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Power Demand and Supply Optimization in Islanded Microgrids with Distributed Generation

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Abstract— **In the power sector, a shift from the present fossil-dominated generation to renewable as well as energy-efficient generation and distribution is firmly underway. The transition is mostly driven by the digitalization of the energy systems to what has been coined ENERNET meaning energy network. Numerous benefits for both utility and consumers accrue. Digitalization enables more activity in the power trading market and a large amount of consumer data becomes available in the sector. Overall, strides are being made in the integration of Demand-Side Management (DSM) in the planning of Isolated/Islanded Microgrids (IMGs) as these will potentially reduce total OPEX costs at both customer and utility levels as well as increase renewable energy utilization. However, there is paucity in literature regarding distributed generators (DGs) non-convex cost function. Notably, not much has been covered regarding microgrid optimal load-dispatching especially with regards to optimizing algorithms. In this paper, we focus on formulating the day-ahead dispatch problem of microgrids with DGs subject to non-convex cost function and load dynamics. We first propose an operational framework that addresses the DG's 'valve point" loading effect as well as optimizing its performance. The impact of DSM on convex and non-convex EMS problems with different load participation levels is investigated. Further, the day-ahead scheduling horizon of fifteen-minute resolution time is considered to examine the effect of load dynamics in the microgrid. A Quantum Particle Swarm based approach is employed to solve non-convex DGs cost optimization. It is demonstrated that the proposed algorithm efficiently solves the non-convex EMS problem. Simulation results yield a 5% reduction in OPEX costs without compromising customer satisfaction.**

Keywords—Microgrids, Energy Management, Non-convex cost, Quantum Particle Swarm Optimization, Dynamic Loading.

I. INTRODUCTION

The ever-increasing world population has led to global attention towards addressing environmental problems that among others seek to exploit new approaches to energy generation. In that way, carbon pollution will be reduced. It is generally noted that power demand is ever-increasing in both urban and rural areas. According to UN statistics, approximately one billion people mostly in developing and poor countries are currently living without electricity. It is therefore important to promote the development of energy-efficient power systems and grids that will maintain environmental friendliness. This imperative has resulted in attention to the incorporation of renewable energy sources (RESs) in Microgrids (MGs) [1]. As a result, MGs are gradually increasing in popularity due to their simplicity and high energy efficiency and becoming an appealing solution for the coordination of multiple conventional generators (CGs) and renewable generators (RGs).

In the long term, this gradual increase in the incorporation of RESs might trigger instability in power grids if it is not regulated and managed properly. In this regard, the MGs are gradually gaining popularity in the sector. By definition, an MG is a domain of clustered power loads and distributed energy resources (DERs) acting as a controllable entity that can be connected to the grid as the need arises. It can operate in autonomous (islanded) mode [2], [3], or grid-connected mode. Whereas an MG can operate in on-grid or islanded modes, the islanded mode provides a more appropriate solution to electrifying rural areas or isolated communication facilities or military posts. In other words, an islanded MG (IMG) is ideal for supporting the provisioning of power supply to isolated loads, and at the same time, facilitating the integration of RESs into a reliable electricity supply system, reducing carbon footprint, and ultimately lowering energy prices,[4]. A typical IMG will comprise of distributed generators (DGs) such as micro-turbines (MTs) diesel generators (DGs), and renewable generators (RGs) such as PV panels and Wind turbines. In addition, various strategically located energy storage systems (ESSs) in the form of battery banks, fuel cells, flywheel technologies, etc are under intensified development. This offsets the lack of inertial storage inherent in traditional rotary synchronous generators.

