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Research Article

On Demand and Supply Management in Domestic Microgrids

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Abstract

Standalone or residential microgrids (MG) are becoming increasingly common. Their success is premised on optimal operational strategies like demand side management (DSM). It is not uncommon in optimization problems to deal with competing objectives in the context of multi-objective optimization. In a domestic MG, optimization objectives may encompass minimization of OPEX, maximization of consumers' utility, and minimization of CO2 emissions etc. This article employs a technique which transforms a bi-objective energy optimization problem into a single objective problem then solving the problem using the heuristic technique of binary particle swarm optimization (BPSO). The random phenomena associated with the statistical load profiles and multiple renewable energy sources (RESs) are modelled using established statistical ap-proaches. Results obtained using simulation show that the pro-posed model can minimize the OPEX of isolated MG whilst sim-ultaneously meeting the utility expectations of consumer.

Keywords: *Microgrid, multi-objective optimization, Demand side management and Utility levels*

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Introduction

Many countries are grappling with increasing demand for electricity whiles facing diminishing fossil fuels reserves, aging transmission and distribution infrastructure, the need for energy conservation, imperatives to reduce CO_2 emissions levels and general minimization of environmental impact of energy generation [1][2]. Technologies to extract electrical energy from abundant and freely available solar and wind energy have advanced to the level that for their energy demand some e.g., the Nordic countries in Europe target to have 100% RESs, [3][4][5] in the near future.

Intelligent microgrid technologies incorporating distributed energy resources (DERs) are one of the possible means to mitigate energy demand challenges [6]. Typically, a microgrid consists of loads, battery energy storage systems (BESS), Renewable Energy Generators (REG) such as wind turbine (WT), photovoltaic (PV) modules, Diesel Generators (DGs), Fuel Cells (FC) etc. A MG can operate in grid tied mode or in isolated mode [7]. The major shortcoming of RESs is their intermittency [8], [9] and stochastic behavior. Due to this stochasticity in both output and load, the uncertainties that impact the operation of MG emanate from both supply and demand side. Within such an environment balancing supply and demand requires systematic control and regulation [5][10]–[12].

Review of Previous Work

DSM has become a crucial methodology to balance supply and demand in MGs. This helps to mitigate microgrid instability that can be induced when demand is more than generation or the reverse. Excess energy supply can also result in “spill-over” problems which induce instability in QoS parameters such as voltage profile and frequency. The enabler of DSM is information and communication technologies (ICT), as well as advanced smart metering technologies (ASMT) [2]. For successful implementation, DSM depends on pricing models that incentivize optimal usage of electrical power according to on-peak or off-peak demand times. Tariffs such as Critical Peak Pricing (CPP), Real Time Pricing (RTP), Inclining Block Rate Tariff (IBRT) and Time of Use (ToU) are commonly used,[13]. Without energy management in MGs reliability, power quality, sustainability will suffer impairing the very growth of these environmentally friendly technologies.

System that manage customer consumption of power in response to supply conditions are generally referred to as Demand Response (DR). DSM is a broader concept than DR as it encompasses techniques that include energy efficiency whereby energy consuming devices automatically adjust their operating regimes within the order of seconds with the objective of increasing the diversity factor for a given set of loads [14]. The literature [15][16][17][18] give expositions of developments in pricing signals for electricity distribution systems and reviews some of the available demand-response programmes. Studies on relevant DR smart technologies and markets are covered in [19] [20]. The authors demonstrate the extent of energy savings and other efficiencies. attainable Traditionally DSM was applied to energy consuming loads with the SG hosting easily controllable energy sources such as PV, WT and BESS. More flexibility for DR is introduced from the generation side. The operational strategy of MGs in the context of DR involves optimization, which considers all the components in addition to the traditional loads. Optimization simulations [21] using GA algorithm have shown that DR based on traditional load curtailment can achieve reduction of grid power whiles simultaneously increasing RES supply to the grid.

