pricing scheme (3.2). For this case, we set T_{start}, T_{final} , LOT, and e_h parameters as discussed in section (3.6). Unscheduled power consumption for *N* appliances with random initial values is shown in Fig. 6-16 and Fig. 6-17. During peak morning, afternoon and evening, the electricity cost is high due to more power usage probability during these hours and vice versa. Fig. 6-17show the difference between unscheduled and scheduled power consumption. From this figure, unscheduled energy consumption is high during high pricing hours, but scheduled consumption is comparatively low. The latter is due to energy consumption limits arising from cost optimization.

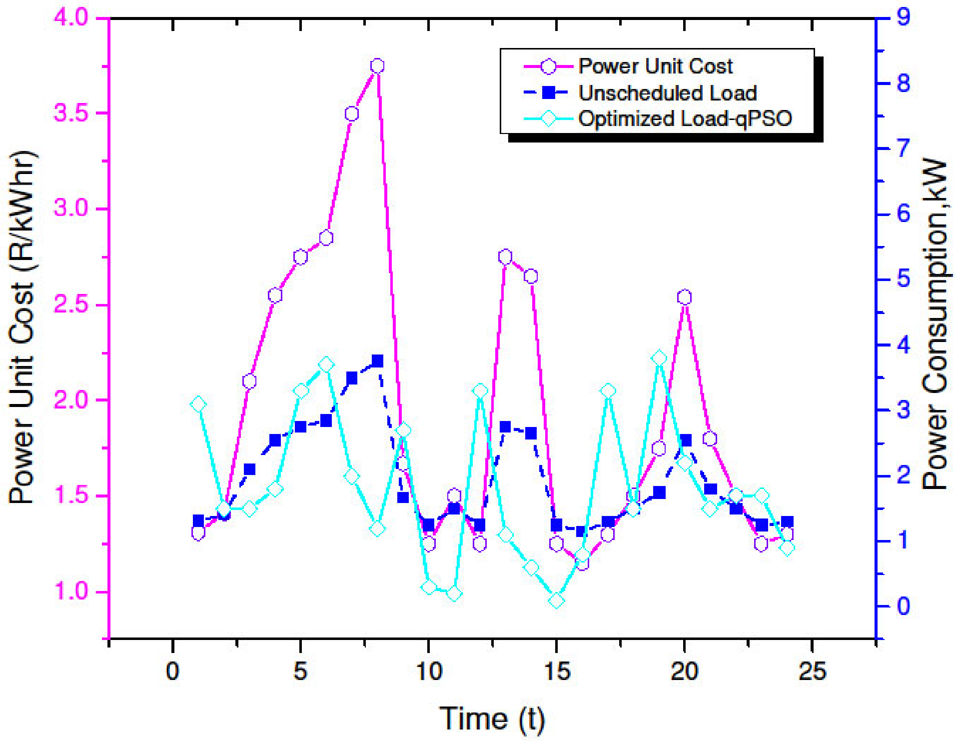


Fig. 6-17. Power consumption of the scheduled and unscheduled household load

1.26 Conclusion

In this work, a new microgrid energy management problem with a non-convex cost function with load dynamics is expressed and solved by adopting Quantum Particle Swarm Optimization. Four case studies were studied to demonstrate the benefit of various demand-side participation levels on IMGs while solving the non-convex problem. The utility-induced load shaping is introduced in the objective function to reduce the grid's energy import. Further, the dynamic load dispatch of the microgrid is obtained within a 15, 30 or 60-minute time frame, and the effect of demand-side management on its overall operating cost is investigated. The QPSO algorithm demonstrably solves the non-convex problem efficiently. Simulation results yield a 4.34 % reduction in operating cost compared to the case where demand-side management participation is lower. Finally, due to the VPE, costs for the non-convex DGs increase in comparison to DG units with convex cost functions. The methodology can nevertheless assist MGs operator to minimize costs while benefiting customers with peak reduction hence lower energy consumption during peak periods. Consumer utility can be safeguarded by appropriate scheduling wherein the consumer has a say.

The novelty and contribution of this portion of the research work are:

- Optimal scheduling solution of a grid-tied MG with multiple DGs with a non-convex cost function.
- Controllable DG sources and non-controllable sources are integrated into the load supply mix.
- A utility-induced flexible load shaping strategy is adopted to control the non-critical loads without compromising customer satisfaction.
- The day-ahead scheduling horizon is taken on a 96-interval time resolution to investigate the proposed method's effectiveness by considering load dynamics in the IMG.
- Finally, the QPSO algorithm is devised to minimize the MG operating cost and utility power exchange cost in the presence of DG units subject to non-convex and MILP/quadratic cost functions. The simulation results are compared between the cases with various levels of DSM penetration.

Chapter 7 Framework for Optimal Power Dispatching in Future Smart Grids

1.27 Introduction

In this chapter, the focus is on optimising power dispatching. This can be either in a single MG or a fully-fledged SG. As already alluded to in earlier chapters, the key to successfully optimized dispatching would be to embark on a strategy that minimizes the OPEX and CAPEX associated with traditional and renewable generators, the transactional costs of the transmittable power, maximized Utility's demand response benefits, concurrent with satisfying the load demand constraints. This is achieved by effecting real-time management of power generation, distribution, and usage in the SG or MG. Overall the primary objectives include;

- Integrating renewable generation sources into the main power grid. These sources can be from individual households or Public-Private Partnership Public-Private Partnership (PPPs).
- Real-time constant monitoring of electrical power consumption and its depletion in the SG.
- Acquisition of key grid measurements and as well as billing-related data.
- Constant achievement of optimised balancing of demand and power energy consumption by end-users.
- Effecting regular interactions between end users and the Utility. This is normally facilitated by an enabling ICT subsystem.
- Constantly guarding and enforcing both privacy and security within the entire system.
- Enhancement of reliability by way of allowing degrees of autonomy in management.
- Ensuring the maximized efficiency in terms of assets used in the SG.

A vision of future SG is shown in Fig. 7-1. Notably, a full duplex ICT subsystem is incorporated to interlink the various entities communication-wise. In that way, end-users can trade effectively by, e.g. maximising power trading with the grid. This is because they would have acquired market-related information, as well as grid status, before trading any excess power to the grid.

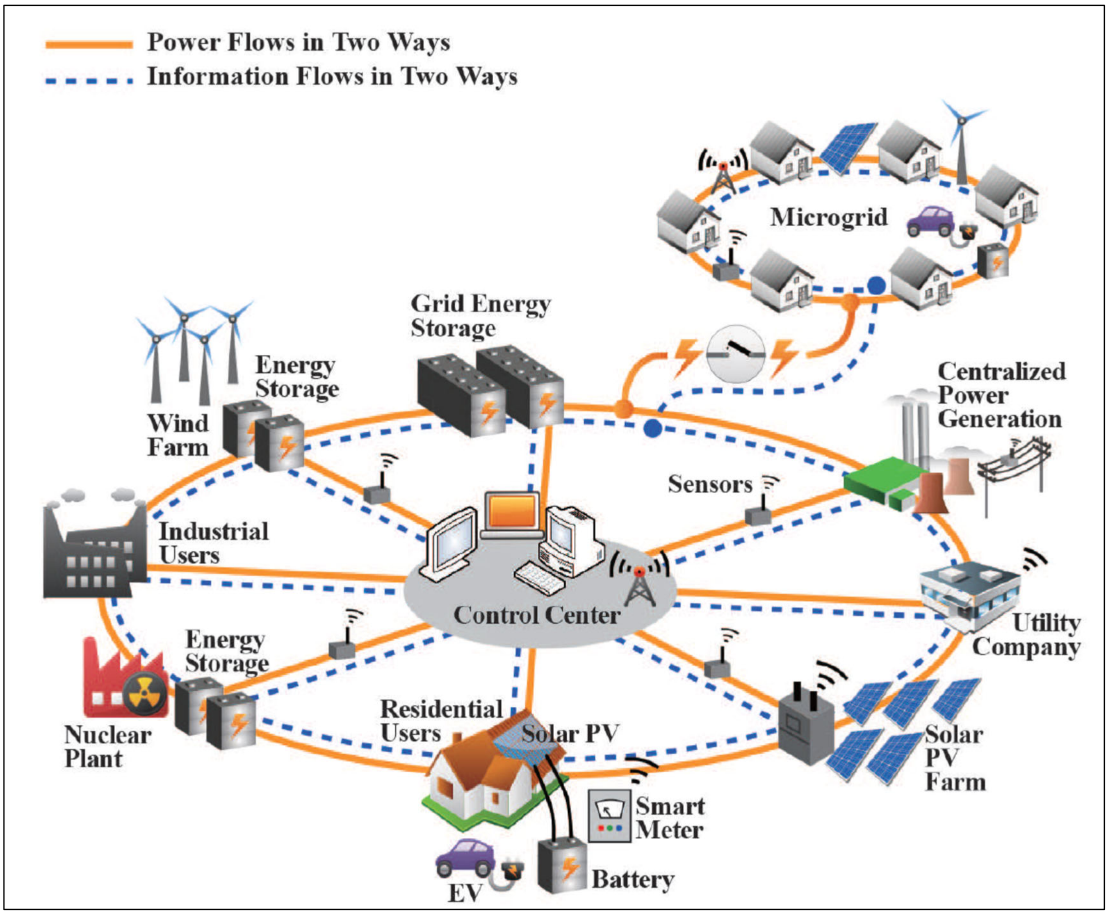


Fig. 7-1 Envisaged future generation SG

At the functional level, the SG system encompasses various applications, and services, concurrently with advanced management and operation to ensure efficiency in balancing supply and demand. Envisaged services and applications are summarised in Fig. 7-2. In summary, the operation functions in envisaged future SGs aggregately bring about a multitude of services / or applications that will associate with:

- The exchange of power/energy generation-associated information and processing it at strategically located dedicated processing entities (such as servers).
- Gradual integrating of miniature power generating sources from both end-users and PPPs.

- Regularised smoothening of SG power fluctuations. This is often triggered by switch gearing, and more often, the injection of extra power from end-users renewable generators.
- Acquisition and logging of data from components such as actuators and frequency sensors. These elements are essential for coordination within the SG in that they can quickly signal abnormal conditions(states) that would then be immediately addressed before the effects propagate further thus possibly causing major disruptions.
- Utilizing synchronised and coordinated servers in the grid to timeously make inferences on acquired data.
- Constant monitoring and diagnosing of key SG elements to ensure that they are operating normally as per design specifications. This is also to ensure that such elements/devices do not fatigue because of processing excessive loads.
- Incorporating the usage of power factor regulating transformers (PFRs), flexible alternating current (AC) transmission systems (FACTS), ultra-low resistance superconductors, and surge suppressors in the form of series-connected capacitances.
- Readjusting of protective relay's settings. This is normally implemented by way of constantly acquiring control (feeder)signals from incorporated sensors.
- Automated isolating as well as reconfiguring of malfunctioning sections of power transmission cables. Once more specialised sensors are mounted along the distribution /transmission lines to detect any anomalies.
- Automating the power transmission and distribution network sections.
- Monitoring and regulated control of power factor within the SG using sensors.
- Global monitoring of the entire SG for any abnormalities. This should be detectable in real-time scales.
- Usage of triangulation to locate points of faults occurrences.
- Automated billing of prosumers' power consumption via AMI systems.
- Remote controlling of end users' appliances such as geysers so that better management of demand and supply of available power can be achieved.
- Fast feeder reconfigurations to possibly ease the load on equipment, improvements in assets utilization, distribution system efficiency, thus in the process enhancing the system's overall performance.

- Constant updating prosumers about prevailing power tariffs. This helps them to make informed decisions on when to use, and trade power.