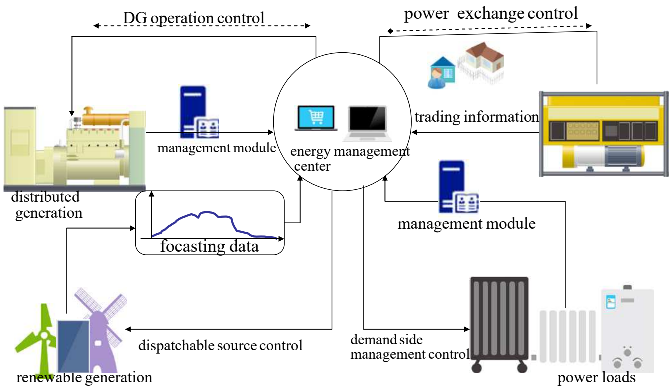

Fig. 1. An Islanded MG distributed generation model

As mentioned before, the uncontrolled high penetration of RGs, may compromise voltage stability, resiliency, robustness, and operation management optimization of the IMG. Significant challenges related to this penetration include among others, span supply reliability; frequency fluctuations induced by load intermittency; operational coordination of multiple RGs with possible conflicting requirements; and coordination between supply EMS and DSM.

Thus to mitigate these issues and challenges, a few control and energy management frameworks are being investigated. Both centralized and decentralized control framework architectures have been explored. The latter implemented as a hierarchical control architecture appear more practical given that they are organized in multiple distinct levels which can individually differentiate the multiple response turnaround time responses in IMGs operational environments. The first level of control is characterized by relatively swift turnaround times (typically in the order of milliseconds) and is mostly associated with local measurements. The middle-level control layer (secondary control) is relatively slower (in the order of minutes) and typically oversees the PC [5]. The last control layer (tertiary control) is relatively sluggish (i.e. in the order of several minutes) is responsible for guaranteeing sustainable optimal operations of the IMG , [6], 7]. The operating policies of the IMG are set by external agents. Normally the external agents take into consideration various operational-related data and other factors. A loads managing system (LMS) module manages the IMG power's demand and supplies to within certain defined goals. Typically, it will encourage power selling by consumers when it is conducive to doing so. This is achieved by applying various regulating techniques [8]. The EMS also dedicates overall managing and monitoring of energy flows (exchanges) among all the DGs. The IMG's EMSs can be categorized in accordance with their architectural framework design and implementation layout, namely centralized, decentralized, and distributed. The centralized architecture though characterized by simplicity in implementation suffers from high computational and infrastructure costs, low reliability, and low flexibility. The decentralized architectural framework is often highly reliable, flexible as well as coupled with low computational and infrastructural implementation costs. Note however that its implementation is relatively complex since it might not attain a comparable optimal performance to centralized architectures. Thus, the approach combines the best features of centralized and decentralized architectures. It is reliable, flexible, and as well as generating lesser computational burdens [9], [10].

Overall, the IMG concept is geared towards integrating as many renewable sources as possible into the SG. It will interconnect a variety of distributed energy resources (DER) with different types of consumers in LV or MV distribution network. In this paper, a novel Quantum Particle Swarm Optimization (QPSO) based algorithm is introduced to assist in optimizing a given MG's day-ahead power schedulings. The novelty and the contribution of this research work are:

- The overall power scheduling problem in a given MG that has DG units.
- The controllable and non-controllable DG sources are integrated into the MG to supply the load demand.
- An adaptive strategy is proposed to control existing non-critical loads without compromising customer satisfaction.
- The day-ahead scheduling horizon is taken on a 15 minutes resolution time with 96 intervals to investigate the proposed method's effectiveness by considering load dynamics in the IMG.
- Finally, the QPSO algorithm is applied to minimize the MG operating costs. A comparison of simulatied results with respect to scenarios DSM participation are carried out.

II. ISLANDED MICROGRID MODEL

A generic model of an MG is adopted in this work. As shown in Fig. 2, three feeders namely residential, commercial, and industrial feeders in the MG are connected to the utility via the point-of-common coupling. Solar PV, Wind turbine (WT), Diesel Generator (DG), Microturbine (MT), and Fuel Cell(FC) are considered in powering both curtailable and non-curtailable loads in the same MG. A MGCC together with local controllers cooperates in properly scheduling the available power. In particular, the MGCC periodically feeds power reference values to the local controllers. .