A critical analysis of state-of-the-art techniques for power scheduling in smart homes is provided in [22][23] with possible future directions for research. Of the many exact, games theory approach and metaheuristic DR algorithms techniques [24][25], the literature lacks clarification on the suitability of methods applicable to specific real practical problems. For simpler models focusing on a single time instant optimization, the optimal solution can be found easily in closed form or by polynomial algorithms [26]. However, optimization problems that investigate discrete time horizon consisting of none homogeneous time periods, use heuristics solvers which sometimes result in suboptimal solutions, [26].

With DSM, the focus is the interaction between the overall microgrid control vs demand experienced by different end-user sub-microgrids. Exact load demands are hard to know, yet the elasticity of the systems will be low without demand management and QoS may also worsen [27]. Direct load control methods can deal with unpredictable load changes, but they compromise users' comfort [16], [28]–[31]. Various microgrid control methodologies have been enunciated in the literature [32][33]. Heuristic techniques [34] dominate the landscape. Demand compensation and proper energy marketing models are still subjects of much active research [35].

The development of smart ways of energy utilization at the consumer end is a top priorities across the globe e.g., the European Strategic Energy Technology Plan [36] and by extension realization of Renewable Energy Directive II [37]. The concept of Smart Home (SH) towards energy efficiency has gained global traction. SH refer to residences, apartments, etc. [38] equipped with smart meters, controllable loads, RES or BESS systems making-up autonomous, and reliable energy supply systems [39] [40][41]. Key variables in these systems i.e., RES yield, electricity market price and residential consumers' energy demand are stochastic in nature. Home Energy Management Systems (HEMS) to schedule local generation and consumption are therefore imperative. [42]. Some of the energy management algorithms are explored in [43].

Various DR methods targeted at load flatting and peak clipping, have made it feasible for prosumers in the residential and other sectors to accrue financial benefits by selling electricity to the grid or optimizing usage of costly grid electricity [44]. An algorithm for utilities and prosumers to reduce demand at specific times when aggregate network load demand is high is presented in [45]. The algorithm is based on Day Ahead (DA) energy cost minimization via optimizing energy consumption in SHs equipped with AMI and smart appliances. In this instance the optimization algorithms only flatten the load curves, the duel problem of cost reduction still requires matching ToU tariffs carefully designed by the electricity utility. Success of the optimization plus attractive tariffs can entice consumers into flexible and pay less energy saving DSM schemes.

The contributions of this paper is that a grid-tied microgrid under DSM is modelled subject to load uncertainties and REGs. Binary particle swarm optimization is used on the dual probabilistic problem involving both load and RES generation uncertainty. Dynamic Weighted Aggregation (DWA) is applied to deal with dual-objectivity of the optimization problem [46]. Constraints of power-shiftable appliances, time-shiftable appliances are subject to user choices.

The subsequent sections of the paper are organized as follows; Section III illustrates structure of a radial grid-tied residential MG architecture and model elements. Section IV formulates the mathematical optimization problem and outlines the solution technique. This is followed by section V and VI where simulation results and conclusions are done.

Grid-Connected Residential MG

Fig.1 shows a schematic of a typical MG model. The MG has WTs, PV generating modules, DEs, MTs, BESS, and smart households where each household has AMI. The microgrid has a central Microgrid Network Controller (MGNC) that co-ordinates the ICT infrastructure. The model considered in this paper has N smart prosumers. Each prosumer has installed a smart meter (SM) to which various smart appliances connect. A network aggregator links all N smart meters in a neighborhood. It receives consumption information from all households and forwards the same data to Central Control algorithm for optimization of the MG operation. Optimization and optimal scheduling of household appliances is done by the aggregator. $\alpha_i^c, \alpha_j^d, C_j^e, D_j^f$ etc. are unit consumption parameters for each MG.