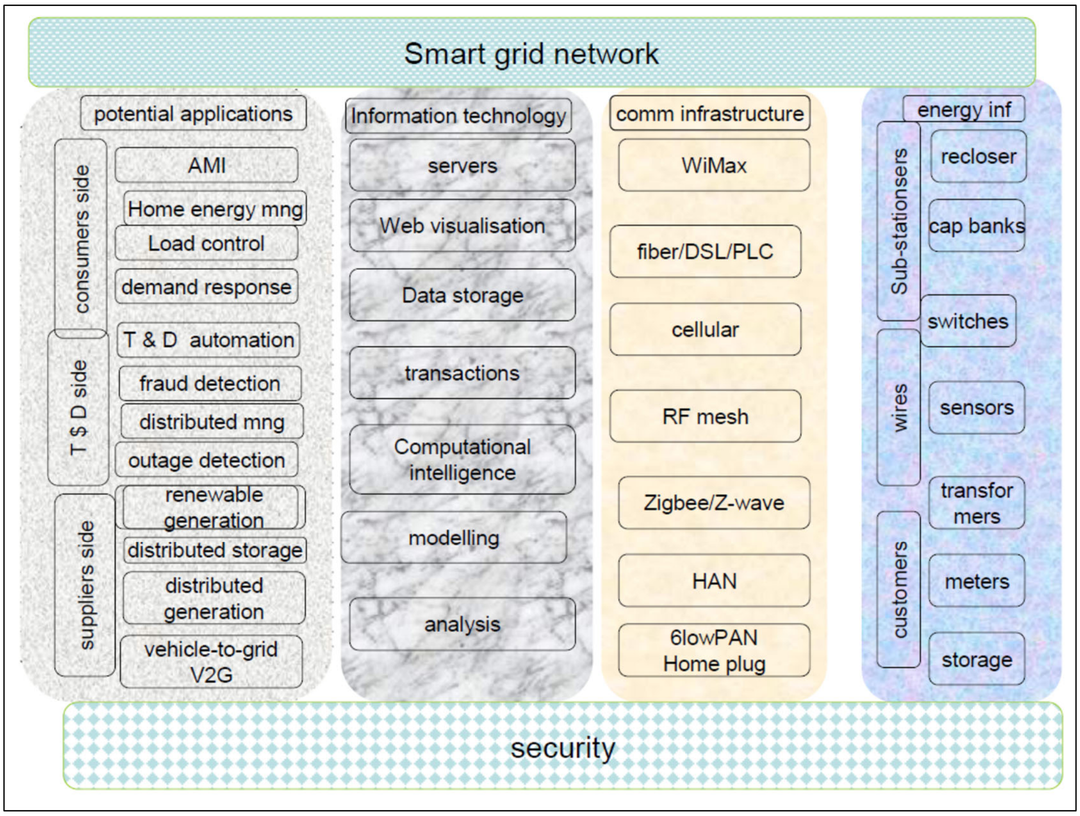


Fig. 7-2. Present and future SG's applications and services

In this chapter we propose a hierarchical energy dispatching framework to balance demand and supply, trading profits maximisation, as well as optimised energy storage capacity in a typical SG. In our proposal, we do not exactly distinguish between an MG versus cooperative MGs. In short, the SG essentially is composed of multiple cooperative MGs. We will use both analytical and simulation approaches to evaluate the proposed framework. In summary, our focus in this chapter would be to;

- Provide a model of such a framework, as well as a brief analysis and modelling.
- Secondly, detail a hierarchical optimal dispatching framework based on both non-predictive and predictive controls for the SG.

The next section will explore hierarchical versus distributed optimised dispatch.

1.28 Hierarchical versus Distributed Dispatch Framework

As alluded to earlier, a functional SG would comprise three distinct levels namely, power generation and distribution, control, and management, and lastly communications and security. Key two main factors to enable the reliable and efficient operation of MGs/SGs would be stabilised and economic control. As can be recalled since a typical SG comprises several interconnected and cooperative MGs, each with its control, thus the interconnected structure will result in a distributed dispatch control architecture framework. This section presents two different control approaches for microgrids. With regards to a hierarchical structure, we have both localised controllers that monitor and supervise each resource. This is followed by a supervisory controller at the individual MG level whose role is to oversee the entire MG domain. Further to that, we will have the last level controller that now interconnects all the MG supervisor controllers throughout the SG. We thus briefly describe and mitigate both hierarchical and distributed architecture to ascertain which would be an ideal choice for our proposed framework. Both types of control configurations will rely on the provisioned ICT subsystem of the SG to achieve efficient as well as harmonious coordination among the various DERs (energy generators, be they renewable or otherwise).

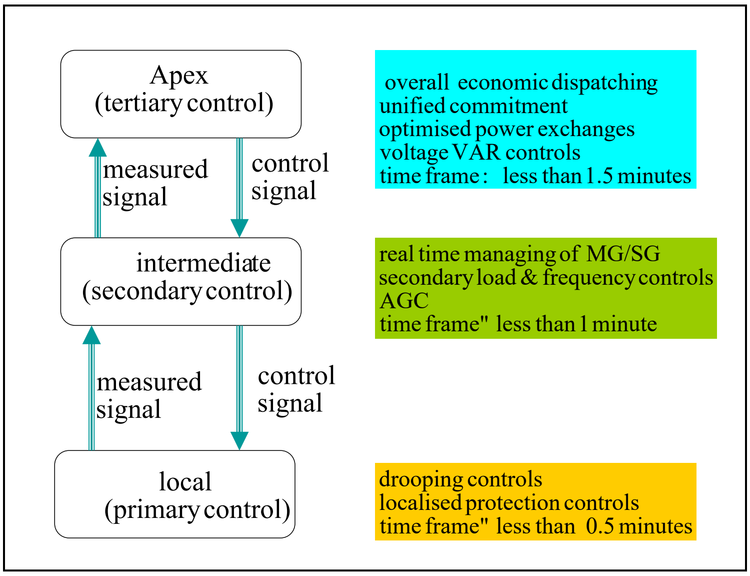


Fig. 7-3. Generalised SG control flow structure

Fig. 7-3 illustrates the general control operations of an SG. As can be noted from the same depiction, they are three levels and both control information and data are afforded a duplex linking among the three same levels. In that way the overall SG's main primary objectives of reliance, efficiency and resilience are achieved. The lowest level controller regulates localised resources such as grid frequency (i.e., frequency sensors), whereas the top-level controller plays a supervisory role and hence is involved in key decisions making.

Hierarchical Structure

Such a control structure thrives to achieve key objectives of an overall SG as cited earlier by employing a centralized controller at the apex (tertiary level). The same level hierarchy will blend these objectives with operational constraints to ultimately define the base optimization problem. It is important that this level of control hierarchy be efficient and reliable. Ultimately it integrates various homogeneous generating sources (DERs) and at the same time is able to generate and cast real-time tariff signals to prosumers. In addition, it can forecast loads. Note that the key to achieving the projected objectives is having a reliable and efficient ICT subsystem via which it communicates with other entities within the SG domain.

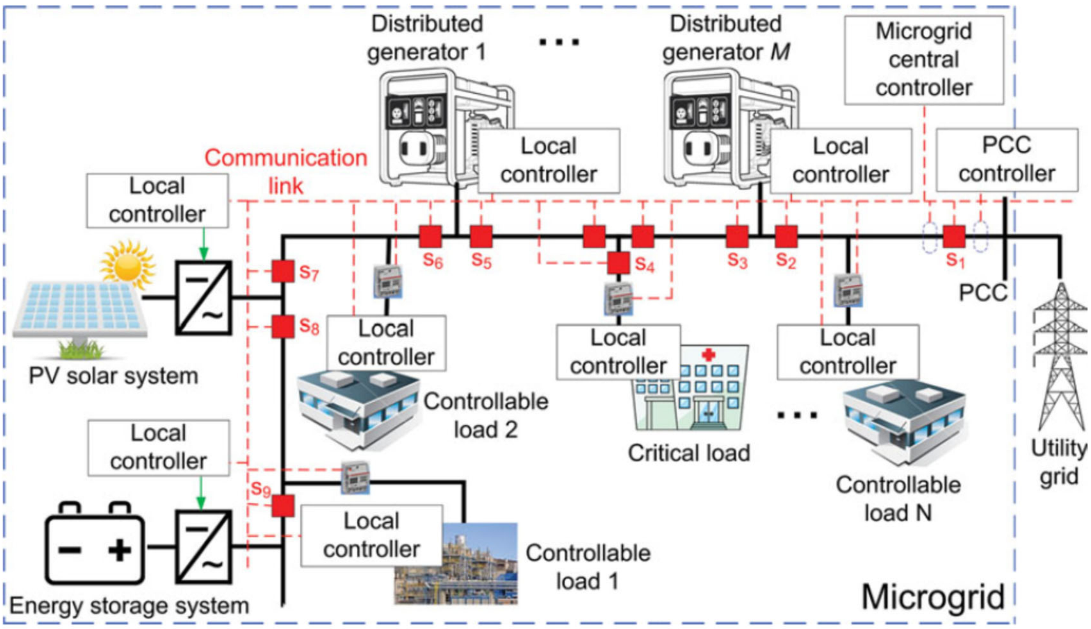


Fig. 7-4. The hierarchical control structure

The next level hierarchical control level (secondary control) addresses as well as ensures overall system level stability of the SG. Typically, it is involved in near-to real-time power load management, frequency regulation as well as automized power generation control (APGC). It is generally relied upon as a pacer or set pointer for primary-level controllers in a dynamic fashion. Note that the voltage control problem is defined at this level of hierarchical control.

Distributed Control architecture.

A distributed control structure relies on peer-to-peer communications to make informed decisions regarding the state and management of the overall SG.

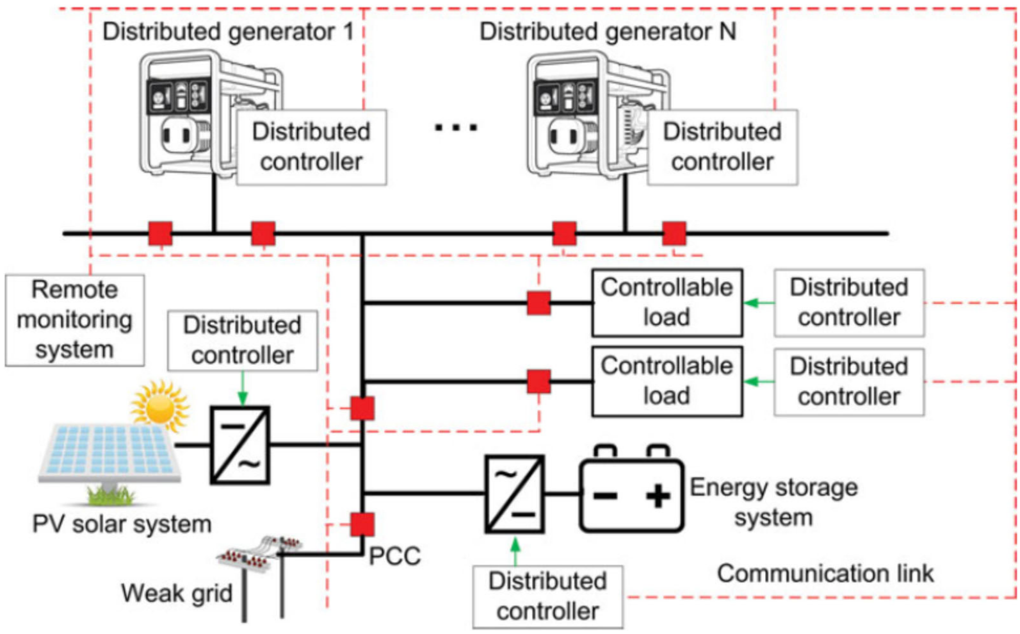


Fig. 7-5. Distributed control architecture configuration

Its flexibility in nature makes it relatively easy to add additional renewable generators, without impact on other already existing online system generators. A desirable turnaround time for distributed control architectures would be no worse than in the order of 0.1 seconds. Any failure in the system remains localised and hence does not propagate and grind the entire SG grid to a halt. However, note that such architectures rely on some sort of heuristics laws in executing control decisions and ultimately provide a suboptimal solution

Such a control architecture is depicted in Fig. 7-5. From this diagram, we note that it relies on a centralized controller to monitor the entire portion of the grid (typically an MG domain). It is further enhanced with distributed controllers that execute control functions. The facilitated peer-to-peer communications enable the harmonious coordination of control entities (controllers) to achieve the overall SG's objectives. By comparison, we conclude the following;

- In terms of control system reliability and efficacy, a hierarchical control architecture's top-level failure will affect the entire system since coordination among the various controllers is lost, hence optimal operation is not possible. However, with a distributed control architecture, the fault's effects are localised.
- In terms of economics, a hierarchical structure is optimal whereas its distributed equivalent is relatively suboptimal.
- Concerning design complexities, a distributed architecture is relatively easier to design.
- Scalability-wise, a hierarchical structure shows more flexibility, whereas a distributed equivalent can only accommodate a limited type of DERs.
- In terms of computational complexities, a hierarchical structure has a much relatively higher computational demand. This is because, in the case of a distributed architecture, such loads are distributed throughout the participating peer controllers.
- Typically, a hierarchical controller (apex level) is implemented in the form of a high-performance PC, whereas an embedded controller will suffice for its distributed equivalent.
- Because of the absence of peer-to-peer communications, a hierarchical structure will generally operate at very low bandwidth, whereas its distributed equivalent will always require high bandwidth provisioning.

