Optimization Techniques for Operation and Control of Microgrids – Review

C. Suchetha and J. Ramprabhakar

Department of Electrical and Electronics Engineering, Amrita School of Engineering, Bangalore, Amrita Vishwa Vidyapeetham, India
E-mail: csuchetha@gmail.com; j_ramprabhakar@blr.amrita.edu

Received 20 August 2018; Accepted 30 November 2018
Publication 17 December 2018

Abstract

Microgrid systems show great promise in integrating large numbers of distributed generation systems, based on renewable energy sources into future power systems. The characteristics of power generated by renewable energy sources is random, unregulated and highly unreliable, vowing to the stochastic nature of the sources like wind, solar etc. While integrating the locally generated power into grid sounds very attractive, there are many operational and planning concerns. Also, a major chunk of power generated is weather dependent, this makes an energy storage system and/or back-up power generation system an imperative part of microgrids. A proper planning and designing is the first step towards integrated power. Optimization techniques justify cost of investment of a Microgrid by enabling economic and reliable usage of resources. This paper summarizes various optimization methodologies and criterion for optimization of Microgrids. Extensive study of published literature show that computational alternatives like evolutionary, heuristic and non-classical algorithms show better results when compared to other conventional methods. The study of multi-objective optimization problems shows superior performance by combining intelligent optimization algorithms with adaptive techniques.

Journal of Green_Engineering, Vol. 8_4, 621–644. *River Publishers*
doi: 10.13052/jge1904-4720.847

Keywords: Microgrids, Multi-objective optimization, Stochastic method, Particle swarm optimization, Intelligent algorithms, Adaptive techniques.

1 Introduction

Fossil combustibles like coal, oil and natural gases are the worlds primary sources of energy. Understanding the nature of their depleting reserves, scientists around the world are trying to find alternative sources of energy. Hydro, wind and photovoltaic are most popular alternate energy sources.

For remote locations and critical loads renewable energy sources are considered as an attractive alternative. When microgrids are connected to main grid, its control and protection functions become more complicated. This provokes a burden to the network operation, also, some technical limitations will appear when a great number of distributed generations are installed. Without ideal use of sustainable power sources the cost of venture on a microgrid cannot be supported. The control and operational concerns of a Microgrid are mentioned in [1] are listed below.

- Maintaining power quality and balance between active power and reactive power.
- It should operate in both stand-alone and grid-connected mode.
- Suitably planned energy storage system to provide back up.
- Cost effective operation must be ensured by energy scheduling, economic load dispatch and optimal power flow operations. System security should be essentially be maintained.
- Temporary mismatch between generation and load should be alleviated by effective load and generation forecasting.

The paper discusses different optimization strategies employed for different operational issues of a microgrid individually. The Sections 2, 3 and 4 review various methods employed for power quality control, energy management and optimal load dispatch respectively. Section 5 explores the possibility of handling all operational concerns at the same time with multi-objective optimization. The paper is concluded in the last section.

2 Power Quality Control

Exponential growth in number of electronic gadgets and LEDs, have increased demand for higher power quality. The provision to control frequency, voltage and load locally and fast responding energy storage system makes microgrids more than suitable for providing higher power quality. Harmonic interferences arise as a result of interconnection between grid and installed solar panels are reduced by converting the system into an autonomous microgrid [4]. The harmonics generated in a voltage source inverter (VSI) based renewable energy source of a microgrid are filtered using specially designed frequency selective filters in [5]. These frequency selective filters are designed in three phase space-vector quantities.

A residential complex is supplied with high quality power along with continuous supply [6] by designing it as DC microgrid with co-generation system with each house. The total power output which is shared between houses can be controlled by adjusting the number of co-generation units running. In this system super capacitors are chosen as energy storage system. The standard series-parallel structure is adapted in a set of grid-interfacing system in [7]. An example of the series parallel structure applied for coupling the utility grid and a local grid/micro-grid is shown in Figure 1. These layouts have been compared with conventional series-parallel systems and shunt connected systems, shows flexible applications.

Microgrids can operate in both grid-connected mode and in autonomous mode, and the control variables of both modes are different. Different control strategies are to be employed for optimal operation of the system to operate in two modes. A microgrid operating in autonomous mode is equipped with two control loops. The inner loop which is equipped with current and voltage PI controllers rejects high frequency disturbances and attenuates the output filter there by avoiding resonance with external network. The outer loop is for droop control, it shares the fundamental real and reactive powers with micro-sources in the grid. An optimisation problem is formulated for design

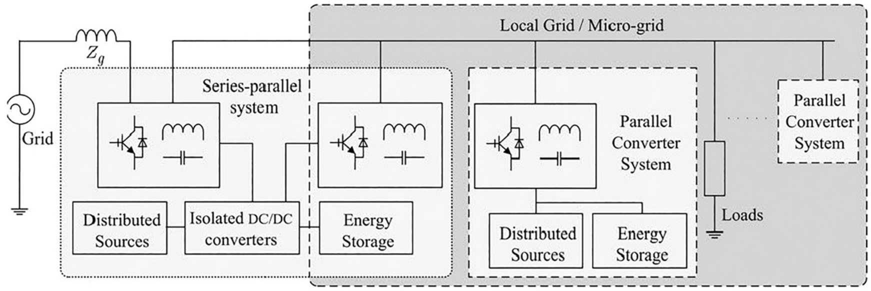

Figure 1 The series parallel structure applied for coupling the utility grid and a local grid/micro-grid [7].

controllers, filters and power sharing coefficients with the objective to improve the system stability in [8]. Particle swarm optimisation (PSO) algorithm is used to obtain optimal settings. The power sharing between AC and DC loads of a hybrid microgrid is improved by adapting droop control method for controlling interconnecting converter in [9]. An adaptive virtual impedance control method is used to improve power sharing problem by enhancing droop control characteristics in [10].