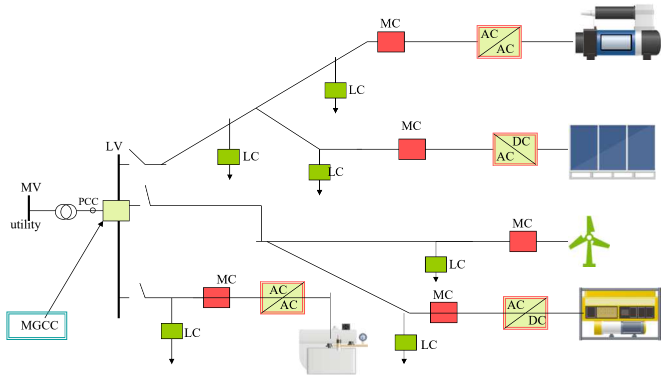

Fig. 2. A generic model of an islanded Microgrid

A: Modeling of DG Units

MGs with embedded distributed generation and ESS devices are expected to assume growing significance in future power systems. However, achieving efficient distributed economic dispatch in MGs is still a challenge in part due to stochastic phenomena and nonlinearity in DG units and loads.

Solar PV

Solar PV (photovoltaic) systems, generate d.c power utilizing an array of parallel-series interconnected photovoltaic modules. Primarily, the array absorbs sunlight and then consequently converts it to d.c current which flows to a DC bus or through DC-AC conversion to an AC bus. PV generators are mainly characterized by three key factors i.e solar irradiance (w/m^2), ambient temperature ($T_{amb}(^oC)$), as well as overall PV characteristics in determining their output power performance. Thus a PV generator output power (P_{pv}) is computed according to

$$P_{pv} = P_m \frac{1}{100}(1+\rho(T_{pvc}-25), watts \quad (1)$$

where; P_m (watts) is the maximum power of the PV module generator under standard test conditions, $\rho(^oC^{-1})$ is its temperature coefficient, and T_{pvc} is the PV cell temperature in degrees Celsius (^oC). T_{pvc} is related to $T_{amb}(^oC)$ and the module's nominal temperature (T_{NT}) as follows:

$$T_{pvc} = T_{amb} + \frac{1}{800} * (T_{NT} - 20) \tag{2}$$

Wind Turbine Generators

Wind turbine(WT) generators rely on wind power to drive an electric motor-generator. Typically a WT generator structure comprises a tower, rotor with three blades connected at the hub. When the wind passes over the blades, it exerts a turning (rotating) force, which in turn rotates an electrical motor. Ultimately electricity is generated. The power output of a WT generator (3) depends on the available wind speed $v(m/s)$ as well as the power generation characteristics of the WT generator unit itself.

$$P_{WT} = \begin{cases} 0, & v_{ct} < v \leq v_{cn} \\ \frac{v^2 - v_{cn}^2}{v_n^2 - v_{ct}^2} \times P_{nWT}, & v_{cn} < v \leq v_n \end{cases} \tag{3}$$

This is subject to;

$$P_{n,} v_n < v \leq v_{ct} \tag{4}$$

Where, P_{nWT}, v_n, v_{cn}, and v_{ct} are the nominal WT generator power (watts), nominal speed (m/s), cut-in velocity (m/s), and cut-out speed (m/s) respectively.

Diesel Generators (DG)

DG units comprise fossil fuel-based engines coupled to electric synchronous generators to produce electrical energy. The DG works based on air compression and fuel. 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 causes a turning effect. The DG's fuel consumption F_{DE} is normally characterized by its kW power rating according to [19]. This quadratic cost function can be modified to a non-convex function of its valve–point loading effect (VPE) as follows:

$$F_{DE} = a_{DE}^2 + b_{DE}^2 + c + d \sin\left| eP_{DE} - eP_{DE}^{\min} \right| \tag{5}$$

Where, a, b, c, d and e are non–convex coefficients of the diesel generator, $P_{DE}^{\min}$ and P_{DE} represent the minimum and nominal power outputs from the diesel generator respectively.