A. WTs and PV Stochastic Power Generation

Both the WTG and PV output power depend on stochastic wind velocity and solar radiation phenomenon. Due to this behavior, the power output of the two RES are represented by stochastic models such as Weibull, Beta, and Log-normal pdf. Wind and solar power generation are modeled by the Weibull distribution function [47] and Beta distribution function respectively [48][49]. In each hour the required pdf parameters of wind variation and solar irradiation are estimated from the previously hourly data. The models of wind and solar power generation are given by (1)-(3). The Weibull pdf distribution function $f_w(w)$ at the *t*th hour and wind speed w is mathematically represented as;

$$f_w(w) = \begin{cases} \frac{v}{\lambda}\left(\frac{w}{\lambda}\right)^{v-1} . e^{-\left(\frac{w}{\lambda}\right)^{v}}, & w \geq 0 \\ 0, otherwise \end{cases} \quad (1)$$

v is the shape, and λ the scale parameters respectively at time *t*. The Weibull distribution interpolates between the exponential and Rayleigh distributions and for certain shape 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 by (2).

$$P_w = \begin{cases} 0, \quad v \leq v_{in}, \ v > v_{out} \\ P_r\left(\frac{v-v_{in}}{v_r-v_{in}}\right), \quad v_{in} \leq v \leq v_{in} \\ P_r, \quad otherwise \end{cases} \quad (2)$$

P_r is the rated WT power output. v_r rated speed, v_n is rated cut-in and v_{out} is rated cut out wind turbine speed.

The Beta probability density function (3) [2], is a continuous distribution function characterized by shape parameters. It is used to model uncertainty of success of an event of which there are two outcomes, either success expressed by x or failure expressed by $1 - x$. In (3), the beta density function, a and b are the lower and upper limits of the solar irradiance data respectively. p and q are shape parameters of the Beta distribution

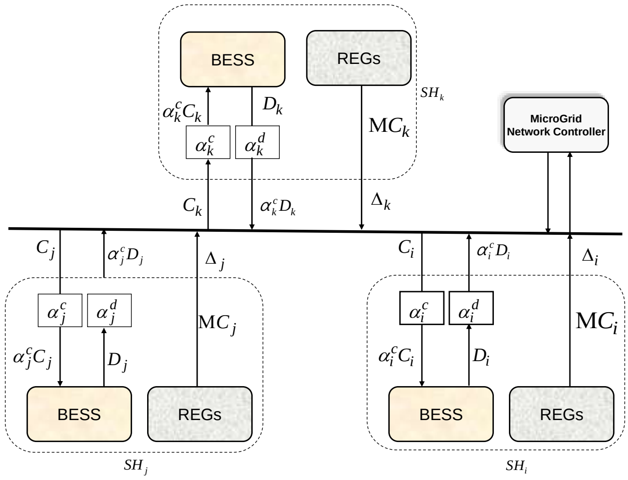

Fig. 1. Configuration of the residential MG model

function. x is the variable under analysis i.e. solar irradiance. The estimation of the shape parameters p and q given solar irradiance data is done from the moments' method[5],

$$g(x') = \frac{1}{\mathrm{B}(p,q)} \frac{(x'-a)^{p-1}(b-x')^{q-1}}{(b-a)^{p+q-1}},$$

$$x' = \frac{x-a}{b-a}$$

$$\mathrm{B}(p,q) = \int_0^1 x'^{p-1} \cdot (1-x')^{q-1}\, \mathrm{d}x' \qquad (3)$$

where $0 < x' < 1$ for $p > 1$ and $q > 1$. Integration of (3) configures the probability distribution function of solar irradiance for the occurrence for any value of irradiance, x within the considered interval. The hourly produced energy P_{pv} from the PV module is expressed as,

$$P_{pv} = \eta P_{PV,r} \cdot f_{PV}\left(\frac{G_T}{G_{T,STC}}\right) \cdot \left(1 - \alpha_p(T_c(t) - 25^o)\right) \qquad (4)$$

η is efficiency and $P_{PV,r}$ is rated power output of PV panel under STC. $f_{PV}(*)$ is the derating factor of panel, G_T is solar radiation on a tilted surface, $G_{T,STC}$ is radiation under STC. $T_c(t)$ is the PV cell temp temperature at time t. The power from the PV station will be the integral of (4) multiplied by the Beta (3) pdf. Over a period, the average PV energy is average power times the number of hours.

