Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Quantum PSO-Based Power Demand and Supply Management algorithm for Micogrids

Mgobhozi Bhekinkosi, Bakhe Nleya

Department of Electronic and Computer Engineering, Durban University of Technology, Durban, South Africa

In this paper, we formulate a day-ahead dispatch problem of microgrids with distributed generation (DG) sub- ject to the non-convex cost function. An operational frame- work is proposed to address the DGs 'valve-point' loading effect and optimize its performance. The valve-point effect induces a ripple in a 'fuel-cost' curve. The impact of demand side management (DSM) on convex and non-convex energy management system (EMS) problems with different load par- ticipation 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 opti- mization algorithm, Quantum Particle Swarm Optimization (QPSO), is employed to solve the non-convex DGs cost optimi- zation problem. It is demonstrated that the algorithm effi- ciently solves the EMS problem. Simulation results point to a 5% reduction in OPEX costs with a minimal penalty on cus- tomer satisfaction or Utility.

Keywords: smart Grid, prosumers, OPEX and CAPEX, hi- erarchical, distributed generation, battery energy storage system (BESS).

1. Introduction

The key to energy utilization efficiency in future smart grids (SGs) is optimized DSM with time-related pricing. Intelligence in the SG with "closed-loop" control of demand implies that small and numerous renewable energy sources (RESs) will be easier to control and coordinate. However, the intermittency and geographic spread of RESs require high computing power. Energy optimization using schedul- ing alone is limited by the flexibility of schedulable loads and the consumers' willingness to compromise their com- fort due to appliances' switch-on time delays. The residen- tial tariffs should directly offer monetary incentives for PAR reduction strategies to work. Otherwise, customers will not desire to flatten their peaks on the load curves. Be- sides shifting base load appliances, deploying electrical storage is a complementary method of optimizing house- holds' energy consumption. Suppose ToU tariffs and elec- tricity storage are used. In that case, 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, avoiding expensive grid supply. Overall, the key to successfully optimized dispatch- ing would be to embark on a strategy that minimizes the OPEX and CAPEX associated with traditional and renew- able generators, the transactional costs of the transmittable power, and maximizes the Utility's demand response bene- fits concurrent with satisfying the load demand constraints.

This is achieved by effectively managing power genera- tion, 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 indi- vidual households or PPPs.
- Real-time constant monitoring of electrical power consumption and its depletion in the SG.
- Acquisition of key grid measurements as well as billing-related data.
- Constant achievement of optimized balancing of demand and power energy consumption by end- users.
- Facilitating regular interactions between end-users and Utilities. An enabling information and Com- munications Technology (ICT) subsystem nor- mally facilitates this.
- Constantly guarding and enforcing both privacy and security within the entire system.
- Enhancement of reliability by way of allowing de- grees of autonomy in management.
- Ensuring the maximized efficiency in terms of as- sets used in the SG.

A full duplex ICT subsystem is incorporated to inter- link the various entities communication-wise. In that way, end-users can trade effectively, e.g., maximize power trad- ing with the grid. This is because they would have acquired market-related information and grid status before trading any excess power to the grid. Note that at a functional level, the SG system encompasses various applications and ser- vices concurrently with advanced management and opera- tion to ensure efficiency in balancing supply and demand. In summary, the operation functions in envisaged future SGs aggregately bring about a multitude of services / or applications

2. Related Works

There is a phenomenally exponential rise in published work on DSM for microgrid optimization [1], [2], [3]. Gen- eral constraints, various objective functions, problem for- mulation methodologies, and topologies of the smart grids exist in the literature. The authors in [4] identified five typical microgrid optimization objectives and outlined a matrix of these criteria vs twenty-two optimization tech- niques. The characteristic optimization problems in the area are summarised as;

- Electricity cost minimization.
- Consumer utility or comfort function maximiza- tion,

- Aggregate power usage minimization,
- Minimization of both cost and total power con- sumed.
- The comfort maximization and aggregate power consumption minimization.

A constrained multi-objective function formulation of the optimization is considered in [5]. This achieves multi- objectives related to 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.