The unpredictable nature of natural resources demands the use of more sophisticated algorithms like PSO, GA for controlling output. In [11] dynamic control scheme for a microgrid feeding both AC and DC loads is proposed. In this control scheme, five controllers are used to control power flow, and to track reference speed trajectory. Minimum cost recovery tariff for a microgrid is achieved by using PSO as a global optimising tool in [12]. Under the condition of positive cash flow the results of exhaustive search are taken as reference for testing and validation of PSO. Figure 2 shows the Flow Chart of PSO algorithm used.

An attempt is made to optimize power quality and reliability of overall power system that the microgrid is connected to in [13] by designing a flexible AC distribution system device. The device design uses model predictive control algorithm which optimises steady state and transient state control issues separately, thereby improving computational time. The main drawback of FACTS devices is its high cost. This is overcome by using knowledge based smart parks in [14]. In [15] model predictive controller is used to minimize voltage imbalance and enhance current limiting. Controller with MPC is shown in Figure 3. The distributed energy sources are protected from overloading by using a decentralized control technique. The MPC is enhanced with droop method to concoct coordinated operation with fast dynamic response.

A 3-stage hierarchical control system architecture is proposed in [16]. The three control levels are:

- local micro source controllers (MC) and load controllers (LC)
- microgrid system central controller (MGCC)
- distribution management system (DMS).

The power electronic interface provides local information to MC for controlling voltage and frequency of microgrid during transient conditions. When the MGs are connected to power grid the local MCs perform local optimisation following the demands of central controller. The local optimisation includes active and reactive power control and load tracking and load management.

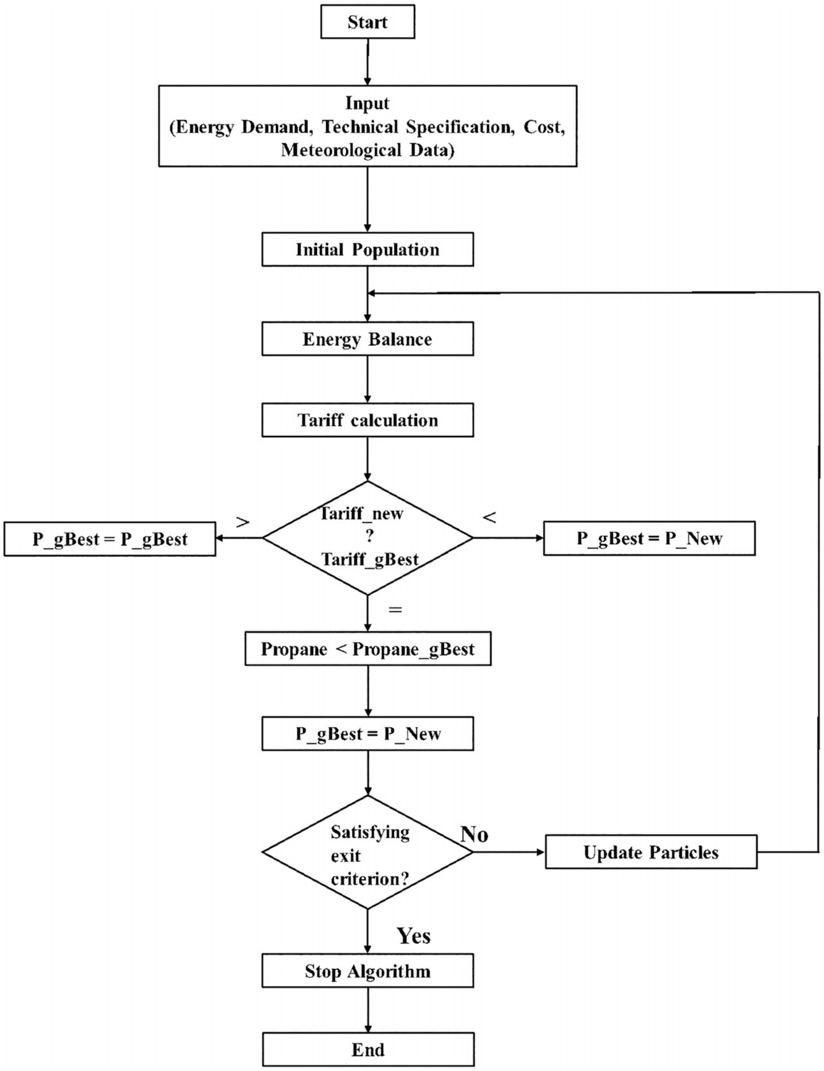

Figure 2 Flow Chart of Particle Swarm Optimization algorithm [12].

The MGCC uses market prices of electricity and fuel to evaluate the amount of power microgrid should buy from grid, thus optimizing power produced.

A branch-based power flow technique capable of incorporating practical isolated microgrid operating constraints and can handle cases involving multiple DGs and droop-control operating mode is proposed in [17].

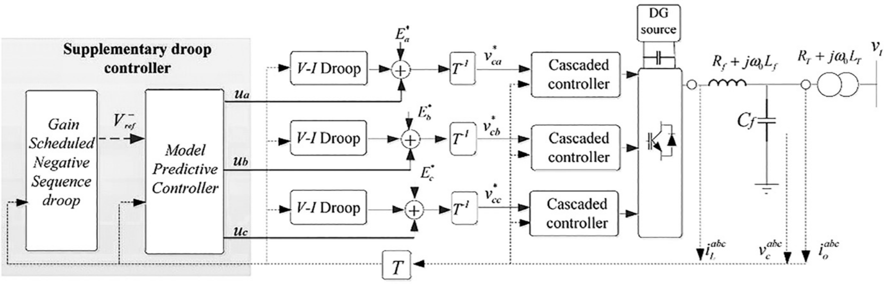

Figure 3 Controller with MPC [15].