B. Uncertainty modelling of Non-Shiftable Loads (NSA).

One of the main hurdles of modelling home electricity load curves is availability of load data for given occupancy. The demands of data requirement has limited the implementation of current approaches [50]. Load curves depend on occupancy and consumption activities. Over prolonged time periods, electricity consumption dependents on external variables that evidently have similar diurnal patterns over successive years such as the mean outside temperature and daylight hours [3]. The domestic daily electricity consumption is easily obtained from household monthly/seasonal energy bills. Over 24 hours, the load pattern has generally four identifiable zones, [50] [51][52][53].

Kernel estimators smooth out the effect of each detected data point within a local region of that point. The influence of the actual data point x_i to the estimate at a point $\hat{x}_i$ depends on how far apart x_i and $\hat{x}_i$ are. The degree of this influence is dependent upon the shape of the kernel function adopted and the bandwidth it is accorded. The Kernel Density Estimation (KDE)[54] is a nonparametric estimation technique[2] whose pursuit is to approximate a pdf $\Psi(x)$from data observation barring assumptions on prior knowledge of shape of the data distribution. This estimate $\widehat{\Psi}(x)$ of $\Psi(x)$ is constructed from n data points as;

$$\widehat{\Psi}(x) = \frac{1}{n\lambda}\sum_{i=1}^{n} K(u), \ u = \frac{X - X_i}{\lambda} \quad (5)$$

Where $X_i = X_1, X_2, \dots, X_n$ are n sample observed data points $\lambda \in (0, \infty)$ is bandwidth. The kernel function $\mathrm{K}(*)$ is a non-negative function such that $\int_{-\infty}^{\infty} K = 1$. A number of choices for the Kernal function exist such as uniform, triangle, epanechnikov but the gaussian kernel (6) is used.

$$\mathrm{K}(u) = \frac{1}{\sqrt{2\pi}} \mathrm{Exp}(-u^2) \quad (6)$$

The value of the bandwidth λ is estimated using Scott's rule of thumb[55]. The bandwidth of the kernel is a free parameter with a strong influence on smoothness of the resulting estimate. Small λ leads to spiky estimates (not much smoothing) while larger λ lead to over smoothing.

$$\lambda = \left(\frac{4\hat{\sigma}^5}{3n}\right)^{0.2} \quad (7)$$

$\hat{\sigma}$ is standard deviation and *n* is size of observed data [2]. Optimal bandwidth is commonly chosen using Asymptotic Mean Integrated Squared Error method (AMISE). Power demanded from a MG is uncertain given the random daily demand of various prosumers and weather elements.

C. Uncertain MG load Model

Currently, it is often difficult to obtain private domestic energy consumption demand data. House electricity usage depends on activities of the occupants and appliances that are switched on at a given time. Load models of domestic electricity consumption can be derived from active occupancy patterns, and activity profiles. A synthetic and reconfigurable high resolution electricity load demand generator accounting for main home appliances freely downloadable[56] was used. This model can be re-configured to own requirements.

Other load modeling methodologies underpinned by requiring smaller samples of individual demand profiles can be processed with highly-efficient synthetic demand simulation models [57]. Such methods can be applied to yield high-resolution individual synthetic profiles, which in turn can be used to generate aggregated demand profiles. Prediction engines like ANN can self-learn then carry out prediction upon training. In smart homes they can be used to forecast the PV power yield and load demand. The literature has many types of ANN for such applications [58].

The uncertain hourly load for both time shiftable appliances(TSA) and power shiftable appliances (PSA) can be represented by normal distribution [50]. The total load demand of none-shiftable loads (NSA) imposes the most random constraints in the model. For a variable x, with mean $\bar{\mu}$ and standard deviation σ the normal distribution function is;

$$f(x) = \alpha \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\bar{\mu})^2}{2\sigma^2}} \tag{8}$$

For a given MG, if the corresponding half hourly normal distribution parameters are $\bar{\mu}_i$ and σ_i then the overall MG daily load can be formulated as;

$$f(L_k) = \sum_{i=1}^{N_k} \left(\alpha_i \frac{1}{\sqrt{2\pi}\alpha_i} e^{-\frac{\left(L_k - \bar{\mu}_i\right)^2}{2\sigma_i^2}} + \beta_i \right) \tag{9}$$

β_i is a base load peak shifting parameter and α_i is the peak scaling factor of the synthesized load, *Figure 1*.