Microturbine(MT) and Fuel Cell(FC)

A fuel cell, via an electrochemical redox reaction, converts the chemical energy of a fuel, often hydrogen and an oxidizing agent, oxygen into electricity. FCs can continuously produce electricity for as long as H_2 and O_2 are supplied. Like DG, the cost function of the *MT* is considered as non-convex to address the VPE; It can be expressed as follows:

$$F_{MT} = aP_{PM}^2 + bP_{MT} + c + d * \sin\left| eP_{MT} - eP_{MT}^{\min} \right| \tag{6}$$

Where, P_{MT}, P_{FC} are the power outputs of MT and FC respectively, $P_{MT}^{\min}$ is the minimum power output obtained from MT. The FC 's power output cost can be approximated using the following equation:

$$B_{FC} = C_f \frac{P_{FC}}{\eta_{FC}} + C_{inv} \tag{7}$$

Where C_f is the diesel (fuel) costs, η_{Fc} is the FC's efficiency in generating power. C_{inv} takes into account the approximated fixed period's investment cost.

III. OPTIMIZATION PRELIMINARIES

. As discussed earlier, with the involvement of VPE, the DG cost function will become non-convex. Hence, our paper's main objective is to solve the *MG* optimal scheduling problem by considering a non-convex DG cost function. This is opposed to the traditional convex approaches. The MG's aggregated costs are summarised by equation (1). We can thus summarise the MG-EMS problem as per the following equation:

$$\text{Min } E(\alpha\alpha) = \sum_{t=1}^{T} OC \\ \sum_{t=1}^{T} \left\{ \sum_{i=1}^{NG} \left[u_i^t B_{DG_i}^t P_{DG_i}^t + S_{DG_i} \left| u_i^t - u_i^{t-1} \right| \right] + p_u^t B_{grid}^t \right\} \tag{8}$$

where;

$$B_{DG_i}^t = \alpha_i p_{G_i}^2 + b_i p_{G_i} + c_i \tag{9}$$

$$P_{DG_i}^t = \alpha_i p_{G_i}^2 + b_i p_{G_i} + c_i + d_i \sin\left| e_i p_{G_i} - e_i p_{G_i}^{\min} \right| \tag{10}$$

$$\alpha = \left[p_{G_1}^t, p_{G_2}^t, .., p_{G_N}^t, p_{ut}^1, u_1^t, u_2^t, .., u_i^t \right] \tag{11}$$

Equation (2) introduced earlier expresses the bid costs of DG units are represented in (2). When further analyzed it is noted that its cost coefficients a_i, b_i, c_i are of quadratic nature. Equation (3) introduces additional cost coefficients, namely d_i, e_i and α.

A) Active power balancing

The aggregated active power generated by all sources will cater for the total load demand in the MG P_l^t at any arbitrary time t for NL load levels.

$$\sum_{i=1}^{NG} P_{G_i}^t + P_{ut}^t = \sum_{l=1}^{NL} P_l^t \tag{12}$$

B) Aggregated Active Power Limitations

Aggregated active power output is limited within a lower bound ($P^t_{G_{\min}}, P^t_{u_{\min}}$) as well as upper bound ($P^t_{G_{\max}}, P^t_{u_{\max}}$).

$$\begin{cases} P^t_{G_{\min}} \le P^t_{G_i} \le P^t_{G_{\max}} \\ P^t_{u_{\min}} \le P^t_{ut} \le P^t_{u_{\max}} \end{cases} \tag{13}$$

According to [8], incorporating the DSM program into the proposed non-convex EMS problem is to bring the controllable load consumption profile like the desired load profile. As far as the DSM program is run, initially, the DSM controller acquires the day-ahead load forecast data before simulating an overall desired load profile. In the process, all regulated loads will be controlled either to be in the ON or OFF states. We thus have;

$$\text{minimize} \sum_{t=1}^{T} \left(TL(t) - DL(t)\right)^2 \tag{14}$$

$$TL(t) = \varphi(t) + \phi(t) - \Delta\phi(t) \tag{15}$$

In routine operation, at any arbitrary time, the desired load profile DL_t is obtained by feeding the targeted load information ($TL(t)$) to the DSM controller. The targeted load is mainly dependent on the following three types of loads: predicted ($P_{pred}(t)$) connected ($P_{con.}(t)$) as well as disconnected ($P_{dis.}(t)$).