The methodology developed is derivative-free and inversion-free hence it is fast and scalable for a large number of buses with no overwhelming computational time and no diminishment in accuracy. The problem associated with applying a branch-based power flow for solving isolated microgrids is overcome by the concept of the novel forward-return-forward-backward sweep (FR-FBS) technique that is capable of providing a power flow solution.

A distributed cooperative control is proposed in [18], to regulate active power fluctuations at point of common coupling (PCC) in a microgrid integrated with grid. An attempt is made to reduce the additional regulation burden on the main grid by controlling the charge and discharge cycles of multiple energy storage units (ESU). The state of charge (SoC) and the ratio of power (RoP) of each ESU is modelled as a multiagent system. A designing control algorithm is used to maintain SoC and RoP of the ESUs at the same level. Reactive power sharing among the sources is improved by wireless reactive power sharing based on virtual impedance optimization in [19]. Reactive power droop slope is included in the objective function, making it more adaptive to different capacity systems. Power sharing and load voltage control is optimized by a distributed control method in [20]. The power coordination and voltage optimization happen parallelly, thus fulfilling the generation-demand gap. Grass-hopper optimization algorithm is implemented in [21] for optimizing parameters of a load frequency controller. The Table 1 shows the various optimization methods employed to meet various power quality issues. From the table it can be concluded that the more complicated system calls for a more advanced optimization control.

Table 1 Comparison of optimization methods used for microgrid operation

Reference No.	Type of system	Sources	Objective	Method employed	Remarks
[7]	grid interfaced microgrid	PV array, wind turbine and battery	Voltage quality enhancement	Reconfigured series parallel structure for grid interfaced controller	System exhibits a stable operation under different test conditions
[10]	Islanded microgrid	Two DGs in parallel	improve power sharing	adaptive virtual impedance control method	improved power sharing
[11]	Grid connected microgrid with hybrid load	PV array, Fuel Cell, Battery bank and Diesel generator	Minimise 1. Voltage fluctuations 2. power loss 3. total control deviation error	Dynamic control system with multi objective particle swarm optimization (MOPSO)	Improved voltage stability, reduced power loss and normalized mean square error reduced from 0.05266 to 0.005984
[12]	Hybrid energy systems	PV array, Thermal energy storage system, LPG fuelled engine generator and battery	Optimum power flow control	Particle swarm optimisation	Faster convergence and reduced use of combustible fuel
[13]	AC microgrid in autonomous and grid connected mode	PV Array and Battery bank	Improve P and Q reliability of the system	Model predictive control	THD improved from 18.39% to 1.5%.
[15]	Microgrid in islanded mode	distributed generators	Power quality improvement and protection from overload	Model predictive control	Improved power sharing
[18]	Grid connected microgrid	PV array, wind turbine and Battery	Optimal charging and discharging of energy storage unit	Second order multi agent system	The control strategy is able to track P and Q at PCC and maintaining SOC and ROP of ESU

3 Energy Management Systems

An efficient and optimal energy management system is the building block of a microgrid to garner all its advantages. Researchers have developed various techniques and methods for optimal operation of microgrids. Energy Management System (EMS) of a MG is a comprehensive automated system primarily aimed at optimal resources scheduling: it is based on advanced Information technology and can optimize management of distributed power and energy storage devices within the microgrid [22]. The basis of a scheduling problem is accurately forecasting load and source data, a comparative analysis on wind speed forecasting is discussed in [23].

The decisions on how devices and systems should be operated for optimal operation are made based on the information available by implementing intelligent algorithms. An optimal generation scheduling model considering the degradation cost of energy storage system for virtual power plant (VPP) is proposed in [24]. The energy storage system is an important part of a microgrid for flexible dispatch because of its controllable and schedulable behaviour. Through the comprehensive analysis for the effects of degradation cost on optimal VPP scheduling it is found that day-a-head market rates vary very less and batteries with lower degradation cost are more dispatched by the VPP. In [25] capacity and sizing of energy storage system of a microgrid are optimized jointly. The optimization problem takes into consideration various realistic constraints. The problem is solved piece wise to reduce the computational time and to reduce complexity.

Heuristic algorithms are suitable for energy management systems as they reduce the decision-making time. An original heuristic algorithm for energy management on microgrids is developed in [26]. This algorithm is focused on the principle: avoid wastage of the existing renewable potential at each time interval. The reduction in output power due to converter failure, shading of the panels, and accumulation of dirt on the PV panels is controlled using model predictive control scheme in [27]. The objective of the energy management system (EMS) is to minimize the energy taken from the grid. The balance equation is expressed as Equation (1).

$$P_{Load}(t) = P_{PV}(t) + P_{Grid}(t) + P_{Batt}(t) \tag{1}$$

where, $P_{PV}(t)$, $P_{Batt}(t)$, $P_{Grid}(t)$ and $P_{Load}(t)$ are the power generated by PV, provided by the ESS and power grid, demands from the load, respectively.