Further, the authors [6][7][8] present an in-depth analysis of pricing signals as well as demand-side programs. Studies on relevant demand response smart technologies and markets are covered in [9] [10], and they demonstrate the extent of energy savings and other efficiency metrics that have been achieved in the electricity markets. Demand response archi- tectures are described in [11], highlighting their require- ments, benefits, costs, and implementation progress in vari- ous Power utilities worldwide. The works in [12],[13],[14],[15] focus on enabling technologies such as smart meters (SMs), energy controllers (EC), and cyber-physical communication systems needed to deploy DR in SGs.

Traditionally DSM was applied to energy-consuming loads. With the SG hosting easily controllable sources such as photovoltaics (PVs), wind turbines (WTs), and energy- storing systems (ESSs), more flexibility for DR is intro- duced from the generation side. The operation strategy of Microgrids in the context of DR involves optimization, which means considering all the components in addition to the traditional loads. Optimization analysis and simulation done in [16] Using a Genetic Algorithm, we show that DR based on traditional load curtailment can reduce grid power while simultaneously increasing RES grid supply.

Of these numerous exact, games theory approach and meta- heuristic DR algorithms techniques [2],[5], the literature is unclear as to which methods are specifically suitable to 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 [7],[1]. Simpler optimization models dealing with single-time instant have solutions that can be computed easily in closed-form or by polynomial algorithms [6]. Nevertheless, the class of optimization that investigates multiple intervals discrete-time problems, is characteristically solved by heuristic techniques that may result in suboptimal results. The author in [17] introduced the concept of a simple Multi-Period Energy Tariff Optimi- zation Problem and proved that all such problems are NP- hard. The area of application has mainly been around resi- dential appliance scheduling using price-based DR pro- grams and inputs of:

- Electricity price TOU or day ahead RTP signals ob- tained from utility or energy retailer SM.
- Consumer utility function from which the optimiza- tion algorithm makes decisions.
- Environmental factors such as temperature, occu- pancy, 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 over centralized approaches as they require minimal information sharing. Various offline techniques for distributed optimiza- tion and power flow models are summarised in [18]. The Dual Decomposition, Alternating Direction Method of Mul- tipliers, Analytical Target Cascading, the Auxiliary Prob- lem 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 off-line microgrids are available in [19],[20][21]. The population-based meta-heuristic optimization methods that have found application in power system optimization generally belong to three classes, namely swarm intelli- gence (SI) [22], evolutionary algorithms (EA), and the hy- brid of the two techniques [23]. Popular evolutionary meth- ods 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 [24]. Firefly, Particle Swarm Optimization, Artificial Bee Colony, Ant Colony Optimization, etc., [25] 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. Figure 2 provides an anatomy of commonly applied DR optimization techniques well elucidated in the literature.

Meta-heuristic techniques can tackle multi-objective opti- mization 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 per- formance of these techniques subject to tuning certain tun- ing parameters. Standard deviation means the value of solu- tions obtained, and convergence rates are measures used to compare the performance of the various methods. The weakness of GA is that they are prone to get stuck in local optimum, and their search space is small. DE methods though they have been shown to possess average conver- gence rates and have a greater degree of complexity, in their favour is easy applicability to a wide variety of prob- lems that include practical scheduling.

Currently, no single method is well suited for both standard and practical formulations. There is, therefore, a need to find such standard benchmark functions to help with select- ing appropriate optimization methods for general cost opti- mization problems [7].

Gamarra and Guerrero [10] provide an extensive review of optimization and other techniques applied to four common micro-grid optimization problems of power mix selection, sizing, siting as well and 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 tech- niques [13].

Observability, controllability, and security are im- peratives for successful MG operations [18]. 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 a lack of real-time system controls, societal bar- riers to market deregulation, and insufficient time to avail consumers the time-varying pricing information. Load pre- diction and control state estimation can be employed to enhance observability in intelligent distribution networks using, e.g., an agent-based control approach whose architecture derives from distributed control rather than a tradi- tional centralized paradigm. The resultant DEG networks will have enhanced flexibility and adaptability of automa- tion systems, generally contributing to speeding the pro- gress of Smart Grids. What is needed now is an effort to develop a standardized and integrated vision for SG [20]. Electric vehicle technology will also in the future have a great Impact on SG development. Consequently, there ex- ists a huge potential for research both for backup and DSM as well as provision of flexibilities for main grid management [18], [26].