We thus conclude from this comparison that a hierarchical control configuration would be ideal for future generation SGs.

1.29 Hierarchical Dispatch Model Framework Description

In this section, we detail a hierarchical-based Dispatch Model framework for energy generation supply, demand, and trading in an SG, Fig. 7-6. The first step is for us to specify the model's formulations.

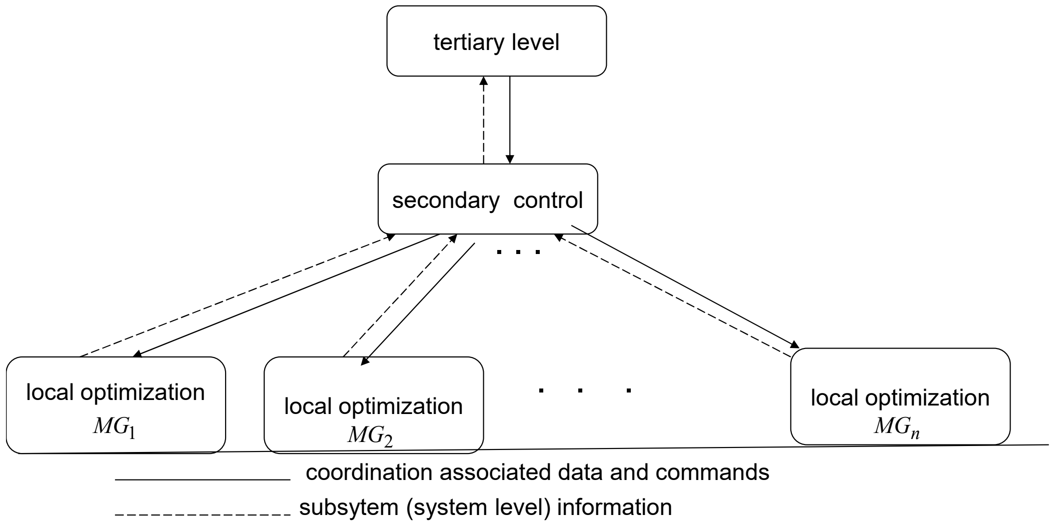


Fig. 7-6. System model (a) system structure (b) communication flow

In this regard, we will assume a "look ahead policy" i.e., data pertaining to power usage in the past one-day period (24 hours) is known apriori. This data included the following:

- 15 minutes interval power demand forecasting for the day ahead.
- 15 -60 minutes of PV solar and wind generation potential forecasting.
- Approximated cost functions of the DERs, and other parameters such as maximum and minimum power generation limits.
- The state of the BESS, i.e., its initial charge levels.

The SG operates all its connected MGs in either one of the following modes:

Mode I: Standalone mode. In this case, the MG is isolated from the main interconnecting grid.

Mode II: connected mode: In this case, the MG fully connects to the main interconnection grid and power trading may take place.

Mode I:

Given that in the SG, there exist different types of renewable and fossils generators whose cost functions differ, we thus can write;

$F_jP_j(t) = b_jP_j(t) + c_j$ for an FC, and $F_jP_j(t) = b_jP_j(t)^2 + b_jP_j(t) + c_j$ for a DE, where the constants a_j, b_j and c_j are parameters associated with the cost function; In this case, the power demands in a single isolated MG must match its generation capacity. The objective function therefore can be expressed as:

$$Min \sum_{i=1}^{n} \sum_{j=1}^{m} F_j \left(P_j(t)\right) * \tau_j(t) + s_j(t) \tag{7.1}$$

Subject to;

$$\tau_j(t) = \begin{cases} 1, & \text{if } \mathrm{j}^{\mathrm{th}} = ON \text{ at time } t \\ 0 & \text{otherwise (OFF)} \end{cases} \tag{7.2}$$

$$s_j(t) = \begin{cases} sc_j, & \text{if } \tau_j(t) - \tau_j(t-1) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{7.3}$$

Where sc_j corresponds to costs associated with starting the generator j. This is subject to;

1. $p_j^{\min} \le P_j(t) \le p_j^{\max}$, i.e., the power output of the j^{th} generator at an arbitrary time t. .
2. $\sum_{j=1}^{m} P_j(t) = P_{load}(t) - P_{sources(t)-P_{BRSS}(t)}$, i.e., power balances between the total loads and aggregated generation.
3. $p_{BESS}^{\min} \le P_{BESS}(t) \le p_{BESS}^{\max}(t)$. This relates to the BESS's stored power. Note that when $P_{BESS}(t) > 0$ the system is discharging; $P_{BESS}(t) < 0$ - the system is charging, otherwise $P_{BESS}(t) = 0$ there is no generation at all.

Mode II: the MG is connected to the main Grid

We recall that this mode is characterised by the trading of power is possible. This means either the MG can buy power from the main grid to sustain its current needs or vice versa, meaning its excess generations can be traded. We distinguish a few scenarios as follows;

Scenario I: Purchasing power from the interconnecting grid. In this case, if the current tariff is $c_{grid}(t)$, then our objective function can be expressed as:

$$\min\left\{\sum_{t=1}^{n}(c_{grid}(t)P_{grid}(t)+\sum_{j=1}^{m}F_j(P_j(t)*\tau_j(t)+s_j(t)\right\} \tag{7.4}$$

Where, $P_{grid}(t)>0$, is the purchased power, hence the need to balance;

$$\sum_{j=1}^{m}P_j(t)=P_{local}(t)-P_{wind}(t)-P_{pv}(t)-P_{BESS}(t)-P_{grid}(t) \tag{7.5}$$

Scenario II: Selling off the power. We recall that this will mostly occur when the tariffs are favourable to generators of power (including end users). In this case, the objective function is to maximise profits hence we have;

$$\max\sum_{t=1}^{n}\left\{-c_{grd}(t)P_{grid}(t)-\sum_{j=1}^{m}F_j(P(t))*\tau_j(t)+s_j(t)\right\} \tag{7.6}$$

Note that this time around, $P_{grid}(t)<0$, the equilibrium equation now becomes.

$$\sum_{j=1}^{m}P_j(t)=P_{load}(t)-P_{wind}(t)-P_{pv}(t)-P_{BESS}(t)-P_{grid}(t) \tag{7.7}$$

So far, the inference from equations (7.1) to (7.7) is that a properly designed as well as dimensioned SG or MG keeps OPEX in terms of generation at a minimum and at the same time maximises revenues acquired from energy sales.

1.30 Model Reformulation

Ultimately, we wish to use neural network sets (artificial intelligence) to aid us in making informed decisions hence we reformulate (retransform) the two policy scenarios into implementable formats.

In this case, since the objective is to minimise the aggregated power generation costs by all sources in a given MG (or SG), we thus have;

$$\min \ \Pi = \sum_{i}^{N-1} \Pi_i \ x_i, u_i) + \Pi_N(x_N) \tag{7.8}$$

Where x_i and u_i are state and decision vectors respectively. The same equation g_i denotes the degree of correlation between neighbouring vectors, and Π_i a cost function at an arbitrary time i . Equation (7.8)'s validity is subject to satisfying a constraint Ψ defined by;

$$\Psi = \begin{cases} x_{i+1} = g_i(x_i, u_i) & \\ c_{iE}(x_i, u_i) = 0 \quad x_{NE}(x_N) = 0 & i = 1,2,\ldots, N-1 \\ c_{iI}(x_i, u_i) \leq 0 \quad x_{NE}(x_N) \leq 0 & \end{cases} \tag{7.9}$$

Thus, for Mode I of MG operation, we have an equivalent formulation as follows:

$$x_i \equiv \left[P_1(i) \quad P_2(i) \quad \ldots \, P_m(i) \quad P_{BESS}(i) \quad soc(i) \right]^{\mathrm{T}} \tag{7.10a)}$$

Similarly, for Mode II operations we have;

$$x_i = \left[P_1(i) \quad P_2(i) \quad .. \quad P_m(i) \quad P_{BESS}(t) \quad P_{grid}(t) \quad soc(i) \right]^{\mathrm{T}} \tag{7.10b)}$$

$$u_i = \left[\Delta P_i(i) \ \Delta \mathrm{P}_2(i) \ \ldots \Delta \mathrm{P}_\mathrm{m}(i) \ \Delta \mathrm{P}_\mathrm{BESS}(i) \ \Delta \mathrm{P}_\mathrm{grid}(i) \right]^{\mathrm{T}} \tag{7.10c)}$$

Equations (7.10a), (7.10b) and (7.10c) together conform to a discrete multi-cascaded dynamic process whose solution can be best achieved by utilizing dynamic programming. In solving such a problem an input set of decision variables will generate input states for the next stages. The process repeats till the final stage where the output represents a minimal summed cost of the entire multistage process system. The Multistage decision process can be expressed by;

$$x^{k+1} = f^k(x^k, u_k), x^k \in U^k, \quad k \in [0.1, \ldots, N \quad 1] \tag{7.11a)}$$

$$V^N(x^N) = \min_{u0,..,u^N} \left[g^N(x^N) + \sum_{k=0}^{N-1} g^k(x^k, u^k, \right]. \tag{7.11b)}$$

Where in the two above equations;

V^N -represents the aggregated costs of all stages.

f^k - functions characterising state transitions.

g^k - k stage's cost function.

x^k - k stage's state vector

$u^k = k$ stage's corresponding decision vector.

k - time interval count.

Consequently, at any stage k ;

$$V^k(x^k) = \min_{u^k \in U^k} \left[g^k(x_k, u^k) + V^{k-1}(x^{k-1}) \right] \tag{7.12}$$

This is subject to satisfying Ψ ;

$$\psi = \begin{cases} u_{\min}^{ki1} \le u^{k-1} \le u_{\max}^{k-1} \\ x_{\min}^{k} \le x^k \prec x_{\max}^{k} \\ x^k = f^{k-1}(x^{k-1}, u^{k-1}) \end{cases} \tag{7.13}$$

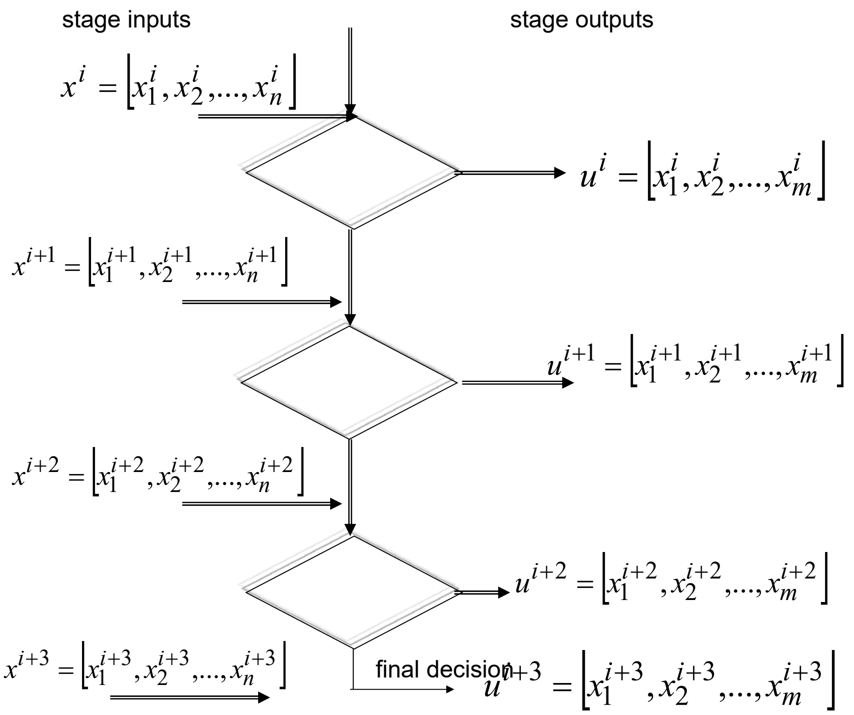
$$x^i = \left[x_1^i, x_2^i, ..., x_n^i \right], \quad u^i = \left[x_1^i, x_2^i, ..., x_m^i \right]$$

$$x^{i+1} = \left[x_1^{i+1}, x_2^{i+1}, ..., x_n^{i+1} \right], \quad u^{i+1} = \left[x_1^{i+1}, x_2^{i+1}, ..., x_m^{i+1} \right]$$

$$x^{i+2} = \left[x_1^{i+2}, x_2^{i+2}, ..., x_n^{i+2} \right], \quad u^{i+2} = \left[x_1^{i+2}, x_2^{i+2}, ..., x_m^{i+2} \right]$$

$$x^{i+3} = \left[x_1^{i+3}, x_2^{i+3}, ..., x_n^{i+3} \right], \quad u^{i+3} = \left[x_1^{i+3}, x_2^{i+3}, ..., x_m^{i+3} \right]$$

In Fig 7-7 a summarised reformulation of the model is provided.