From the above balance equation, the minimization problem is formulated as Equation (2).

$$\sum_{t=0}^{\infty} \| P_{Grid}(t) \|_2^2 = \sum_{t=0}^{\infty} \| P_{Load}(t) - P_{PV}(t) - P_{Batt}(t) \|_2^2 \qquad (2)$$

Optimal day ahead scheduling of electrical and thermal energy resources is achieved through a probabilistic model using a modified scenario-based decision-making method [28]. The simultaneous energy and reserve scheduling method considering demand response has been discussed. Modelling of uncertainties in operational planning problems makes the scheduled results more realistic. Operating cost is effectively reduced by implementing an intelligent energy management system based on near accurate interpretation of generating power and optimised power flow in [29, 30].

An intelligent approach accounts for storage states and frequency of renewable generation. Distributed Intelligent Energy Management System (DIEMS) is used to minimize operating costs of a model photovoltaic (PV) based microgrid. An optimisation scheme is developed with heuristics based forecast of PV generation with the application of Fuzzy Adaptive Resonance Theory (ART) map neural network. In [30] affine arithmetic is used to model the random nature of a microgrid. The cost is minimised using stochastic weight trade-off particle swarm optimisation algorithm. The optimal energy management strategy for energy storage is formulated as a mixed-integer linear optimisation problem (MILP) in [31] to satisfy operational constraints and fluctuating energy demand. The objective is to minimise the overall cost function of the system and the secondary objectives are to satisfy consumers demand and safety. A storage strategy before optimization is discussed, where the energy level of storage system is pre-decided, and another storage strategy where the storage energy level is defined after multi-objective optimization problem presents a set of solutions, and an expert has to choose one of them based on his expertise and history. The planning and operation of a microgrid are optimized using multi-objective optimization in [32]. The multi-objective optimization problem is converted into single optimization problem by implementing fuzzy satisfaction-maximising method. The converted problem is solved using MILP.

An attempt is made to model an energy trading system for power trading. An EMS consisting of various units that work together to achieve energy balancing is modelled in [33]. A general two stage optimization is shown in Figure 4. The model includes two stages namely, the planner and

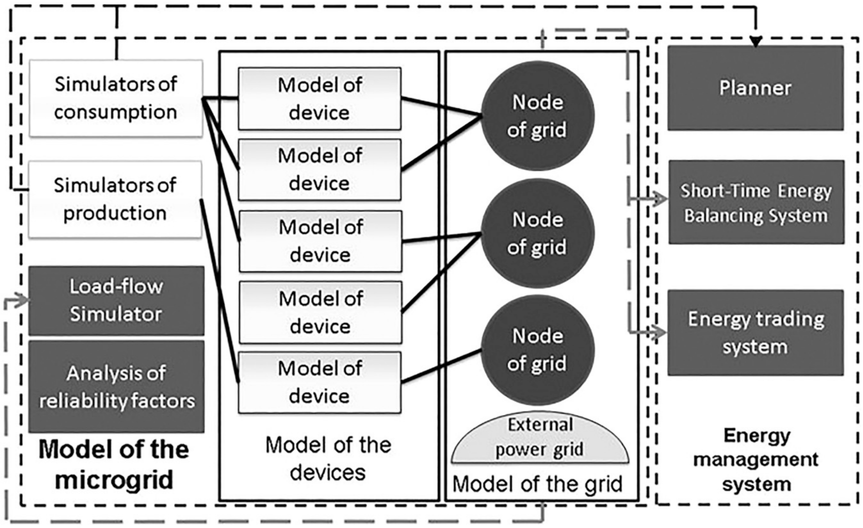

Figure 4 The general structure of two stage optimization system [28].

short-time balancing system. The Planner conceives the scheduling of the various predefined tasks to achieve partial demand side management and to obtain statistics regarding the power usage. The Planner also estimates the background consumption level and forecasts the power production from renewable power sources. A multiagent, distributed system is comprised in Short-Time Balancing system, it can manage controllable sources to achieve power balance in almost real-time. A new concept of energy cooperation is proposed in [34], where the energy management problem of two cooperative microgrids is solved. Initially the optimization is achieved using off-line method. Based on the solutions obtained an on-line optimization method is developed for energy cooperation.

A hierarchical coordination strategy with primary, secondary, and tertiary coordination for the economic operation of an islanded community microgrid is proposed in [35]. The coordination strategy is proposed for the flexible and the optimal coordination of power exchanges while maintaining the normal operation of participating microgrids. The interlinking-converter droop is modified and applied to the coordination of a community microgrid. The stability of a stand-alone microgrid is improved by implementing a radial basis function neural network (RBFNN) incorporating particle swarm optimization (PSO) by controlling both active and reactive power of battery energy storage system online is proposed in [36].

A novel control algorithm for demand response management and thermal comfort optimization in microgrids composed of a PV array, a wind turbine, and an energy storage unit is developed in [37]. The proposed work aims at developing a scalable and robust demand response program, which can integrate the objective of balancing energy generation and consumption with the occupant behaviour. A two-level supervisory strategy is adopted in the proposed algorithm. A local controller at each generating unit acts as a lower level control, and a centralized controller as upper level control. In [38] an operational scheduling problem was formulated in accordance with various incentives like peak time rebate (PTR) and demand response (DR) programming for responsive loads and constraints like optimal scheduling of the batteries and diesel generators.

The main objective is to minimize the overall cost of a microgrid, by modelling the operational planning problem as a MILP in [39]. The source and load uncertainties are linearized using parametric realizations. A microgrid central energy management system which relies on a day-ahead operational planning and an online adjustment procedure during the operation is designed in [40]. Unit commitment (UC) is defined as an optimization problem used to determine the operation schedule of the generating units at every hour interval with varying loads under different constraints and environments in [41]. A dynamic programming-based algorithm is derived to solve the unit commitment problem with a multi-objective function in order to reduce the economic cost and CO_2 equivalent emissions employing a modified genetic algorithm (GA) based method is proposed in [42]. Simulated annealing technique is used to improve the speed of convergence in genetic algorithm.