Overall, the core issue here is to address power dispatching optimally. This task is accomplished in the form of power demand and dispatch intervention programs summarized in Figure 3

We thus, in the next sections propose an optimized neural network-driven model solution.

3. Proposed Optimization Model

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 follow- ing:

- 15 minutes interval power demand forecasting for the day ahead.
- 15 -60 minutes PV solar and wind generation po- tential 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 con- nects to the main interconnection grid and power trading may take place.

The objective is to minimize the aggregated power genera- tion costs by all sources in a given MG (or SG), we thus have

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

Where xi and ui are state and decision vectors respectively. In the same equation gi denotes the degree of correlation between neighbouring vectors, and Πi a cost function at an arbitrary time i .

Equation (1) 's validity is subject to satisfying a constraint Ψ defined by;

$$\begin{cases} x_{i+1} = g_i(x_i, u_i) \\ c_{iE}(x_i, u_i) = 0 \quad x_{NE}(x_N) = 0 \\ c_{iI}(x_i, u_i) \le 0 \quad x_{NE}(x_N) \le 0 \end{cases} \qquad (2)$$

$$i = 1, 2, \ldots, N-1$$

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

$$x_i \equiv [P_1(i) \;\; P_2(i) \;\; \ldots P_m(i) \;\; P_{BESS}(i) \;\; soc(i)]^T \qquad (3)$$

Similarly for Mode II operations we have;

$$x_i = \left[P_1(i) \;\; P_2(i) \;\; \ldots \;\; P_m(i) \;\; P_{BESS}(t) \;\; P_{grid}(t) \;\; soc(i)\right]^T$$
(4)

$$u_i = \left[\Delta P_i(i) \; \Delta P_2(i) \ldots \Delta P_m(i) \; \Delta P_{BESS}(i) \; \Delta P_{grid}(i)\right]^T$$
(5)

Equations (2), (3), and (4) together depict 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 generates input states for the next stages. The process repeats until 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;

$$x^{k+1} = f^k(x^k, u_k), x^k \in U^k, \quad k \in [0,1,\ldots,N \;\; 1] \qquad (6)$$

$$V^N(x^N) = \min_{u0,\ldots,u^N}\left[g^N(x^N) + \sum_{k=0}^{N-1} g^{n}(x^k, u^k,)\right] \qquad (7)$$

Where in the two above equations,

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

f^k - functions characterizing 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 ;

$$V^k(x^k) = \min_{u^n \in U^n}\left[g^k(x_k, u^k) + V^{k-1}(x^{k-1})\right] \qquad (8)$$

This is subject to satisfying Ψ;

$$\Psi = \begin{cases} x_{\min}^{k1} \le x^{k-1} \le x_{\max}^{k-1} \\ x_{\min}^{k} \le x^k \; \square \; x_{\max}^{k} \\ x^k = f^{k-1}(x^{k-1}, u^{k-1}) \end{cases} \qquad (9)$$

In Fig.1 a summarised reformulation of the model is pro- vided.

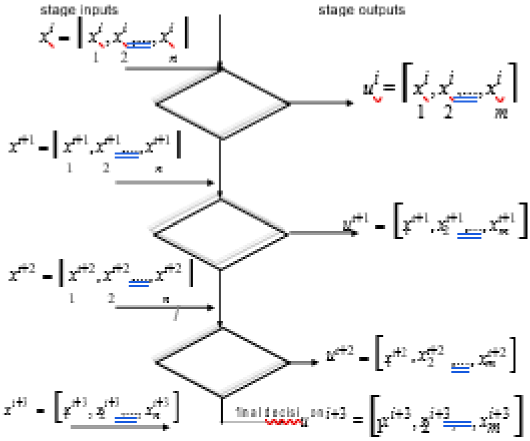

Fig. 1: Modeling Node Policies in Power Dispatching

To ease the computational loads involved in the Frame- work's core modules in all the SG's control infrastructure, we chose to incorporate some NN modules. The model in Fig.2 illustrates one such example NN module. These will also aid in the more precise determination of optimal deci- sions and ultimately optimal dispatching of available power subject to maximizing profits as well as keeping OPEX and CAPEX low.