(7.14)

Fig. 7-7. Reformulated mode policies in power dispatching

1.31 Model Evaluation

In this section, we will use both analytical as well as simulation approaches to evaluate the proposed hierarchical power dispatching framework. For certain aspects of the evaluation, we use the Plexim Simulation Platform. We have chosen a 3-cooperative MG constituting a fully fletched SG will be assumed. This SG system configuration is shown in Fig. 7-8 and the parameter sets provided in Table 7-1 are both used in the evaluation.

Table 7-1. Installed renewable and DGs parameters

unit type		*peak* generating capacit	cos*t function parameters*		
			strat_up	*b*	*c*
MG_1	DG_1	$12kW$	-	-	-
	DG_2	$20kW$	-	-	-
	PV	$4kW$	7	2.75	64
	WT	$6.5kW$	13	3.6	49

	MT	$8kW$	8	3.75	75
	$BESS$	$4kAh$	-	-	-
MG_2	DG_{4-9}	$@15kW$ each	-	-	-
	PV	$4kW$	7	2.75	64
	WT	$6.5kW$	13	3.6	49
	MT	$4kW$	8	3.75	75
	$BESS$	$4kAh$	-	-	-
MG_3	PV	$7kW$	7	2.75	64
	WT	$6.5kW$	13	3.6	49
	DG_{10-11}	$@10kW$ each	-	-	-
	MT	$4kW$	8	3.75	75
	$BESS$	$2kAh$	-	-	-

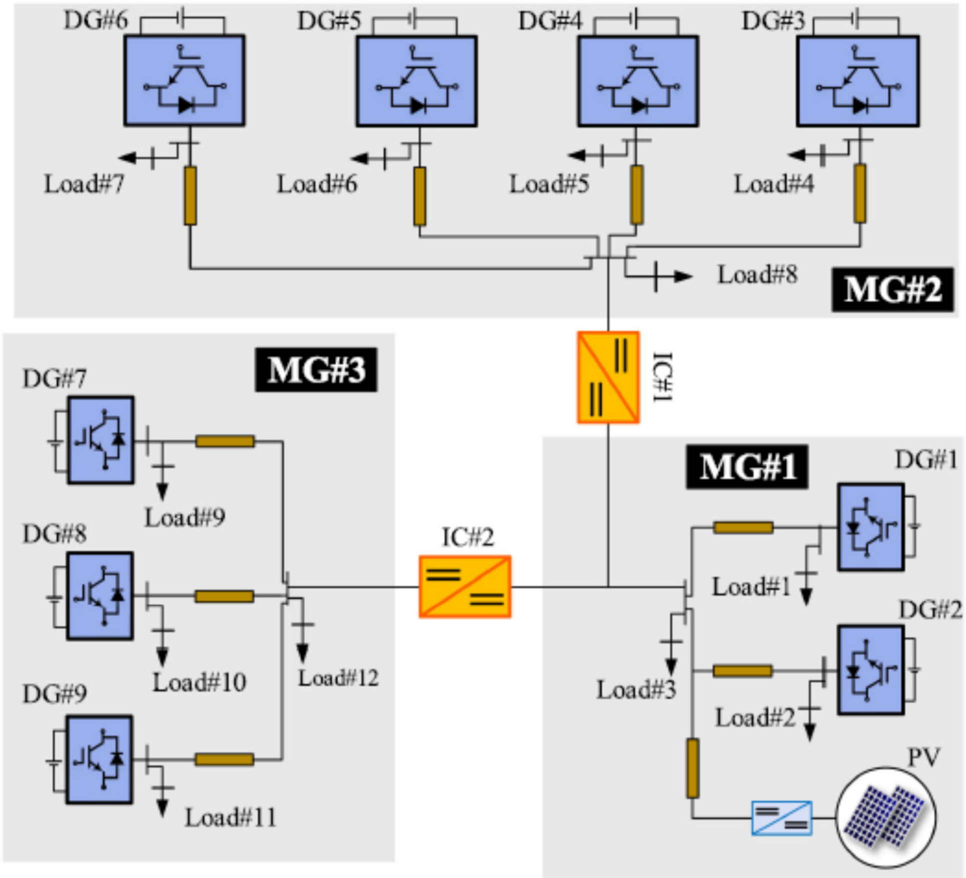


Fig. 7-8. Model of cooperative MGs constituting an SG

As part of our preliminaries, we provide a forecasted combined wind (WT) and solar (PV) generation capacity in Fig. 7-9. Notably, as expected WT sources have the potential to generate power throughout a 24-hour cycle, whereas, PV will optimally generate during mild sunny periods.

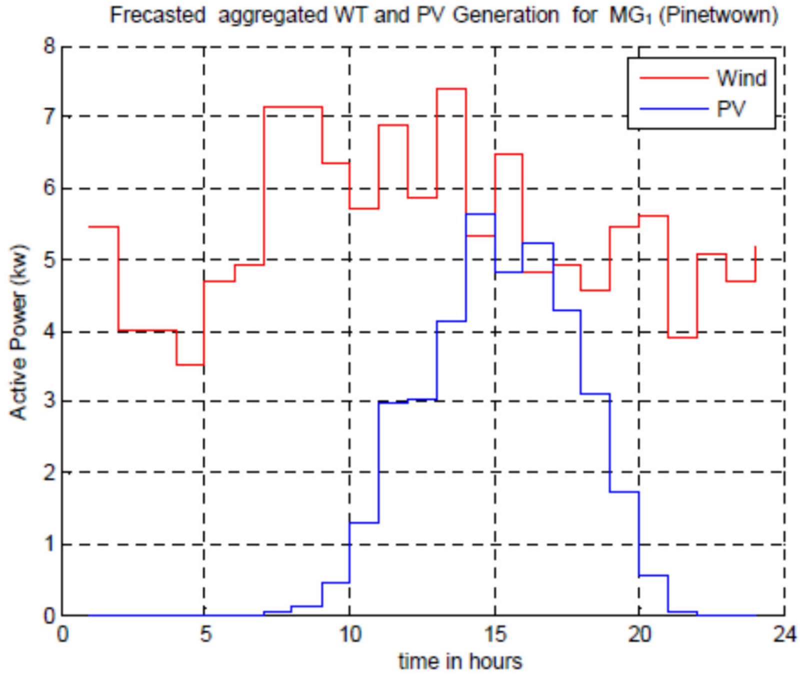


Fig. 7-9. Aggregated forecast Wind/PV generation for MG_i

Similarly, in Fig. 7-10, associated tariffs that are periodically availed (broadcast) to all prosumers are exemplified.

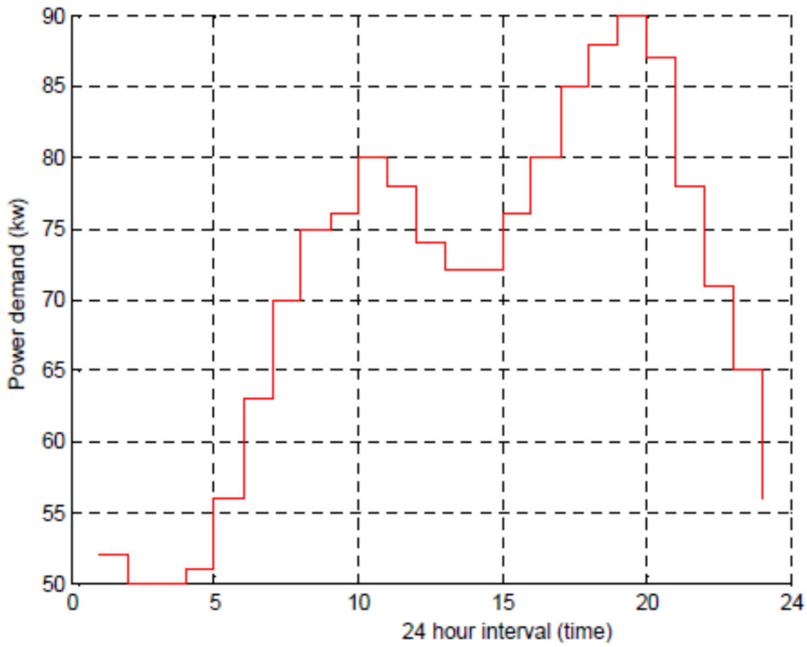


Fig. 7-10. Stand-alone power demands in an MG

It is recalled that from the onset we declared (defined) two modes of MG operations, one of which was in a standalone mode. In such a mode, the load demand will be always lower than aggregated actual (potential) generating capacity. Note that in this scenario, the MG is disconnected from the grid when power selling is not conducive in terms of current tariffs. However, as soon as tariffs improve, the system will connect should there be demand on the interconnecting grid. The power demand variation is plotted in Fig. 7-11.

A comparison of MT, FC and BESS power generation variations and scheduling thereof over a 24-hour cycle is provided in Fig 7-12.

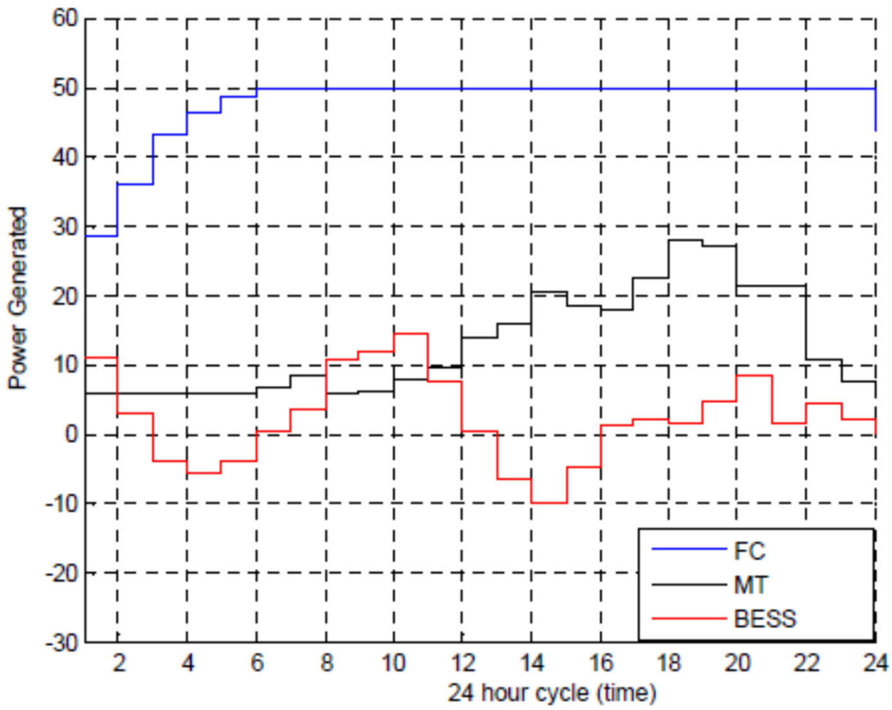


Fig. 7-11. Overall power scheduling over a 24-hour cycle for an MG in stand-alone mode

Note that the BESS will only start storing power (charging) when other sources can handle the current load demand and as well as the BESS itself is partially or critically depleted.

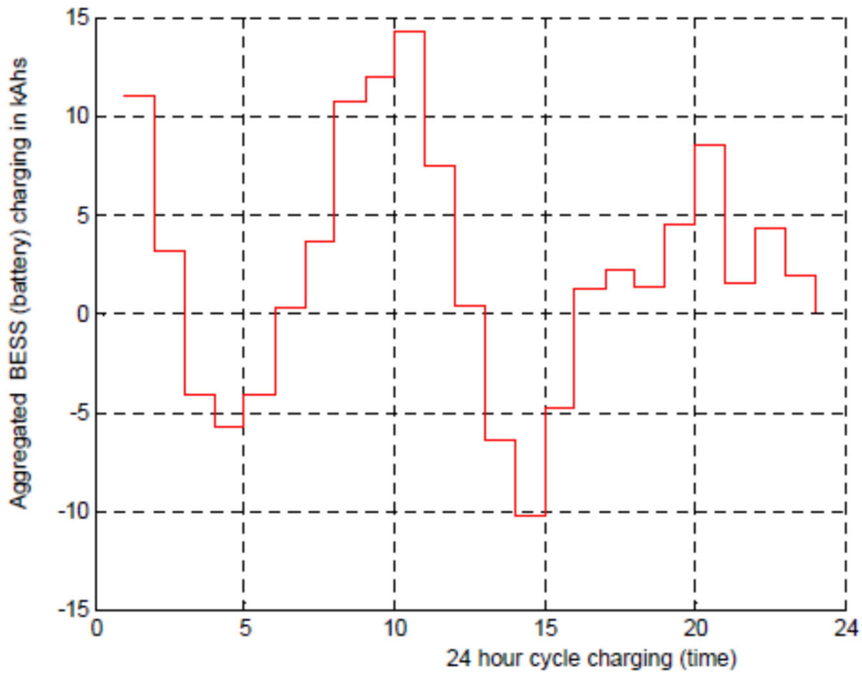


Fig. 7-12. Discharging and charging of the MG's BESS system

The state of charge and discharging for a given MG (in this case MG 2) over a 24-hour cycle is plotted in Fig. 7-12. The charging/discharging curve more or less mimics that of the power scheduling discussed earlier. Notably, when the MG is void of any power demands or is operating at p minimal loads, the BESS system is charging, whilst as the earlier attains near peak loading the latter start discharging to the local grid to help support the demand response curve. Notably is also noted (though not shown) that the BESS system will charge mostly from PV/WT (renewable) power. Also note that in our model framework, the BESS will also discharge to the local power bus, to reduce the dependence on DGs (diesel generators) as their OPEX in terms of fuel cost are quite high.