A multi agent system (MAS) system can provide optimal operation strategies to the microgrids. The restoration and management of microgrid using MAS is discussed in [43]. A hierarchical Energy management system EMS for optimal multi-microgrid MMG operation based on Multi agent system has been developed in [44]. The communication between the agents follows a modified contract net protocol (MCNP). Mixed integer linear programming (MILP) models are developed for each step. Multi-Agent System approach is used in [45] for optimizing a distributed energy management of a microgrid consisting of two solar generators. Java Agent Development Environment (JADE) is used for developing MAS model to achieve cost optimization for power generation under random nature of solar PV system and load. Using this approach enables for a customer to explore all possible logical sequence of options and select the optimal energy management actions to increase operational efficiency in a distributed environment. Multi-layer ant colony optimization-based energy management system for a microgrid is presented in [46]. The main objective is to minimise the power generation cost by hourly day-ahead and real time scheduling. This algorithm tries to satisfy the load demand with minimum energy cost in a local energy market (LEM) structure.

4 Optimal Load Scheduling

In load management, responsive loads are managed at that time when demand is low. To achieve optimal load management, the stochastic nature of load is to be considered. A stochastic model for short term scheduling of microgrid is proposed in [47]. This model considers the uncertainty nature of decision variables with the proposed stochastic variable computational module (SVCM). The Monte-Carlo simulation generates different scenarios, which is further used in SVCM algorithm. This model considerably influences allocation of energy and reserve for units and forced load curtailment. A stochastic programming optimization models with risk neutral and risk averse options is developed in [48]. A genetic algorithm (GA)-based scheduling to minimize both day-a-head and real time adjustment costs is proposed in [49] based on a two-point estimate-based probabilistic real-time optimal power flow. The scheduling problem is formulated as rolling horizon Markov decision process (MDP) in [50]. The feasible base policy is constructed using greedy algorithm.

Economic dispatch of responsive loads is solved by implementing a multi-period artificial bee colony optimization algorithm [46]. An artificial neural network combined with a Markov chain (ANN-MC) approach is used to forecast non-dispatchable power generation and load demand considering uncertainties. The scheduling is improved by including penalties in order to encourage the use of the renewable energy sources and to guarantee a high state of charge in the storage system for the future [51]. Linear models are proposed for the scheduling which are implemented in General Algebraic Modelling System (GAMS). The total energy purchase cost is minimised by a microgrid energy trading model (METM) that coordinates power forecasting and day-ahead trading together to get proper day-ahead trading electric demand in [52].

The excessive loading or generation during Islanding occurs because the power exchange at the point of common coupling is forcedly made zero. probability of successful islanding (PSI) is developed in [53]. PSI calculates the probability of a microgrid maintaining enough spinning reserve (both up and down) to meet local demand and accommodate local renewable generation after instantaneously islanding from the main grid. The time sequential simulation method is applied to optimize material demands of the Islanded Microgrid with Photovoltaic and Energy storage systems (IMPE) [54].

A bi-level optimisation problem is solved in [55]. In the proposed model maximising the distribution company's profit is the upper level objective and the objective of lower level is to reduce microgrid's cost. Another interactive operation strategy for microgrid cooperated with a distribution system based on demand response is proposed in [56]. Relationship between the interaction capacity and interaction cost of microgrid via sensitivity analysis is obtained. In [57] probabilistic constrained approach is used to incorporate the uncertainties of renewable sources and load demands into the unit commitment (UC) and economic dispatch (ED) problems. The UC is solved using stochastic dynamic programming. The optimal power dispatch problem is solved by considering probabilistic behaviours [58]. The power generated by each source and the load connected to each source is represented using probability distribution function (PDF). The power dispatch problem is solved after obtaining PDFs of random variables using imperialist competitive algorithm (ICA).

A hierarchical load management policy is used in [59] while integrating large, populations of heat pumps and electric vehicles into conventional power dispatch system. The proposed method improves the efficiency of the power system both technically and economically. The building thermal mass is used in combination with simple control methods to accommodate large load fluctuations. In [60] load fluctuations are controlled by a self-regulating air-source heat pump (HP) cycling. The power and voltage ramping rates are improved by adapting bus level control. A generalized formulation to determine the optimal operating strategy and cost optimization scheme for a Microgrid (MG) for residential application is proposed in [61]. The proposed problem is formulated as a nonlinear constrained multi-objective optimization problem.

5 Multi-objective Optimization

Multi-objective optimization is a field of multiple basis decision making, related to optimization problems involving one or more objective functions to be optimized simultaneously. In a microgrid power management problem the objective functions and constraints are non-linear in nature. Also, these objective functions are partly incompatible and contradicting. Here the need of introducing pareto optimality arises. When multiple objective functions are optimised simultaneously, the solution obtained may not be optimal but cannot be improved without deteriorating the other, such solution is called pareto optimal solution. The decision maker will select a solution which is more appropriate according to the preferences. The problem can be written mathematically as Equation (3).

$$max/\min F(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \ldots, f_n(\vec{x})] \tag{3}$$

where, $\vec{x} = [x_1, x_2, \ldots, x_n]^T \in R^n$
subject to:

$$G(\vec{x}) \leq 0,\ G = [g_1, g_2, \ldots, g_p]^T$$
$$H(\vec{x}) = 0,\ H = [h_1, h_2, \ldots, h_q]^T$$

where,

- F is the vector containing m objective functions (f_1 to f_m)
- x_r is the vector of variables to be optimized known as the decision variables with an order-*n*
- G represents the vector of inequality constraints with an order-*p*
- H represents the vector of equality constraints with an order-*q*

For defining a multi-objective optimization problem for a microgrid, first step is to define the preferences. The preferences include a number of objectives that are to be met for proper operation of power system, also few non-conventional operations. These preferences depends on the relative importance of the consumer.