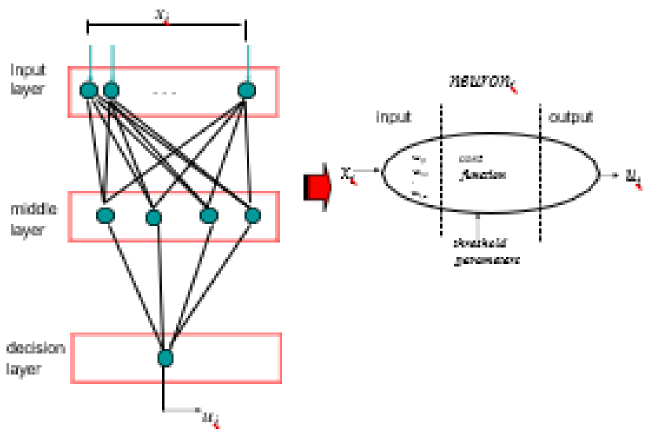

Fig. 2: The Neural Network Set Module illustration

The PSO algorithm is primarily based on generating ran- dom approximated solutions before searching for an opti- mal one through exhaustive iterations. It tends to up the computational loads and signalling overheads among the entities constituting the hierarchical dispatching frame- work. Neither does it timeously converge to a localized optimal decision. Its successor, the quantum PSO (QPSO), has a faster convergence rate and a more précised fitness valuing. It treats each particle as a quantum state and then uses the Schrodinger equation to formulate an equivalent wave function. Ultimately, the particles will gradually con- verge to a global solution.

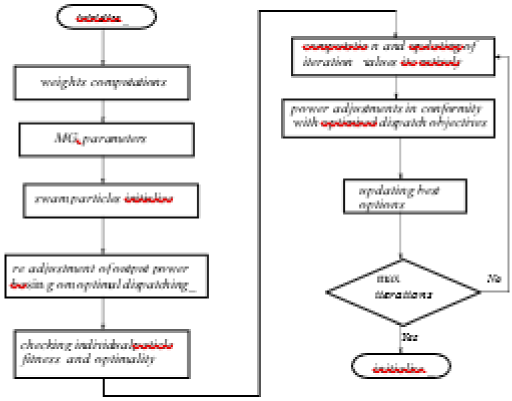

Fig. 3: QPSO algorithm-based dispatch algorithm

The QPSO algorithm, as summarised in Fig. 3, will be implemented in the Neural Network modules to implement the optimization as summarised by the reformulation pro- vided in Fig. 1.

4. Model Evaluation

Note that in this case, we rely on the VPSPICE simula- tion platform, which, among other things, has the necessary pre-trained NN sets. To enhance the "look ahead" forecast- ing, we initially ran trail rums for both PV and WT genera- tors. The data used is provided in Table 1.

Table 1. 24-hour interval climatic data captured for analysis purposes

time	*temperature*(^oC)	*wind velocity*	$I(kW/m^2)$
1	12	5.05	0.001
2	11.3	6.04	0.001
3	10.2	6.6	0.001
4	11.5	7.3	0.001
5	11.7	7.2	0.001
6	11.8	7.2	0.001
7	11.9	6.9	0.003
8	12	6.9	0.15
9	13.2	7.9	0.3
10	15.1	8.5	0.8
11	20.1	11	0.99
12	26.2	7.6	1.12
13	27	7.332	1.903
14	27.39	7.253	0.8
15	27	7.2	0.55
16	25.4	6.4	0,11
17	19.3	6.5	0.001
18	18.8	7.6	0.001
19	18	5.7	0.001
20	16.7	5.71	0.001
21	11.3	5.2	0.001
22	9.3	6.1	0.001
23	7.9	5.06	0.001
24	7.6	5.3	0.01

The climatic data is captured hourly over a 24-hour cy- cle period. To capture more realistic data characterizing the typical climatic conditions of the vicinity (area), we aver- aged 5 consecutive captures. Specifically, the typical data includes temperature, wind velocity, and solar intensity.