$$P_{con}(t) = \sum_{t=1}^{t-1}\sum_{i=1}^{N} N_{l,i,t} \circ P_{1,l} + \sum_{j=1}^{k-1}\sum_{i=1}^{t-1}\sum_{l=1}^{N} N_{l,i,(t-1)} \circ P_{(1+j)i} \tag{16}$$

Following equation (16) we can also determine the magnitude(s) of the disconnected load(s) according to the equation [10]:

$$P_{dis.}(t) = \sum_{q=t+1}^{t+m}\sum_{l=1}^{N} N_{l,i,q} \circ P_{1,l} + \sum_{j=1}^{k-1}\sum_{q=t+1}^{t+m}\sum_{l=1}^{N} N_{l,(t-1),q} \circ P_{(1+j)l} \tag{17}$$

The procedure for incrementing or decrementing the power loads is explained in more detail in [10].
The maximum permitted time delay is denoted by m.

$$\sum_{t=1}^{T} N_{l,i,t} \le N(i) \tag{18}$$

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

$$N_{lit} = 0, \ \forall (t-i) > m \tag{20}$$

Equation (19) represents the inequality constraint where the number of shifted devices at a given time t cannot exceed the maximum available number of controllable devices $N(i)$.

IV. EMS SUMMARY ALGORITHM/FRAMEWORK

The algorithm is summarized in Fig. 3.

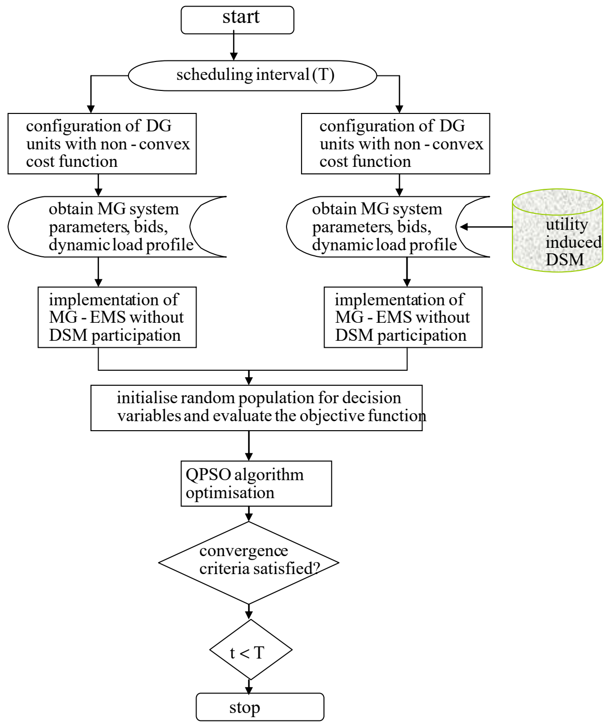

Fig. 3 . QPSO flowchart for solving non-convex EMS problem

V. EVALUATION

we rely on forecasted data of an Mg with distributed generation sources obtained from [11], these are tabulated in Table 2. The MATLAB R2021a release incorporates a QPSO algorithm which we rely upon. To ensure the reliability of our simulated results, we make several trail runs. The simulation results are compared with its classical counterpart PSO to prove the efficacy of QPSO. We maintain an end-user size of 50. We also limit the number of iterations for each algorithm (convex versus non-convex) to 200. Several additional assumptions were made before implementing the algorithm as follows::

- Booth PV and WT are kept at full throttle in terms of power generation throughout the simulation.

- All sources will provide active power whose power factor is close to unity.
- We distinguish the various categories of end-users as well as their respective loads.

Ultimately, in the core simulation we consider four scenarios as follows:

Case-1 entails non-convex and convex DG cost functions. The implementation of DSM program in the base case is neglected for the time being.
Case 2, the DSM participation of 10% is evaluated with both convex and non-convex DG cost functions.
Case 3, deals with the DSM participation of 20% with both convex and non-convex DG costs.