A set of intelligent methods assimilate a variety of techniques like heuristic and evolutionary algorithms. They can address many objectives simultaneously with less computational time and derive solution. In [62] an optimization model is proposed, for a microgrid operating in both grid-connected and autonomous mode on a 24-hour time horizon. Two optimization models are suggested: the deterministic model and stochastic model. The deterministic model reduces the operation cost of a microgrid, according to the forecasted electrical power generation from renewable energy sources. The stochastic optimization model accounts for the randomness in renewable energy sources power output based on assigned scenarios occurring probabilities. A multi-objective and multi-constraint optimization methodology is discussed in [63–66]. The demand for robust and faster solutions in power management problem is increasing, as result computationally intelligent methods are used in [63]. To achieve economic and environmental optimization for a stand-alone microgrid, a multi-objective stochastic optimal planning method and a stochastic chance-constrained programming model is presented in [64]. In [65] plug in electric vehicles (PEV) are viewed as a stochastic factor. The objective functions of the problem are voltage security margin to be maximized and the minimization of total power losses, the total electrical energy costs, and the total emissions of power sources.

A bi-level planning method is adapted in [67, 68]. The optimal allocation is done in [67] by bi-level planning taking economic constraints into consideration. At the upper level the objective is to determine the capacity of each power plant by minimising the daily fixed cost of investment (DFCI), load loss probability (LLP), and excess energy rate (EER), with which it determines the capacity of each power supply. Economic dispatch is considered at the lower level, by minimizing the cost of operation and management (COM) and cost of pollutant disposal (CPD), with which it determines the output power of each distributed generator (DG). In [68] two-stage stochastic optimization method is adapted to address the uncertainties in solar generation, loads and EV profiles. A comprehensive cost function is considered and the problem is formulated as a MILP problem. Multi Objective Particle Swarm Optimization (MOPSO) is used for controlling PID controller parameters, dynamic filter/capacitor compensation (DFC) and the Green Power Filter (GPF) AC and DC schemes using real time dynamic self-regulating error tracking is presented in [11]. In MOPSO n number of particles are initialized in the decision space at random. Each particle *i*, has a position x_i with a velocity v_i in the decision space. The particles move towards the best solutions found so far. The non-dominated solutions from the last generations are kept in the archive. The velocity of the particles moving towards optima can be calculated from Equations (4) and (5).

$$V_{id} = \omega V_{id} + C_1\, \mathit{rand}_1(P_{pd} - X_{id}) + C_2\, \mathit{rand}_2(P_{rd} - X_{id}) \tag{4}$$

$$X_{id} = X_{id} + V_{id} \tag{5}$$

where,

- P_{pd}, P_{rd} are guiding positions that are randomly chosen from a single global Pareto archive.
- ω is the inertia factor affecting both local and global abilities of the algorithm.
- V_{id} is the velocity of the particle *i* in the d^{th} dimension.
- C_1 and C_2 are weights affecting the cognitive and social factors respectively.
- rand_1 and rand_2 are two uniform random functions in the range [0, 1].

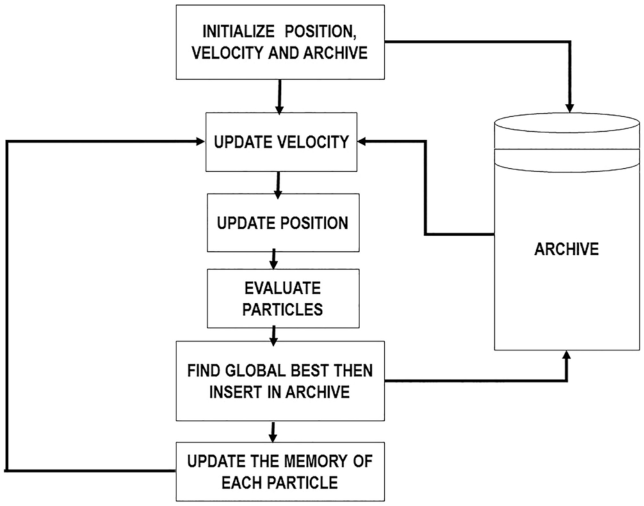

Figure 5 Flow chart of the Multi-Objective Particle Swarm Optimization.

By running MOPSO for multiple iterations a relatively large set of Pareto-optimal trade-off solutions can be obtained. Figure 5 shows the flow chart of the Multi-Objective Particle Swarm Optimization MOPSO. A self-tuned PID interface is used to control the proposed integrated renewable energy scheme. The optimization results show that, to control power transfer from renewable sources to various DC loads in autonomous mode and to the grid in connected mode, MOPSO is very effective and can maintain optimal power quality also.

Multi-agent system along with cooperative game theory are implemented in [69] to solve energy saving power generation dispatch problem. Belief-Desire-Intention (BDI) bus agents are formulated as players and a distributed tree network as the collaboration formation. A pareto optimal operating point is provided by The Nash Bargaining Solution (NBS) for near efficient dispatching of the generated power to the tree configured power network. A multi-criteria decision analysis (MCDA) based approach is presented for scheduling the dispatch in microgrids [70]. Goal attainment programming is used to solve the multi-objective dispatch functional and discrete compromise programming (DCP) is applied as the MCDA technique for ranking the dispatch alternatives each hour for the decision maker (DM). A bio inspired optimization algorithm, Levy-Harmony is proposed in [71] to deal with multiple objectives. A triangular aggregation model is developed to calculate the best value of objectives. A well-balanced accuracy and search velocity are achieved.