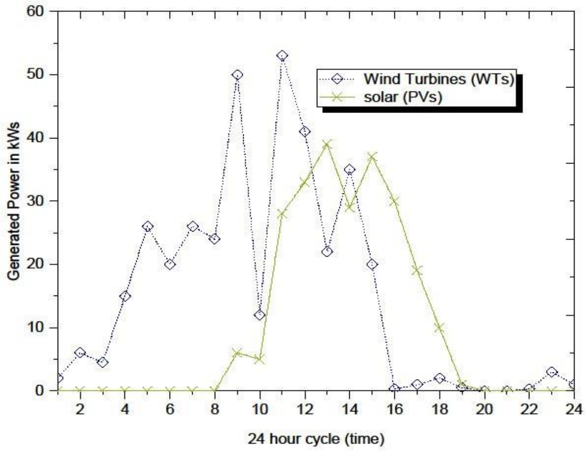

Fig. 4: Aggregated Power from PVs and WTs over a 24 Hour interval.

The plot of Aggregated Power from PVs and WTs over a 24 Hour interval.

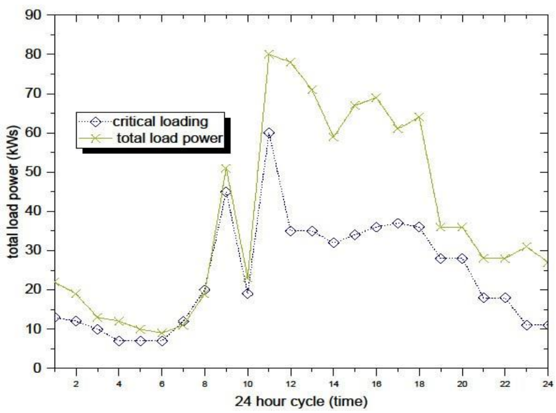

Fig.51: Aggregated(total) SG load and its critical loading.

As expected, the graph shows that ambient tempera- tures coupled with optimal solar radiation intensity (and correct inclination angle) will generate more power. PVs typically yield power during daylight hours from around 8 a.m. to 19 a.m., whereas WTs still generate power at night. We also provide a variation of critical versus noncritical grid loads over a 24-hour period. These are captured at 60- minute intervals and are shown in Fig.5.

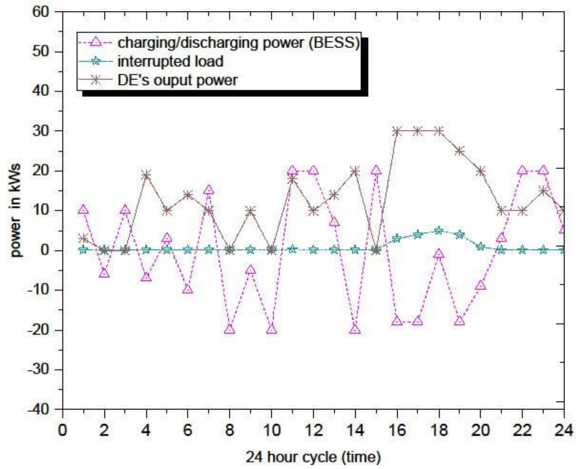

Fig. 6: Varying of BESS charging/discharging versus DEs optimality.

We once again reiterate that the objective of the proposed framework is 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, and power supply reliability in the grid. The optimal charging/ discharging times can be deduced from the plot provided in Fig.6 and Fig. 7.

Table 2. Pollutants and associated costs

type	$(g/kWhr)$	$\cos t\_coeff$ (ZAR/Kg)
nitrogen oxide	9.9	63
sulphur oxide	0.199	14.01

We make use of the pollutant associated tabulated values and associated costs (Table 2) 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.