According to the other mode of operation of the individual MGs constituting the SG, in grid non-isolated (connected) mode, power is being purchased to help sustain the local load in the affected MG.

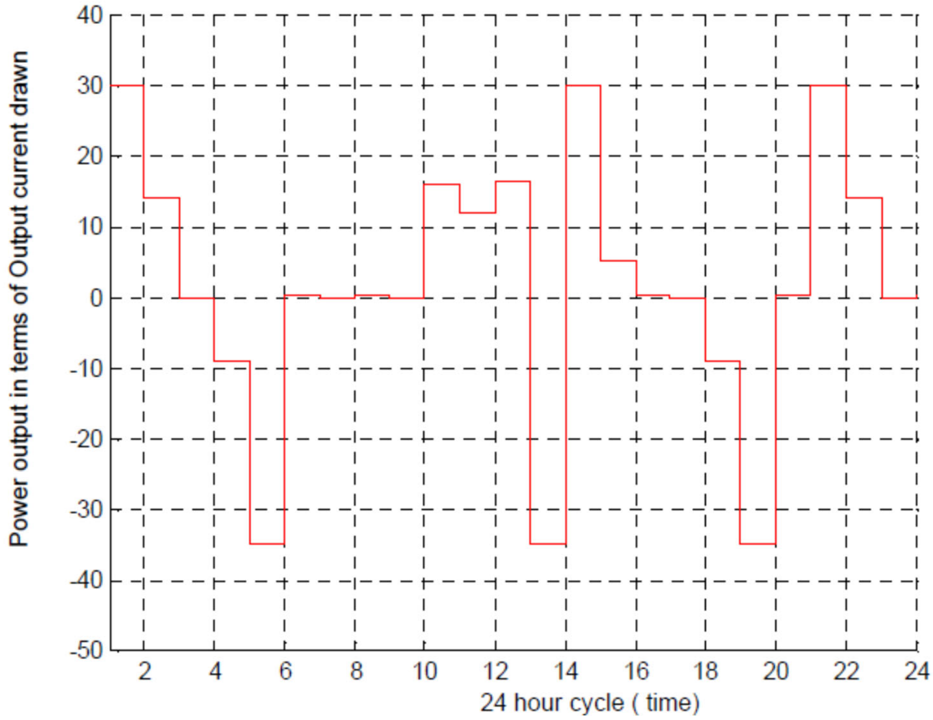


Fig. 7-13. Power derived from BESS

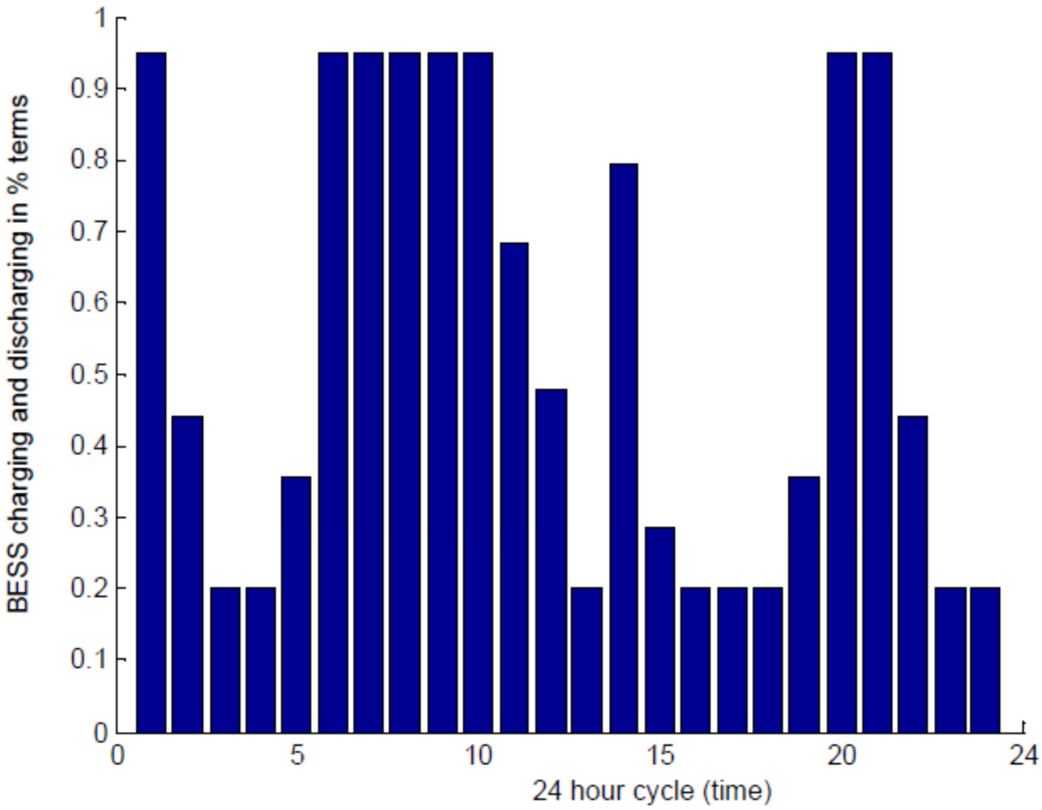


Fig. 7-14. Charging and Discharging concurrent with power purchasing from the BESS

Note that in this case, the power derived from the BESS as plotted in Fig. 7-13 is wholly drawn towards supporting the current load demands.

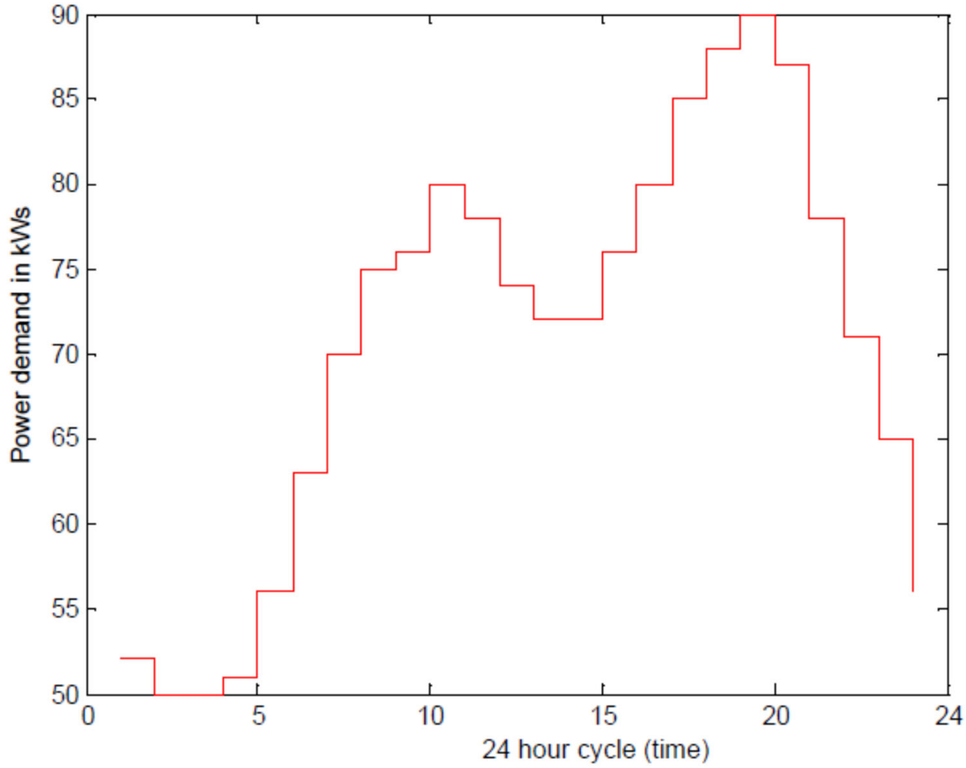


Fig. 7-15. The aggregated power demand for the MG in grid-connected mode

Fig. 7-14, Fig. 7-15 and Fig. 7-16 when inferred together and concurrently we note the following:

- That charging is taking place when tariffs are relatively low, typically at dawn as well as in the early evening.
- Discharging to support the local MG is mostly when tariffs are high and during peak hours.

We also consider a scenario of trading energy to the grid, i.e., to support other MGs in distress.

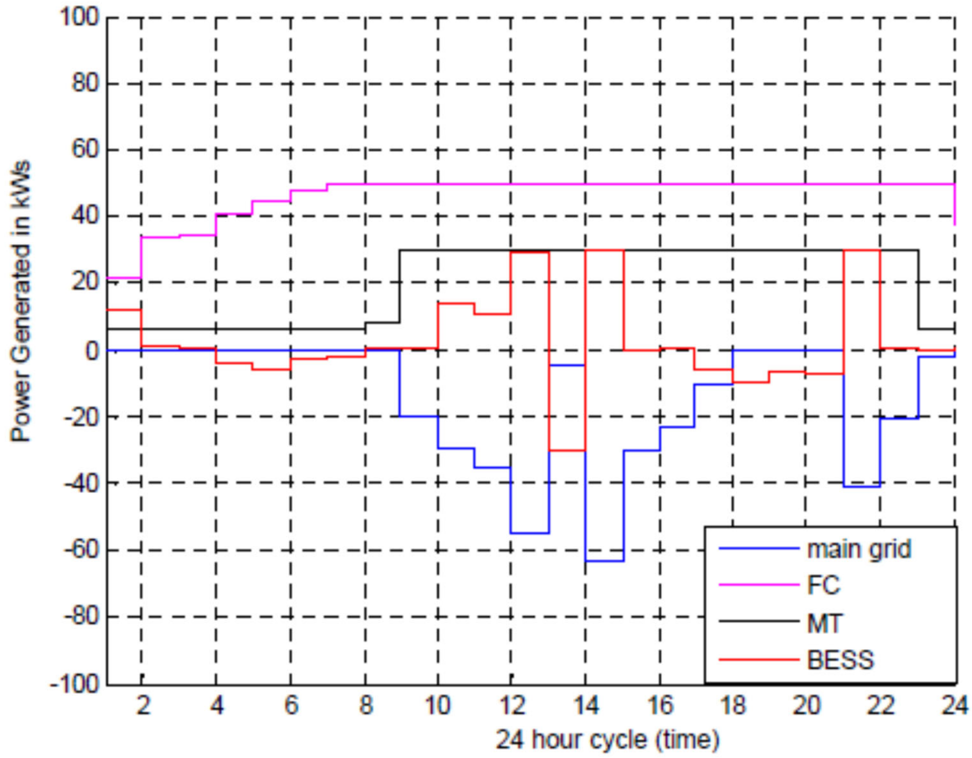


Fig. 7-16. Power scheduling concurrent with trading with the grid when MG is trading(selling mode)