6 Conclusion

An extensive survey of optimization of microgrids with distributed renewable energy resources in both grid-connected mode and stand-alone mode is presented in detail. Several optimization methods and intelligent optimization algorithms are explained with their pros and cons. The review carried out gives the reader an idea about the tools and methods equipped by researchers for different objectives like power quality enhancement, energy management, load scheduling and reliability. By combining two or more objectives which are mutually contradicting is framed as a multi-objective optimization problem. The study of multi-objective optimization problems shows superior performance by combining intelligent optimization algorithms with adaptive techniques.

In a more advanced power system configuration, the microgrid will be providing clear economic and environmental benefits. Further research is suggested in developing reliable methods for forecasting the potential reserve available, a network-level response control algorithm based on the distribution-level control etc., Also, intelligent algorithms may integrate with adaptive reinforcement learning to enhance online deep training of microgrids performance in future.

References

[1] Chowdhury, S., and Crossley, P. (2009). *Microgrids and active distribution networks*. The Institution of Engineering and Technology.

[2] Bifano, W. J., Ratajczak, A. F., Bahr, D. M., and Garrett, B. G. (1979). Social and economic impact of solar electricity at schuchuli village. *Solar Technology in Rural Settings: Assessments of Field Experiences*.

[3] Hina Fathima, A. and Palanisamy, K. (2015). Optimization in microgrids with hybrid energy systems A review. *Renewable and Sustainable Energy Reviews* 45, 431–446.

[4] Cobben, J. F. G., Kling, W. L., and Myrzik, J. M. A. (2005). Power quality aspects of a future micro grid. In *Proc. Int. Conf. Future Power Syst.*, 1–5.

[5] Illindala, M. and Venkataramanan, G. (2012). Frequency/sequence selective filters for power quality improvement in a microgrid. *IEEE Trans. Smart Grid*, 3(4), 2039–2047.

[6] Kakigano, H., Miura, Y., and Ise, T. (2010). Low-voltage bipolar-type DC microgrid for super high-quality distribution. *IEEE Trans. Power Electron.*, 25(12), 3066–3075.

[7] Wang, F., Duarte, J. L., and Hendrix, M. A. M. (2011). Grid-interfacing converter systems with enhanced voltage quality for microgrid application concept and implementation. *IEEE Trans. Power Electron.*, 26(12), 3501–3513.

[8] Hassan, M. A. and Abido, M. A. (2011). Optimal design of microgrids in autonomous and grid-connected modes using particle swarm optimization. *IEEE Transactions on Power Electronics* 26(3), 755–769.

[9] Manju, S., Seema, P. N., and Rajendran, Arun (2016). A novel algorithm for power flow management in combined AC/DC microgrid. *1st IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES-2016).*

[10] He, J., Li, Y. W., and Blaabjerg, F. (2013, September). An accurate autonomous islanding microgrid reactive power, imbalance power and harmonic power sharing scheme. In *Energy Conversion Congress and Exposition (ECCE), 2013 IEEE (1337–1343).* IEEE.

[11] Adel, M., Sharaf, Adel, and El-Gammal, A. A. (2010). A novel efficient PSO-self regulating PID controller for hybrid PV-FC-diesel-battery micro grid scheme for village/resort electricity utilization. *IEEE Electrical Power & Energy Conference*.

[12] Sigarchian, Sara Ghaem, Orosz, Matthew S., Hemond, Harry F., and Malmquist, Anders (2016). Optimum design of a hybrid PVCSPLPG microgrid with particle Swarm Optimization technique. *Science Direct Applied Thermal Engineering*, 1031–1036.

[13] Tan, K. T., So, P. L., Chu, Y. C., and Chen, M. Z. Q. (2013). A fexible AC distribution system device for a microgrid. *IEEE Trans. Energy Convers.*, 28(3), 601–610.

[14] Divya. R. Nair, Devi. S, Manjula. G. Nair, and Ilango, K. (2016). Tariff based fuzzy logic controller for active power sharing between microgrid to grid with improved power quality. *IEEE.*

[15] Golsorkhi, Mohammad S. and Lu, Dylan Dah-Chuan (2016). A decentralized control method for islanded microgrids under unbalanced conditions. *IEEE Transactions on Power Delivery*, 31(3), 1112–1121.

[16] Tsikalakis, Antonis G. and Hatziargyriou, Nikos D. (2008). Centralized control for optimizing microgrids operation. *IEEE Transactions on Energy Conversion*, 23(1), 241–248.

[17] Nassar, M. E., and Salama, M. M. A. (2017). A novel branch-based power flow algorithm for islanded AC microgrids. *Electric Power Systems Research*, 146, 51–62.

[18] Huang, C., Weng, S., Yue, D., Deng, S., Xie, J., and Ge, H. (2017). Distributed cooperative control of energy storage units in microgrid based on multi-agent consensus method. *Electric Power Systems Research*, 147, 213–223.

[19] Zhu, Y., Fan, Q., Liu, B., and Wang, T. (2018). An Enhanced Virtual Impedance Optimization Method for Reactive Power Sharing in Microgrids. *IEEE Transactions on Power Electronics*, 33(12), 10390–10402.

[20] Barik, A. K. and Das, D. C. (2018). Expeditious frequency control of solar photovoltaic/biogas/biodiesel generator based isolated renewable microgrid using grasshopper optimisation algorithm. in *IET Renewable Power Generation*, 12(14), 1659–1667.