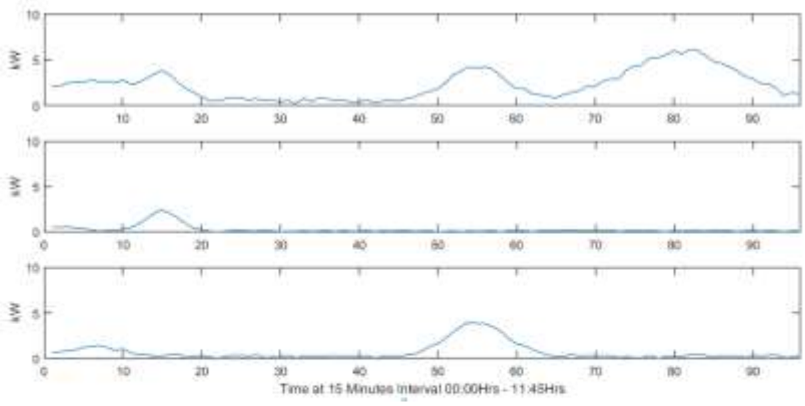

Figure 1.House synthesized Load using Gaussian pdf Kernel

From the top in ***Figure 1***, the total, morning and afternoon synthesized loads using normal distribution kernel.

Optimization Formulation

A. MG Cost function

The optimal strategy is formulated with dual objectives i.e. minimization of daily operational cost and minimization of consumers' discomfort each day. The cost is made up from REGs and costs elements from energy trading with the main grid as the MG can be buying or selling electrical energy. This objective function is formulated as; minimize,

$$C_{k} = \sum_{h=1}^{H}\sum_{i=1}^{N}\{e^{c}P_{i}^{h}\Delta t + \Omega_{i}^{h} + m^{E}\,ES_{i,dis}^{h}\} + \{e_{b}^{h}P_{fg}^{h} - e_{s}^{h}P_{tg}^{h}\}\Delta t \tag{10}$$

P_i^h , Ω_i^h and Ω_{sto}^h are the output power, generation and storage costs of i^{th} dispatchable REG at time instant h. P_{fg}^h and P_{tg}^h represent power sold to and bought from the main grid at time h. e^c (R/kWhr) is the maintenance cost of the i^{th} REG. H is the number of time slots in a day, e_b^h and e_s^h are unit buying and selling energy price. $ES_{ts,dis}^h$ is discharge rate over time h of storage systems and m^E is the unit maintenance cost.

B. Consumers' Comfort Index Formulation

To the consumer, satisfaction in the DSM process means acceptable levels of comfort due to delayed appliances on-time. The mathematical measure of this comfort is normally an index whose value lies between 0 and 1. Zero means complete discomfort, and 1 the opposite. For an appliance with x_{k,a_i}^h nominal power consumption, and x'^h_{k,a_i} curtailed power during the h^{th} time interval, discomfort or dis-utility function can be formulated as (11) or (12). The parameter, ω_x depends on type of appliance and the function has a minimum of zero when they is no deviation meaning power is supplied as demanded.

$$\upsilon = \omega_x\left(x_{k,a_i}^h - x'^h_{k,a_i}\right)^2 \qquad \text{or} \tag{11}$$

$$\upsilon = \left|T_{start,a_i}^h - T_{end,a_i}^h\right| \tag{12}$$

$$\Upsilon = \sum_{i=n}^{N} \xi\left|T_{start,a_i}^h - T_{end,a_i}^h\right|^{\mu} \tag{13}$$

The comfort function due to an appliance on-delays [30] at $t = h$ can be formulated as in (12). For all the N appliances of a household in each interval, this can be re-formulated as (13). An alternative formulation [59] of user comfort as a function of delay is according to (14).

$$\Upsilon = \frac{\sum_{i=n}^{N} \xi\left|T_{unscheduled\,start,a_i}^h - T_{scheduled\,start,a_i}^h\right|^{\mu}}{\sum_{i=1}^{N} t_{scheduled\,start,a_i}^h}, \tag{14}$$

Where $\mu = 1$, $\xi = 1$ are design cost factors per choice.