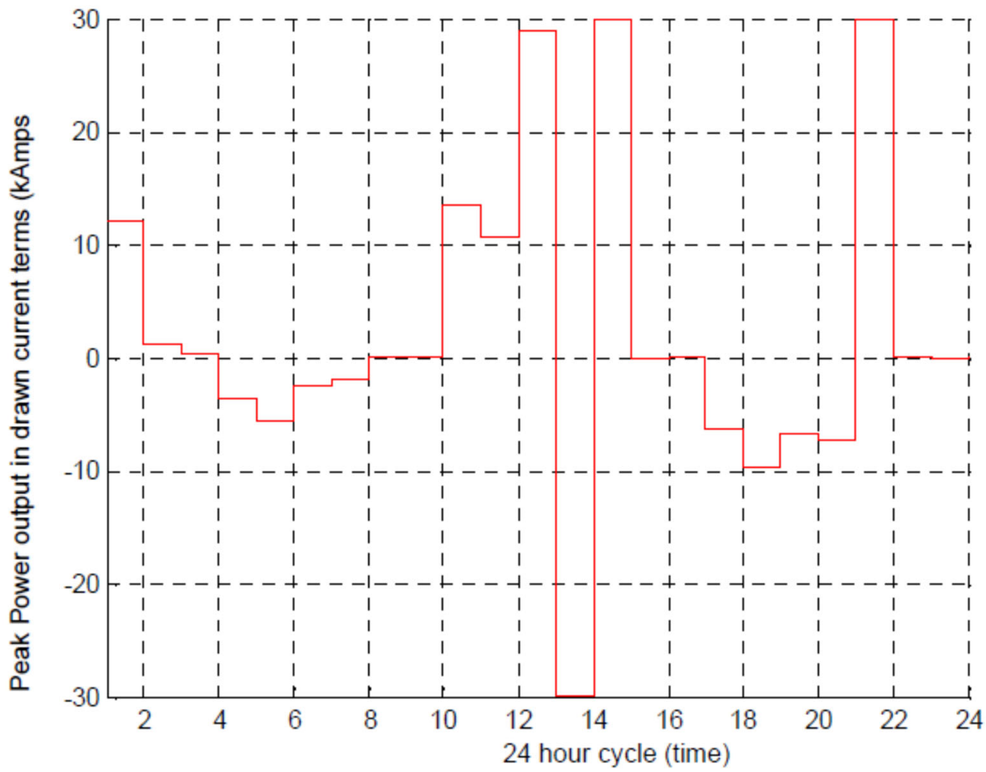


Fig. 7-17. State of charging and discharging when MG is trading (selling mode)

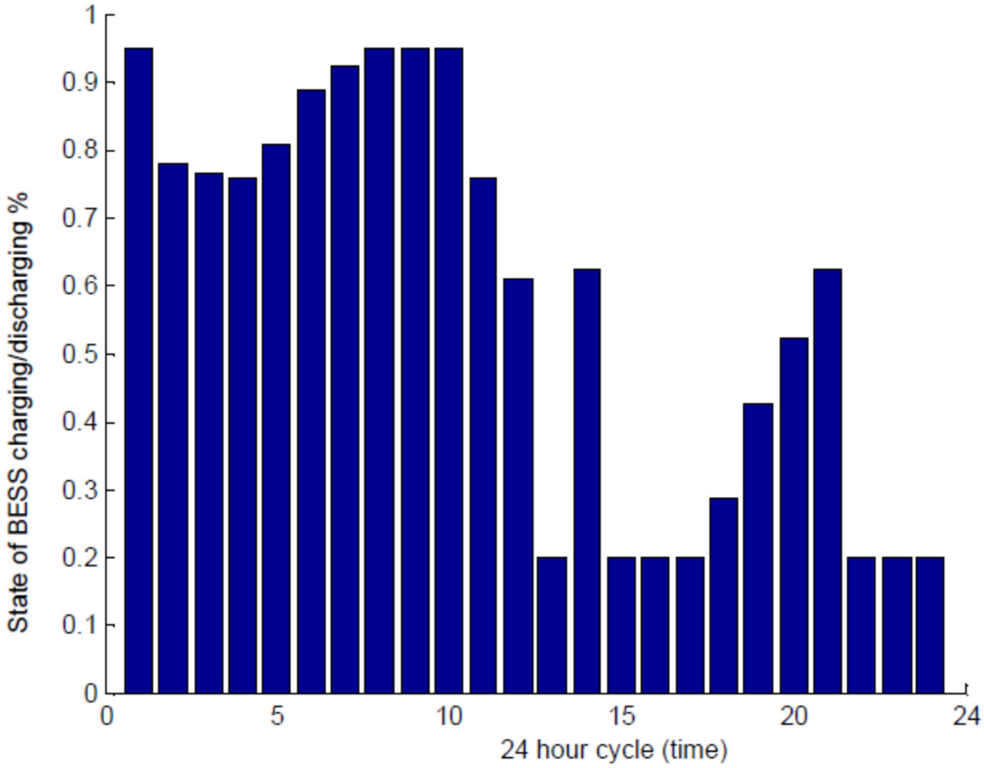


Fig. 7-18. BESS discharging /charging when MG is trading(selling mode)

From the last three plots, i.e., Fig. 7-16, Fig. 7-17 and Fig. 7-18 we can infer the following:

- That once again, power storage in the BESS systems occurs when tariffs are low.
- During favourable trading (selling) tariffs, power is discharged from the same BESS systems and sold to the grid. In that way prosumers maximise revenues.

1.32 Incorporation of Neural Networks Modules in Nodes

In a further attempt to ease the computational loads involved in the Framework's core modules in all three hierarchical stages, we chose to incorporate some artificial intelligence (AI) modules, Fig. 7-19. These will also aid in the more precise determining of optimal decisions and ultimately optimal dispatching of available power subject to maximising profits as well as keeping OPEX and CAPEX low.

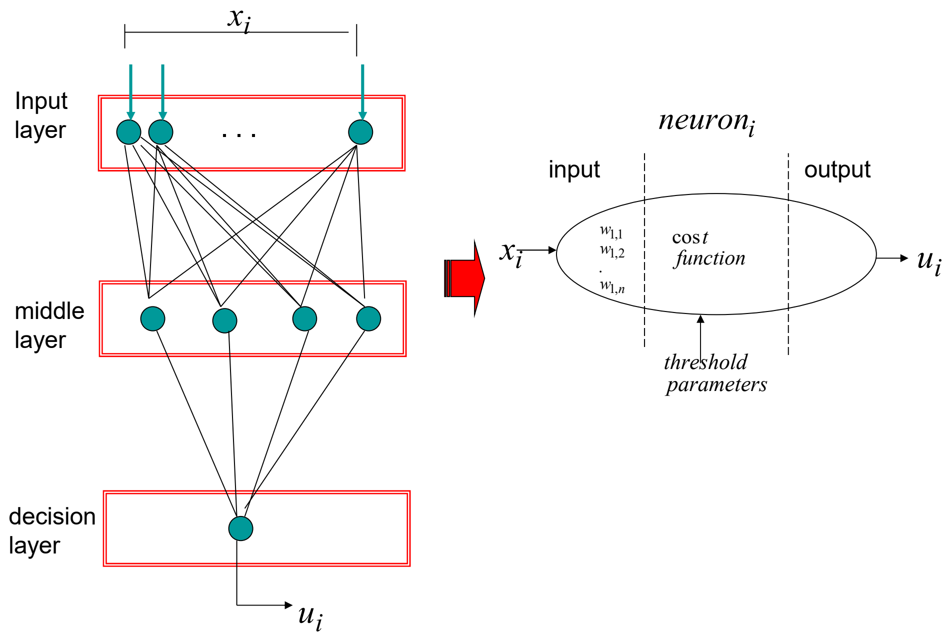


Fig. 7-19. The Neural Network set module illustration

As explored extensively, in the preceding chapter, the particle swarm optimization (PSO) algorithm which is primary bases on generating random approximated solutions before searching for an optimal one by way of exhaustive iterations tends to up the computational loads as well as signalling overheads among the entities constituting the hierarchical dispatching framework. Neither does it timeously converge to a localised optimal decision. Its successor, the quantum PSO (QPSO) has a faster convergence rate as well as a more précised fitness valuing. As elaborated in the preceding chapter (Chapter 6), it treats each particle is characterised as being in a quantum state and then uses the Schrodinger equation to formulate an equivalent wave function. Ultimately, the particles will gradually converge to a global solution.

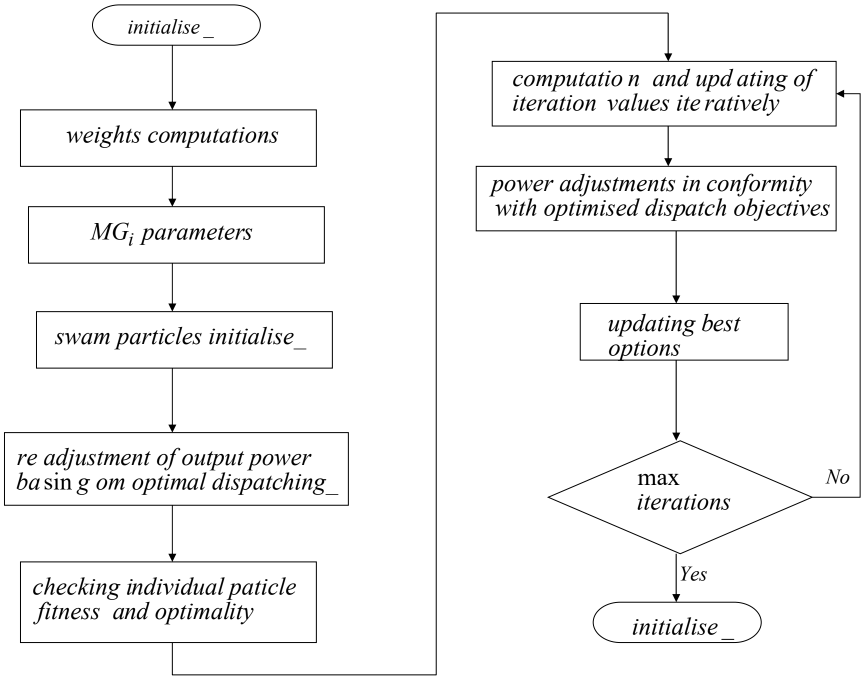


Fig. 7-20. QPSO algorithm-based dispatch algorithm in a hierarchical framework

The QPSO algorithm as provided in Fig. 7-20 will be implemented in the Neural Network modules to implement the optimisation as summarised by the reformulation provided in Fig. 7-7. Note that in this case, we rely on the VPSPICE simulation platform which among other things has the necessary pre-trained NN sets. To enhance the "look ahead" forecasting we initially ran trail rums for both PV and WT generators. The data used is provided in Table 7.2.

Table 7-2. 24 Hour interval climatic data captured for analysis purposes

time	*temperature*(^oC)	*wind velocity*	$I(kW/m^2)$
4#	45#	8138#	31334#
5#	4416#	9137#	31334#
6#	4315#	919#	31334#
7#	4418#	:16#	31334#
8#	441:#	:15#	31334#
9#	441;#	:15#	31334#
:#	441<#	91<#	31336#
;#	45#	91<#	3148#
<#	4615#	:1<#	316#
43#	4814#	;18#	31;#
44#	5314#	44#	31<<#
45#	5915#	:19#	4145#
46#	5:#	:1665#	41<36#
47#	5:16<#	:1586#	31;#
48#	5:#	:15#	3188#
49#	5817#	917#	3/44#
4:#	4<16#	918#	31334#
4;#	4;1;#	:19#	31334#
4<#	4;#	81:#	31334#
53#	491:#	81:4#	31334#
54#	4416#	815#	31334#
55#	<16#	914#	31334#
56#	:1<#	8139#	31334#
57#	:19#	816#	3134#

The climatic data is captured on an hourly basis over a 24-hour cycle period. To capture more realistic data characterising average typical climatic conditions of the vicinity (area) we averaged 5 consecutive captures. Typical data include temperature, wind velocity and solar intensity.

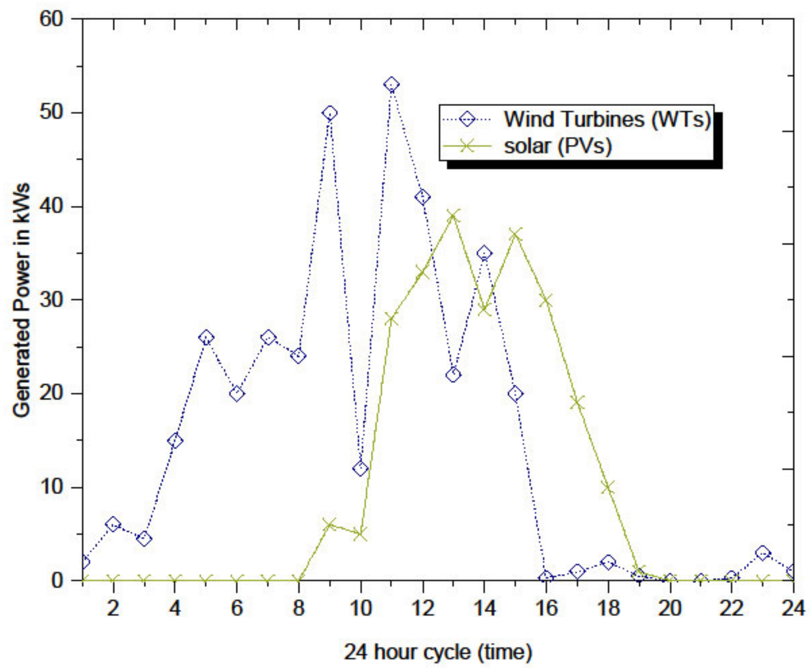


Fig. 7-21. Aggregated power from PVs and WTs over 24 Hour intervals

The plot of Fig. 7-21. Aggregated power from PVs and WTs over 24 Hour intervals shows the power generated from PVs and WTs over a 24-hour cycle.