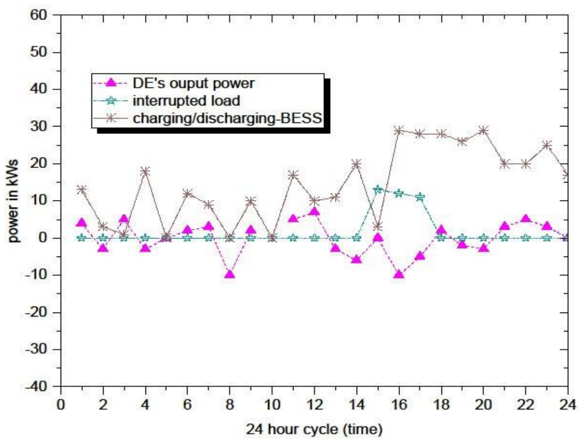

Fig.e 7: Optimality assuming a 50k Ah BESS capacity in the SG

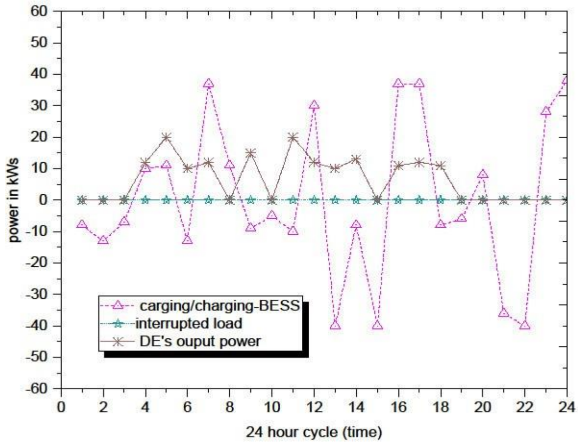

Fig. 8: Optimality assuming a 50k Ahr BESS storage capacity in the SG

Our model framework has a tendency to accommodate more renewable generators such as PVs and WTs than fos- sil-based equivalents such as diesel generating based plants By referring to Optimality assuming a 50k Ah BESS capacity in the SG, Optimality assuming a 50k Ahr BESS storage capacity in the SG Fig. 8 shows that the sizing of BESS systems in an SG / or Mg will significantly impact the 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

5. Conclusion

This paper analyzes and solves a new microgrid energy management problem with a non-convex cost function with load dynamics using the QPSO algorithm. 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 intro- duced 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 re- sults 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 compared to DG units with convex cost func- tions. The methodology can nevertheless assist MGs opera- tor to minimize costs while benefiting customers with peak reduction hence lower energy consumption during peak periods. Consumer utility can be safeguarded by appropri- ate scheduling wherein the consumer has a say.

References

1. M. Y. uddin and S. Ahmad, "A Review on Edge to Cloud: Paradigm Shift from Large Data Centers to Small Centers of
2. Data Everywhere," 2020 International Conference on Inventive Computation Technologies (ICICT), 2020, pp. 318-322, doi: 10.1109/ICICT48043.2020.9112457.
3. C. Lee and A. Fumagalli, "Internet of Things Security - Multilayered Method For End to End Data Communications Over Cellular Networks," 2019 IEEE 5th World Forum on Internet of Things (WF- IoT), Limerick, Ireland, 2019, pp. 24-28, doi: 10.1109/WF- IoT.2019.8767227.
4. M. Y. uddin and S. Ahmad, "A Review on Edge to Cloud: Paradigm Shift from Large Data Centers to Small Centers of Data Everywhere," 2020 International Conference on Inventive Computation Technologies (ICICT), 2020, pp. 318-322, doi: 10.1109/ICICT48043.2020.9112457.
5. Y. Zhao, W. Zhang, M. Yang and H. Shi, "Network Resource Scheduling For Cloud/Edge Data Centers," 2020 IEEE 39th International Performance Computing and Communications Conference (IPCCC), 2020, pp. 1-4, doi: 10.1109/IPCCC50635.2020.9391529.
6. P. Geetha and C. R. R. Robin, "A comparative-study of load-cloud balancing algorithms in cloud environments," 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), 2017, pp. 806-810, doi: 10.1109/ICECDS.2017.8389549.
7. A. Agarwal, G. Manisha, R. N. Milind and S. S. Shylaja, "Performance analysis of cloud based load balancing techniques," 2014 International Conference on Parallel, Distributed and Grid Computing, 2014, pp. 49-52, doi: 10.1109/PDGC.2014.7030714.
8. R. R. Kumar, S. K. Jha, D. Garg and S. Vaishnav, "Evaluation of Load Balancing Algorithm Using Cloudsim," 2018 3rd International Conference on Inventive Computation Technologies (ICICT), 2018,
9. pp. 78-81, doi: 10.1109/ICICT43934.2018.9034367.
10. H. Xu, G. Wang, L. Luo and M. Lei, "The Design of Reliability Simulation of Cloud System in the Cloudsim," 2018 15th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), 2018, pp. 215-219, doi: 10.1109/ICCWAMTIP.2018.8632572.
11. P. Humane and J. N. Varshapriya, "Simulation of cloud infrastructure using CloudSim simulator: A practical approach for researchers," 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), 2015, pp. 207-211, doi: 10.1109/ICSTM.2015.7225415.
12. S. Santra and K. Mali, "A new approach to survey on load balancing in VM in cloud computing: Using CloudSim," 2015 International Conference on Computer, Communication and Control (IC4), 2015,
13. pp. 1-5, doi: 10.1109/IC4.2015.7375671.
14. [M. Haghi Kashani and E. Mahdipour, "Load Balancing Algorithms in Fog Computing: A Systematic Review," in IEEE Transactions on Services Computing, doi: 10.1109/TSC.2022.3174475.
15. J. Yan, J. Wu, Y. Wu, L. Chen and S. Liu, "Task Offloading Algorithms for Novel Load Balancing in Homogeneous Fog Network," 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD), 2021, pp. 79-84, doi: 10.1109/CSCWD49262.2021.9437748.
16. X. Yang, S. Member, Y. Zhang, H. He, S. Ren, and G. Weng, "Real- Time Demand Side Management for a Microgrid Considering Uncertainties," IEEE Trans. Smart Grid, vol. 10, no. 3, pp. 3401– 3414, 2019, doi: 10.1109/TSG.2018.2825388.
17. M. Sun, R. Anaadumba, Q. Liu, X. Liu, and Y. Yang, "A Survey on Demand-Response in HEMS: Algorithm Types, Objectives and Constraints," in 2019 IEEE SmartWorld, Ubiquitous

Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), 2019, 2019,

18. pp. 300–304. doi: 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP- SCI.2019.00095.
19. M. J. Ko, Y. S. Kim, M. H. Chung, and H. C. Jeon, "Multi-Objective Optimization Design for a Hybrid Energy System Using the Genetic Algorithm," Energies, vol. 8, no. 4, pp. 2924–2949, 2015, doi: 10.3390/en8042924.
20. K. S. S. Kumar and M. G. Naik, "Load Shifting Technique on 24Hour Basis for a Smart-Grid to Reduce Cost and Peak Demand Using Particle Swarm Optimization," Int. Res. J. Eng. Technol., vol. 4, no. 10, pp. 1180–1185, 2017.
21. N. Javaid et al., "A new heuristically optimized Home Energy Management controller for smart grid," Sustain. Cities Soc., vol. 34, no. July, pp. 211–227, 2017, doi: 10.1016/j.scs.2017.06.009.
22. H. Cai, X. Lu, T. Du, Y. Wang, S. Xia, and D. Zhang, "A Survey of Artificial Intelligence Algorithm in Power System Applications," in 2019 IEEE 3rd International Electrical and Energy Conference (CIEEC), 2019, pp. 1902–1906. doi: 10.1109/CIEEC47146.2019.CIEEC-2019646.
23. M. S. Ahmed, A. Mohamed, T. Khatib, H. Shareef, R. Z. Homod, and J. A. Ali, "Real time optimal schedule controller for home energy management system using new binary backtracking search algorithm," Energy Build., vol. 138, pp. 215–227, 2017, doi: 10.1016/j.enbuild.2016.12.052.
24. J. Zhu, Y. Lin, W. Lei, Y. Liu, and M. Tao, "Optimal household appliances scheduling of multiple smart homes using an improved cooperative algorithm," Energy, vol. 171, pp. 944–955, 2019, doi: 10.1016/j.energy.2019.01.025.
25. M. T. M. Emmerich and A. H. Deutz, "A tutorial on multiobjective optimization : fundamentals and evolutionary methods," Nat. Comput., vol. 17, no. 3, pp. 585–609, 2018, doi: 10.1007/s11047-018-9685-y.
26. A. Jamil et al., "An Innovative Home Energy Management Model with Coordination among Appliances using Game Theory," Sustain., vol. 11, no. 22, p. 6287, 2019, doi: 10.3390/su11226287.