Table 2: Day-ahead forecast data of renewables power generation, load and market pr

time	PV(kW)	WT(kW)	Load(kW)	MP(kWhr)
1	0	251.60	479	3.4
3	0	280.01	599	3.4
5	25	290.55	719	6.9
7	65.33	245.91	839	6.9
9	160.22	214.98	959	6.9
11	187.33	246.33	1079	11.9
13	185.9	295.99	1199	11.9
14	189.302	314.01	839	11.9
15	140.01	289.91	839	11.9
16	138.9	280.1	960	6.9
17	60.59	289.1	1079	6.9
18	50.19	300.01	1097	6.9
19	36.98	3.31.92	959	11.99
20	18.05	300.93	839	11.99
21	11.76	291	719	6.9
22	0	280.1	599	6.8
23	0	280	719	6.9
24	0	279.99	619	3.4

Case 4, the dynamic loading for 15 minutes duration of 96-time intervals are considered and the results are evaluated with DSM participation of 15%.

A comparison of the best, mean, and worst values of costs with the PSO algorithm is given in Table 3 to prove its efficacy.

Table 3 . Performance of QPSO and PSO

		PSO		
	best	worst	mean	Time(s)
convex	2588.3	2590.1	2292.3	59.7
Non-convex	26 27.3	2629.1	2930.1	73.1
QPSO				
	2589.1	2590.7	2592.1	49.7
	2629.1	2630.7	2632.1	51.2

Generated optimized costs are tabulated in Table 3.

Table 4. Optimized costs in ZAR 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 different participation levels of DSM, we also provide optimized costs with different DSM participation levels in Table 4. Generally, it is noted that the flexible load shaping strategy does indeed brings down the costs.

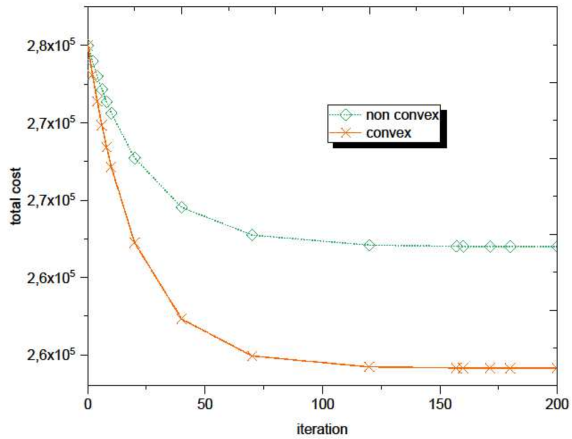

Fig. 4. Convergence characteristics for the non-convex versus convex cases

The VPE attributes to the costs incurred for the non-Convex DGs units considerably exceeding those of the convex cost DG units case. This is illustrated in Fig. 4.

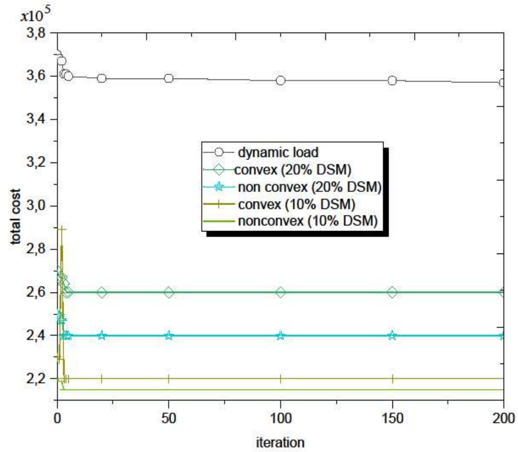

Fig. 5. Convergence characteristics of QPSO with DSM participation

Fig 5 demonstrates the convergence chracteristics of the QPSO with DSM participation.

VI. CONCLUSION

The paper's focus was on formulating the day-ahead dispatch problem of microgrids with DGs subject to non-convex cost function and load dynamics. We first proposed an operational framework that addresses the DG's 'valve point" loading effect as well as optimizing its performance. The impact of DSM on convex and non-convex EMS problems with different load participation levels was investigated. Further, the day-ahead scheduling horizon of fifteen-minute resolution time is considered to examine the effect of load dynamics in the microgrid. A Quantum Particle Swarm based approach was then employed to solve non-convex DGs cost optimization. It is demonstrated from simulation results that the proposed algorithm efficiently solves the non-convex EMS problem. Notably, simulation results yield a 5% reduction in OPEX costs without compromising customer satisfaction.

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