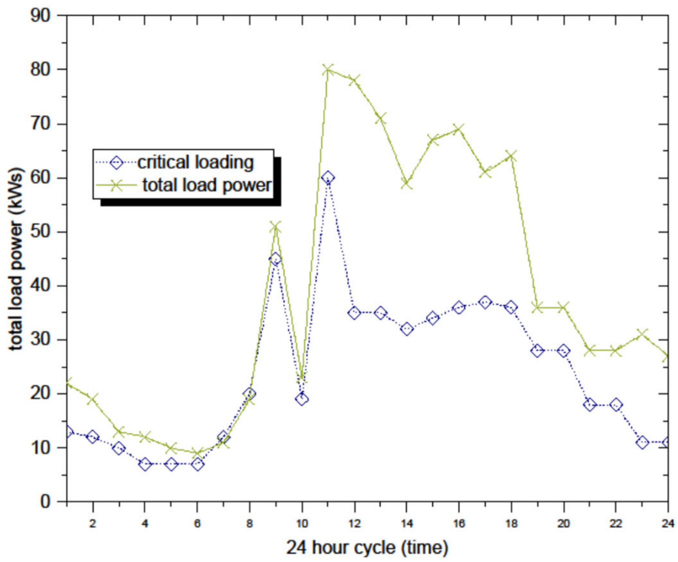


Fig. 7-22. Aggregated(total) SG load and its critical loading

We note from the graph that as expected ambient temperatures coupled with optimal solar radiation intensity (and correct inclination angle) will generate more power.

Typically, PVs will thus yield power during daylight hours from around 8 am to 19 am, whereas WTs will still generate power be it at night. We also provide a variation of critical versus noncritical grid loads over a 24-hour interval. These are captured at 60-minute intervals.

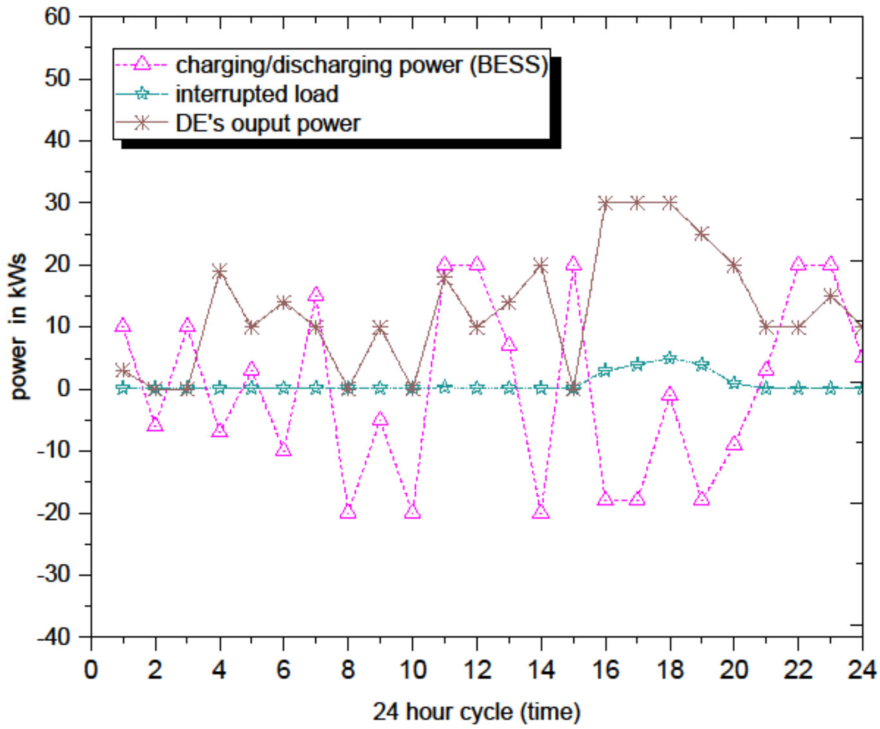


Fig. 7.1: Varying of BESS charging/discharging versus DEs optimality

We once again, reiterate that the objective of the proposed framework is on a hierarchical based optimal dispatch strategy with key desirables such as lowered OPEX and CAPEX costs (i.e., financial/economic viability), non-violation of environment protection from avoidable pollution, as well as power supply reliability in the grid.

Table 7-3. Pollutants and associated costs

type	$(g/kWhr)$	$\cos t\_coeff$ (ZAR/Kg)
nitrogen oxide (NO_x)	9.9	63
sulphur oxide (SO_2)	0.199	14.01
carbon dioxide (CO_2)	651	0.199

We make use of the pollutants tabulated values and associated costs (Table 7-3) to further evaluate optimal BESS capacity. In addition, pairwise comparisons of weights fed to the inputs of the NNs at the primary (local) secondary and apex layers of the hierarchical tree (of the dispatch model) are carried out. It is the results of these comparisons that ultimately feed to the NN inputs at each layer.

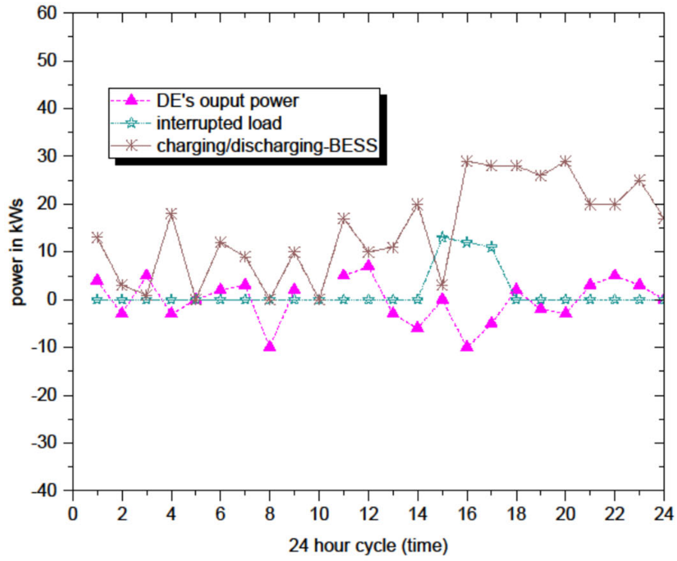


Fig. 7-23. Optimality assuming a 50kAHr BESS storage capacity in the SG

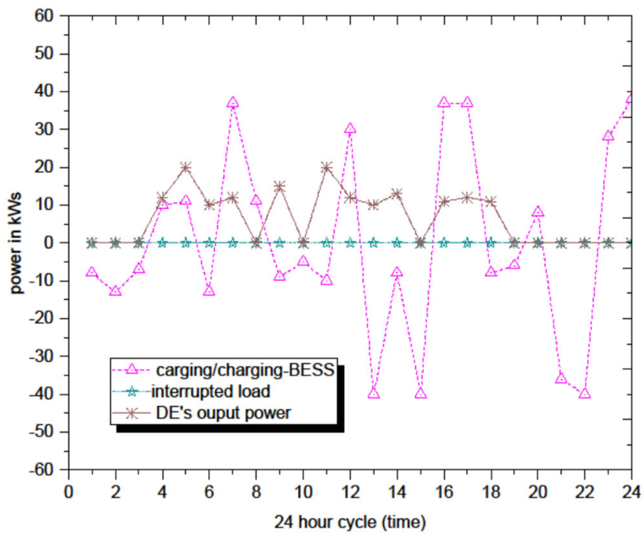


Fig. 7-24 Optimality assuming a 50kAHr BESS storage capacity in the SG

Our model framework has a tendency to accommodate more renewable generators such as PVs and WTs than fossil-based equivalents such as DGs.

By referring to Fig. 7-23. Optimality assuming a 50kAHr BESS storage capacity in the SG, Fig. 7-24 Optimality assuming a 50kAHr BESS storage capacity in the SG and Fig. 7-25, it is noted that the sizing of BESS systems in an SG or MG will have a significant impact on the overall optimal dispatch end results. First, the BESS systems act as a buffer to balance and smooth demand and supply curve rippling. As also observed in the analytical part, there is a tendency to have all redundant be rerouted towards BESS systems for storage.

1.33 Chapter conclusion

The chapter proposed and briefly analysed a hierarchical optimal dispatch framework that relies on several objectives to achieve the overall design goal of a reliable and stable power supply, coupled with economic benefits to prosumers who elect to participate in power trading. First, we mitigated an appropriate dispatch control configuration.

By comparison, we concluded that:

- In terms of control system reliability and efficacy, a hierarchical control architecture's top-level failure will affect the entire system since coordination among the various controllers is lost, hence optimal operation is not possible. However, with a distributed control architecture, the fault's effects are localised.
- In terms of economics, a hierarchical structure is optimal whereas its distributed equivalent is relatively suboptimal.
- With regard to design complexities, a distributed architecture is relatively easier to design.
- Scalability-wise, a hierarchical structure shows more flexibility, whereas a distributed equivalent can only accommodate a limited type of DERs.
- In terms of computational complexities, a hierarchical structure has a much relatively higher computational demand. This is because, in the case of a distributed

architecture, such loads are distributed throughout the participating peer controllers.

- Typically, a hierarchical controller (apex level) is implemented in the form of a high-performance PC, whereas an embedded controller will suffice for its distributed equivalent.
- Because of the absence of peer-to-peer communications, a hierarchical structure will generally operate at very low bandwidth, whereas its distributed equivalent will always require high bandwidth provisioning.

We then described and analysed the proposed framework. Overall, a QPSO algorithm was preferred for the optimization. Both analytical and simulation results were provided. Overall, the chapter work concludes that the combination of appropriately sized BESS systems and renewable type generators such as PVs and WTs will help achieve a stable and reliable power supply to all users in the SG (or MG) and at the same time it affords resilience.

Chapter 8 Conclusion and Further work

The exponential growth in electricity demand unlike in past times is being met by employing embedded REG sources into the grid either in off-grid or grid-tied mode. REGs reduce emissions, present no operational fuel cost, and utility and prosumer installations are viable at both small scale to large commercial and industrial consumers. Installation costs and the subsequent unit costs per kWh may be more than the conventional distributed generators but fall gradually with improvements in technology. However, the attendant drawback of REGs is uncertainty and intermittency which if not properly controlled may cause supply-demand swings. The storage technology is the key solution to mitigate uncertainty in REGs when they are configured in clusters what has become known as the microgrid operating in islanded or grid-connected modes. The supply-demand power imbalance is the main technical factor to be controlled in both grid-tied and off-grid isolated MGs. In a grid-tied MG, power flows between the MG to the utility grid or vice-versa. A proper power control scheme is required to schedule loads, DGs and BESS. Various algorithms have been discussed with the sole purpose of optimal scheduling of load to secure load-supply balance.

The consumer load profile can be re-shaped optimally by using Demand Side Management. Efficient Energy utilization and Demand Response are dual approaches for DSM techniques. The latter entails the use of efficient technology as opposed to less efficient ones and DR through electricity tariffs incentivizes shifting load from peak to off-peak periods thus serving on utility peak demands. The installed capacity of REGs in South Africa is about 10.2MW against a target of 17% of the 44GW generating capacity by 2025. PV, wind power and small hydropower are the dominant RE forms. South African 2019 Integrated Resource Plan (IRP) projects sectoral additional capacity by 2030 broken down as; Wind: 14.4GW, Solar PV: 6.0GW; Coal: 1.5GW EG/DG: 4GW and Gas: 3.0GW. The load shedding constraints of the local utility company are well documented and since 2018 the country has experienced serious and very disruptive load shedding due in part to the ageing generation fleet and a host of other capacity factors. The country envisages 40GW additional capacity by 2030. Such a leap in REGs injection entails extensive impact research will be needed as the depth of penetration of the renewables eclipses the dominance of traditional sources.