Combining (12) and (13) gives the discomfort due to appliances switch-on delays and power curtailment as,

$$\text{Discomfort} = \upsilon + \Upsilon \tag{15}$$

B. DSM load shifting

Table 1. Appliances Loading details

				Operating Interval			
	CLASS OF APPLIANCE	**Hour**	**Rating, kW**	***t_ON***	***t_OFF***	***LOT***	***Diversity***
Elastic Equipment	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**

Home appliances can be shifted in time(TSA) or power(PSA) level or both. In each MG/home identify $N_{t,sh}$ and $N_{p,sh}$ as the number of TSAs and PSAs. The set of shiftable appliances can be defined as $A_{sh} = \{1,2,3,\dots,N_{t,sh}, N_{t,sh}+1, N_{t,sh}+2,\dots,N_{t,sh}+N_{p,sh}\}$. Only the sequencing is represented here**.** For each appliance, the power consumption vector over an H-hour period is defined by;

$$\boldsymbol{x}_{k,a} = [a_{k,a}^{1}, a_{k,a}^{2}, \dots, a_{k,a}^{H}] \text{ for all appliances in } A_{sh} \qquad (16)$$

The start and stop time of shiftable appliances for the k^{th} consumer are confined to the time window, $T_a^k = [\mathcal{T}_{end,i} \quad \mathcal{T}_{start,i}]$. The daily energy consumption L_k over the operation time window $T_a^k$of each appliance is given by (17),

$$L_k = \sum_{i=T_{start,i}^{k}}^{T_{end,i}^{k}} x_{k,a}^{i} \qquad (17)$$

The time constraints over which the i^{th} appliance can be scheduled is expressed as (18);

$$x_{k,i}^{h} = \begin{cases} 0 & if \ \ h \le \mathcal{T}_{end,i} \\ 0 & if \ \ h \ge \mathcal{T}_{start,i} \end{cases}, \ \ 0 < h < \mathrm{H} \qquad (18)$$

$$\mathrm{h} \in [\mathcal{T}_{start,i} \quad \mathcal{T}_{end,i}]$$

Depending on the type of appliance, they is a general delay of Δt_d , a multiple of the stepping operational time interval, h. For each appliance they is an upper and lower bound to the power consumption according to (19),

$$\lambda_{ki}^{min} < x_{ki}^{h} < \lambda_{ki}^{max}, \ \ \mathrm{i} = 1,2,\dots,\mathrm{n}; \qquad (19)$$

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 range of each appliance depends on its LOT. We can denote scheduling horizon of any of the appliances by (19). ToU tariff is applicable in this model such that cost of a unit of energy consumed in each time interval $\mathrm{h}-1 < \mathrm{t} < \mathrm{h}$ changes but it's known a priori to the HEMS. If $e^{\hbar}$ represents this unit cost of energy per hour for the k^{th} household, then the total hourly load l_k^h, for all *n*-appliances is $l_k^h = \sum_i^n a_{ik}^h$. The total daily load $\mathcal{L}_{k}$, for the k^{th} household is given by (17). The corresponding hourly and daily costs of
energy consumption of all appliances are given by (21) and (22) respectively.

$$\mathcal{L}_{k} = \sum_{h=1}^{H} \sum_i^n a_{ik}^h \qquad (20)$$

The corresponding hourly $\mathcal{C}_k^h$, and daily costs $\mathcal{C}_{k}$, for the k^{th} consumer are; Hourly cost for all *n*-appliances,

$$\mathcal{C}_k^h = \sum_i^n e^{\hbar} \cdot a_{ik}^h \qquad (21)$$

$$\mathcal{C}_{\hbar} = \sum_{h=1}^{H} \sum_{i}^{n} e^{\hbar} \cdot a_{ik}^{h} \quad (22)$$

We consider the k^{th} smart home with smart appliances $\boldsymbol{a}_{\hbar} \in \{a_{ik}\}_{i=1,2,\ldots,n}$ where each appliance has its LOT, $\mathcal{T}_i$. Using $\mathcal{T}_i$'s flexibility and operating time constraints, we can divide these appliances into categories or operational regimes for better scheduling and energy management, [60][61].