Demand side management in scheduling home appliances, ToU tariff structure, and reliability implications have been reviewed extensively. The critical strategy encompasses peak load shifting and curtailment in residential, industrial etc. microgrids consumers. In the face of depleting natural resources, energy efficiency and conservation dominated earlier thinking and strategies. Due to advancements in ICT, cloud and other big data soft computing platforms, a new concept of IoE has taken hold. Such new techniques as Reinforcement Learning, Deep Learning and Machine Learning models have been employed for load forecasting to better handle the uncertainty factor present in REGs. Real-Time community energy inter-trading among prosumers to reduce the electricity cost is expected to grow in pre-eminence. The important performance measures of an MG are its PQ parameters, reliability, and operational stability. This dissertation has studied scheduling in the implementation of DSM optimization in a future microgrid from the point of view of household loads and cooperative microgrids scheduling. Available literature covers many other aspects such as economic, environmental, operational, and reliability but they is less focus on aspects of inter-dependency be it among prosumers or neighbourhood microgrids. This aspect needs attention in all future investigations on DSM. The uniqueness of this dissertation has been the application of a new heuristic ASO to the DSM optimization problem. This technique has not been used in the context of the work covered here.

It has been assumed that home appliances are smart. The 'smartness' falls into power level adjustability or elasticity; time elasticity or shiftability and essential or non-shiftable appliances. Optimal scheduling was achieved using atom search optimization to extremize cost, PAR and maintain user utility or comfort. Load forecasting has been utilized to realize day-ahead scheduling for non-convex cost optimization. Difficulties with load forecasting are still challenging for researchers and a lot of work using AI techniques still lies ahead in the opinion of this author. To this end, there is growing research on e.g., big data clustering techniques. AI techniques that have successfully been used include double seasonal exponential smoothing, time-series image encoding techniques, Deep Reinforcement Learning, Q-network, and convolutional neural networks. Using error measures such as average absolute, root mean square and average absolute percentage these techniques have achieved accurate forecasting with minimal data size. Load forecasting still needs Accurate modelling to achieve better results.

The success of demand energy management for the consumer is tariff incentives. ToU-based tariffs have been simulated in a microgrid with a variety of REGs. Robust optimization was achieved to reduce energy and costs. The PV, WT and ESS support the consumers and DSM strategies optimize cost by minimizing exposure to more expensive utility energy. Multi-objective optimization problems were modelled to minimize electricity cost and ultimately GHG emissions from the microgrids. Various mathematical formulations of the objective functions for scheduling have been presented corresponding to specific optimization problems and optimization algorithms. The mathematical models can either be based on MILP type of objective functions and optimization algorithms either derived from analytic or nature-inspired routines. In all situations, DSM seeks to minimize PAR, cost, discomfort, and CO_2 or GHG emissions. In a home scheduling environment, various optimization heuristic techniques for DSM have been compared in a microgrid with various REGs. Heuristic methods give feasible approximate practical solutions in complex and nonlinear optimization scenarios presented by home energy optimization in the presence of constraints due to random sources and storage systems. Meta-heuristics techniques like ASO further improve results by avoiding local trapping at local optimal points. ASO reduces energy costs and peak loading. A test system with 15 household loads was simulated for demand shifting from peak to off-peak hours.

Communication big data analysis techniques, IoT, google firebase cloud, and metering are rapidly improving to reduce the complexity of DSM implementation in microgrids. The load signature or load curve parameters in real-time as well utility pricing signals availability will further easy DSM implementation. However substantial research on securing the homeowner's data is still needed to avoid privacy intrusion issues or litigation even. Fog and edge computing are contenders for energy efficiency as they minimise data transmissions between nodes. In the literature, ToU with inclined block tariff DSM has been implemented employing a smart home with a full WiFi connectivity network. Blockchain-based secure data analytics is another emerging technology for DSM. Pertinent areas of research interest cover data security and privacy, energy intelligent contracts, and standardization. Widespread implementation of smart metering is a milestone yet to be reached in DSM. This problem is tied to the issue of a lack of data concentrators to handle the large volume of SM output for analytics and functional billing. Data compression has been developed to minimize the data flow burden on the smart grid. Privacy consideration also weighs in at the aggregation level as well as data management and trading of the commodity which is electricity in this case.

Control of active power(P) and reactive power(Q) or PQ-flows plays a major role in the overall status of a grid or MG. Variables impacted by PQ issues in DSM are voltage stability, total harmonic distortion (THD), phase unbalance and frequency. In commercial buildings and residential areas where DSM is most viable, there is increasing utilization of energy-saving CFL as well as LED lighting. Improving energy efficiency may lead to escalating PQ problems such as %THD of voltage and current, flicker, and frequency. The REGs themselves when not properly controlled and coordinated may lead to voltage sag and swell. Simultaneous switching of bulk loads may cause voltage sag whereas switching off bulk loads causes voltage swell. In the same breath, bulk ON/OFF switching during DSM of loads at the time leads to PQ problems. Disconnecting large resistive electric heating loads reduces system damping which may result in worse PQ parameters distortion. New random loads like Plug-In Electric Vehicles (PIEV) can also induce PQ problems due to uneven distribution or utilization among the three phases system.

This dissertation has discussed the types of DSM techniques using different optimization techniques. A detailed comparison has been made in the use of different meta-heuristic optimization techniques for scheduling household appliances based on the objective of minimizing utility energy and hence cost using ToU tariffs. The recent advancements in DSM and the impact of DSM on different PQ issues have been examined. This dissertation has shown that the ASO technique can achieve cost reduction with minimum input of optimization parameters. This new optimization technique has not been used in the literature as far as we could tell at the time of writing up this research work. In winding up the work, we proposed a hierarchical optimal dispatch framework that relies on several objectives to achieve the overall design goal of a reliable and stable power supply, coupled with economic benefits to prosumers who elect to participate in power trading. Evaluation of the proposed framework is carried out analytically and by way of simulation.

Optimal control of SGs can be achieved by using rule-based, classical optimization, heuristics, and hybrid techniques. The optimal energy management problem has been formulated as a constrained multi-objectives problem. To solve an extended optimization time horizon problem in the SG, a hybrid MILP with a greedy constructive algorithm has been used resulting in a sub-optimal solution. To better handle variations in REGs energy, a three-layer real-time scheduling scheme with internal minor loop feedback for energy management in MG was introduced in Chapter 4. A hybrid heuristic-differential evolution technique was demonstrated to offer better scheduling. Simulation results showed that the hybrid heuristic technique performs better compared to normal scheduling. Applied in real-time, the three-layer energy management scheduling scheme has the potential to substantially decrease operational costs compared to traditional techniques as the minor loop feedback reduces the error between predicted and actual demand. Simulation results can be improved through the incorporation of random behaviour of REGs.

To ensure reliability, minimize consumer costs and maximize utility at the user level, optimization is also carried out in the context of economic DEGs dispatch in SGs with load uncertainty. This layer is necessary to enable effective coordination of DSM from the load side. A hybrid PV/WT/electrical grid-connected energy system, including a FC and a battery-based ESS, was simulated. Minimum operating cost was achieved by proper scheduling of different energy resources, using a hybrid differential evolution optimization algorithm. This scheduling task is difficult given the uncertainty and intermittency of REGs and random users' behaviour. A strong optimization model with intermittent, stochastic, and non-linear properties is needed. A novel energy optimization model based on the DE heuristic technique has been shown via simulation to be able to optimize the community microgrids by reducing operational costs and maximizing the use of cheap REGs energy.

A smart home mathematical model and an optimization algorithm to reduce the overall electricity bill, as well as peaks during low-price hours, were developed. User comfort was not included. The proposed algorithm will be useful when practically implemented. Future work can enhance this model by inclusion of variable scheduling flexibility, real-time pricing models, user comfort etc. Although the smart home model demonstrates that a significant reduction of energy cost is possible, limitations exist due to user-specific length of operating times which determine acceptable levels of comfort or discomfort.

From Chapter 5 leading to Chapter 6, the smart grid is integrated with DSM and a MILP smart home energy consumption optimization problem is formulated and then solved using a mate-heuristic technique called atom search optimization. Two case studies were simulated. Results showed significant energy cost savings. However, the difficulty in these scenarios is that microgrid energy management problems are generally non-convex, and the loads are variable. When a community of MGs are integrated (IMG) to share energy resources, the degree of complexity also increases. Four case studies were employed to demonstrate the benefit of various demand-side participation levels on IMGs while solving the non-convex demand-side management problem. The QPSO algorithm efficiently solved the non-convex problem. Finally, the QPSO algorithm is deployed to minimize the MG operating cost and utility power exchange cost in the presence of DG units subject to the non-convex cost function. The simulation results are compared between the cases with various levels of DSM penetration.

The closing chapter briefly analysed the proposed framework a hierarchical optimal dispatch that relies on several objectives to achieve the overall design goal of a reliable and stable power supply, coupled with economic benefits for MG-connected prosumers. We conclude that a distributed control architecture is more attractive e.g., it is faults tolerant through localization. In terms of economics, a hierarchical structure is optimal whereas it is relatively easily designed and scalable. The distributed equivalent is relatively suboptimal and requires provisioning adequate high communication bandwidth. In terms of computational complexities, a hierarchical structure has a much relatively higher computational demand. This is because, in the case of a distributed architecture, such loads are distributed throughout the participating peer controllers. Overall, the QPSO algorithm was preferred for the optimization. Both analytical and simulation results were provided. In conclusion, we note that a combination of appropriately sized storage systems and renewable-type generators will help achieve a stable, reliable, and resilient power supply to all users in the SG (or MG).

Further Work

With the momentum around smart cities, smart homes will see more DSM technologies being implemented in the future and beyond. Open questions still exist in energy storage systems to compensate lack of inertia of REGs, PQ control, REG yield prediction or forecasting, load modelling, marketing models etc. The impact of uncertainties when using the most common on-site generations of PV and WT should be investigated versus scheduling and prediction models. Long and short-term REG yield forecasting deviations could be minimized by newer big data analytic techniques for the on-site generators. Other DEGs schedulable sources such as CHP and biofuel-based power units should be included in the microgrid energy mix to improve reliability and overall improvements in resource allocation and load shifting.

As DSM grows so will the proportion of load that will be switched ON/OFF. The attendant PQ problems as discussed above mean that the constraints for optimization problems as discussed need to be widened to cover such limits as the frequency of switching ON/OFF certain loads in DSM, power factor related constraints, voltage deviation constraints etc. in addition to customary power balance, storage/capacity limits. Industrial operations running on fixed cycles are not amendable to DSM, but rather DR. Commercial and residential consumers hold the most opportunity for DSM leaving industrial loads to be scheduled to reduce the peaking where possible. The diurnal nature of both loads can also be exploited in pursuit of DSM. The DSM implementation improves the stability and reliability of an MG with a possible reduction in voltage fluctuation, frequency swings and overall PAR reduction. Reliability also improves with DSM.

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Appendix

AGL	Actual Grid Load
AMI	Advanced Metering Infrastructure
BESS	Battery Energy Storage System
COA	Centralized Online Algorithm
CPP	Critical-peak Pricing
DER	Distributed Energy Resource
DG	Distributed Generation
DOA	Distributed Online Algorithm
DPA	Dynamic Pricing Algorithm
DR	Demand Response
DSM	Demand Side Management
ESS	Energy Storage System

167

EV Electric Vehicle

FACTS Flexible AC Transmission Systems

G2V Grid-to-Vehicle

GCV Generalized Cross-Validation

GHG Greenhouse Gas

GPS Global Positioning System

GRS Grid Energy Storage HVDC High Voltage Direct Current

HPS Hierarchical Power Scheduling

IEA International Energy Agency

IEEE Institute of Electrical and Electronics Engineers

IPM Interior Point Method

JPDF Joint Probability Density Function

MG Microgrid

MGCC Microgrid Control Center MGNC Microgrid Network Controller MLR Multiple

OPDA Online Power Distribution Algorithm

ORPA Optimal Real-time Pricing Algorithm PCC Point of Common Coupling

PDR Peak Day Rebates

PEV Plug-In Electric Vehicles

PGO Power Grid Operator

168

PHEV Plug-In Hybrid Electric Vehicles

PLC Power Line Communication

PLP Peak Load Pricing

PMU Phasor Measurement Unit

PV Photovoltaic

RC Real Consumption RTP Real-time Pricing SC Smart City

SCB Simultaneous Confidence Bands

SCE Southern California Edison

SG Smart Grid

SH Smart Home

SMES Superconducting Magnetic Energy Storage

SVM Support Vector Machines TES Thermal Energy Storage ToU Time of Use

V2G Vehicle-to-Grid

VPP Virtual Power Plant WMN Wireless Mesh Network WSN Wireless Sensor Network