C. Appliance Scheduling Algorithm

The objective is to minimize the electricity cost given in (10) subject to a tolerable maximum switch delay time in (18). $\zeta_{max,a_i} \leq H - \beta_{a_i}$. The on or off state of an appliances is represented by,

$$\alpha_{a_i} = \begin{cases} 0 & if\ off \\ 1 & if\ on \end{cases} \quad (23)$$

PSO is a heuristic optimization technique based on swarm intelligence concepts. It is used solve high dimensional NL optimization problems where analytical methods experience slow convergence due to high dimensionality. Binary Particle Swarm Optimization (BPSO) is a discrete domain version of PSO. BPSO depends on four parameters i.e. the particle initial position, velocity, best position, and global best position among rest of the particles. Initialization parameters were adopted from[12]. In general, we take each particle or feasible solution as being associated with *N* variables. The optimum point is tested by moving the particle in *N*-dimension space. Each particle can take the binary value 0 or 1. For a swarm with M particles, each particle's initial position vector P_i and velocity vector V_i are random.

Each particle/feasible solution looks for the best feasible solution/particle in the vicinity according to valuation of objective function, this is the local best particle/feasible solution with co-ordinate, $\chi_b = \{\chi_{b1}, \chi_{b2}, \ldots, \chi_{b(M-1)1}, \chi_{bM}\}$. The most optimal of the positions or feasible solutions is called the global best and its co-ordinate is designated $\chi_{gb} = \{\chi_{gb1}, \chi_{gb2}, \ldots, \chi_{gb(M-1)1}, \chi_{gbM}\}$. Each of the two positions particle update their velocity using (24);

$$V_i^{h+1}(j) = \rho V_i^h(j) + c_1 r_1 \chi_b(j) - S_i^h(j)(c_2 r_2)\chi_{gb}(j) - S_i^h(j) \quad (24)$$

Where $V_i^{h+1}(j)$ is the j^{th} element of the velocity vector of the i^{th} particle in the $(h+1)^{th}$ iteration. $S_i^h(j)$ is the position of the j^{th} element of the i^{th} feasible solution/particle in the h^{th} iteration and r_1 and r_2 are random numbers with magnitude not greater than 1. c_1 and c_2 are pulls for the local and global best solutions respectively. ρ is the weight of the particle's momentum and it is calculated as;

$$\rho = \rho_{initial} + \frac{t}{t_{max}}\left(\rho_{final} - \rho_{initial}\right) \qquad (25)$$

The parameter t represents the current iteration and t_{max} is maximum number of iterations. $S_i^h(j)$ is a binary function which in unity when , $Sig\left(V_i^{h+1}(j)\right) > r_i$ otherwise its zero. The sigmoid function is defined by [62],

$$\mathrm{Sig}\left(V_i^{h+1}(j)\right) = \frac{1}{1 + e^{-V_i^{h+1}(j)}} \qquad (26)$$

The velocity of the feasible point is confined to some maximum and minimum speed. The fitness for each feasible point is computed from the objective function (10). Feasible solutions are ordered in accordance with their fitness. When t_{max} iterations have expired, the best feasible solution $X_{i,best}$ is chosen as the optimal solution. $X_{i,best}$ is a binary code that specifies on/off status of appliances for optimality in every period h . Every instance the algorithm tries to utilize the RESs to minimize costs.

Simulation Results

The sizes of DG REGs used are adapted from [10]. The respective capacities of PV, WT, DE, MT and BESS are 2kW, 3.2kW, 4kW, 4.4kW and 4.8kW i.e. combined capacity of 18.3kW or 60A single phase load limited system. ToU tariff employed in the model is depicted in . In this simulation, each smart home has 2 PSAs and 3 TSAs. From the data in ***Table 1***, those appliances are randomly selected.

In ***Figure 3*** is shown a typical day's consumption load curves under various optimized scheduling. For the unscheduled scenarios as expected consumption is high during in the morning and evening hours resulting in high energy cost. Once scheduling is introduced using BPSO, PSO or IBFO, consumption and hence cost in the same order. Shifting of peak load in the optimized cases is also evident. Clearly the DSM algorithms reduce the cost. Of the three techniques the BPSO is more promising.

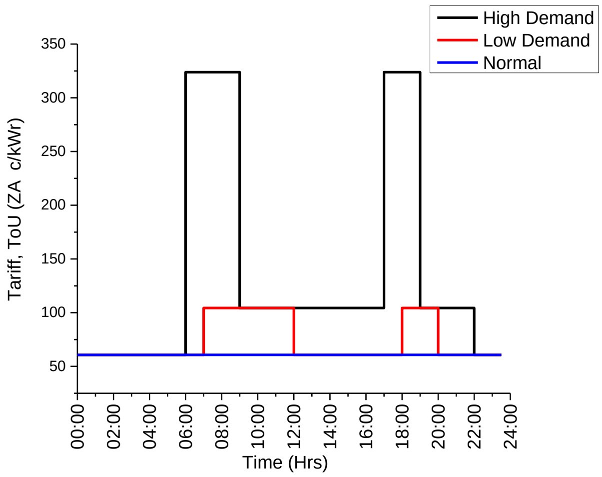

Figure 2. ToU Tariff Structure

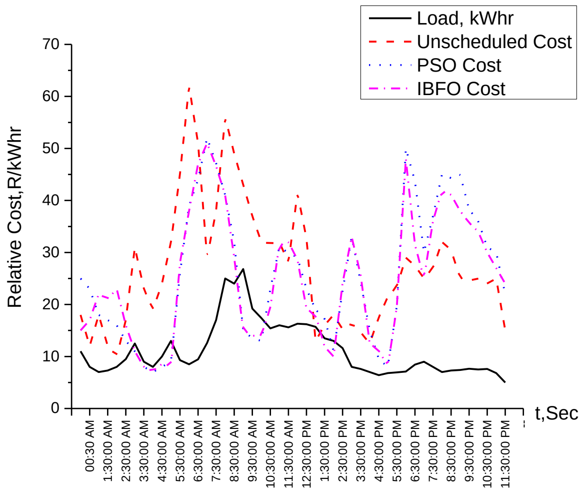

Figure 3. Simulated Results with and without DSM with different techniques

Conclusion

The benefits of optimization for the MG optimal has been simulated on three scenarios with and the other without demand side management scheme. In each case we seek to simultaneously optimize MG operational costs and consumers' utility.

This problem is cast as a multi-objective optimization problem subject to uncertain load and renewable energy generation. DSM can potentially mitigate operational costs incurred without bit. However, there is a significant reduction in the operational costs with PSO compared to the uncontrolled case. The consumer sacrifices some comfort, nevertheless. The PSO and IBFO techniques give somewhat convergent results. The microgrid OPEX reduces by a margin of 7.3% compared to uncontrolled case and the utility index(UI) improves by 13.5%. The simulated scenarios show that the controlled microgrid with DSM can enable lower OPEX with maximized utility given the stochastic nature of the problem.

This article utilizes optimization techniques for MG with RES. The random nature of both RESs and load are jointly considered with the help of statistical paradigms. When DSM is introduced different categories of appliances are included with hard constraints of different smart home appliances. The paper concludes by looking at the DSM effectiveness of three different heuristic techniques which clearly show the potential cost serving under such DSM regimes. The optimization problem is solved using heuristic techniques. In terms of performance of the scheduling algorithms is seen that it tries to shift load from peak to toff-peak periods. Simulation results show that, the electricity load is substantially reduced

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