[21] Moayedi, S. and Davoudi, A. (2017). Unifying distributed dynamic optimization and control of islanded DC microgrids. in *IEEE Transactions on Power Electronics*, 32(3), 2329–2346.

[22] Delfino, F., Rossi, M., Pampararo, F., and Barillari, L. (2016). An Energy Management Platform for Smart Microgrids. In *Intelligent Computing Systems*, (207–225). Springer, Berlin, Heidelberg.

[23] Kiranvishnu, K., and Sireesha, K. (2016). Comparative study of wind speed forecasting techniques. In *Power and Energy Systems: Towards Sustainable Energy (PESTSE), 2016 Biennial International Conference on* (1–6). IEEE.

[24] Zhou, B., Liu, X., Cao, Y., Li, C., Chung, C. Y., and Chan, K. W. (2016). Optimal scheduling of virtual power plant with battery degradation cost. *IET Generation, Transmission & Distribution*, 10(3), 712–725.

[25] Akram, U., Khalid, M., and Shafiq, S. (2017). An innovative hybrid wind-solar and battery-supercapacitor microgrid system—development and optimization. in *IEEE Access*, 5, 25897–25912.

[26] Tomoiaga, B., Chindris, M. D., Sumper, A., and Marzband, M. (2013). The optimization of microgrids operation through a heuristic energy management algorithm. In *Advanced Engineering Forum*, 8–9, (185–194). Trans Tech Publications.

[27] Riar, B., Lee, J., Tosi, A., Duncan, S., Osborne, M., and Howey, D. (2016, June). Energy management of a microgrid: Compensating for the difference between the real and predicted output power of photovoltaics. In *Power Electronics for Distributed Generation Systems (PEDG), 2016 IEEE 7th International Symposium on* (pp. 1–7). IEEE.

[28] Zamani, A. G., Zakariazadeh, A., Jadid, S., and Kazemi, A. (2016). Stochastic operational scheduling of distributed energy resources in a large scale virtual power plant. *International Journal of Electrical Power and Energy Systems*, 82, 608–620.

[29] Chakraborty, S., and Simoes, M. G. (2008). PV-microgrid operational cost minimization by neural forecasting and heuristic optimization. In *Industry Applications Society Annual Meeting, 2008. IAS'08. IEEE* (pp. 1–8). IEEE.

[30] Mohan, V., Suresh, R., Singh, J. G., Ongsakul, W., and Madhu, N. (2017). Microgrid energy management combining sensitivities, interval and probabilistic uncertainties of renewable generation and loads. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, 7(2), 262–270.

[31] De Leone, R., Giovannelli, A., and Pietrini, M. (2016). Optimization of power production and costs in microgrids. *Springer-Verlag Berlin Heidelberg*.

[32] Chen, J. et al. (2018). Optimal sizing for grid-tied microgrids with consideration of joint optimization of planning and operation. in *IEEE Transactions on Sustainable Energy*, 9(1), 237–248.

[33] Radziszewska, W., and Nahorski, Z. (2016). Microgrids and Management of Power. In *Challenging Problems and Solutions in Intelligent Systems* (pp. 161–178). Springer, Cham.

[34] Che, L., Shahidehpour, M., Alabdulwahab, A., and Al-Turki, Y. (2015). Hierarchical coordination of a community microgrid with AC and DC microgrids. *IEEE Transactions on smart grid*, 6(6), 3042–3051.

[35] Rahbar, K., Chai, C. C., and Zhang, R. (2018). Energy cooperation optimization in microgrids with renewable energy integration. in *IEEE Transactions on Smart Grid*, 9(2), 1482–1493.

[36] Kerdphol, T., Qudaih, Y., Watanabe, M., and Mitani, Y. (2016). RBF neural network-based online intelligent management of a battery energy storage system for stand-alone microgrids. *Energy, Sustainability and Society*, 6(1), 5.

[37] Korkas, C. D., Baldi, S., Michailidis, I., and Kosmatopoulos, E. B. (2016). Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. *Applied Energy*, 163, 93–104.

[38] Shen, J., Jiang, C., Liu, Y., and Qian, J. (2016). A microgrid energy management system with demand response for providing grid peak shaving. *Electric Power Components and Systems*, 44(8), 843–852.

[39] Umeozor, E. C.,and Trifkovic, M. (2016). Operational scheduling of microgrids via parametric programming. *Applied Energy*, 180, 672–681.

[40] Kanchev, H., Colas, F., Lazarov, V., and Francois, B. (2014). Emission reduction and economical optimization of an urban microgrid operation including dispatched PV-based active generators. *IEEE Transactions on Sustainable Energy*, 5(4), 1397–1405.

[41] Saravanan, B., Siddharth, Das, Surbhi, Sikri, and Kothari, D. P. (2013). A solution to the unit commitment problem — a review. *Frontiers in Energy*, 7, 223–236.

[42] Liang, H. Z. and Gooi, H. B. (2010). Unit commitment in microgrids by improved genetic algorithm. *IEEE, IEPC*, 842–847.

[43] Boussaada, Zina, Curea, Octavian, Camblong, Haritza, Bellaaj Mrabet, Najiba, and Hacala, Amlie. (2014). Multi-agent systems for the dependability and safety of microgrids. *Springer-Verlag France*.

[44] Bui, V. H., Hussain, A., and Kim, H. M. (2016). A multiagent-based hierarchical energy management strategy for multi-microgrids considering adjustable power and demand response. *IEEE Transactions on Smart Grid*.

[45] Raju, Leo, Rajkumar, Immanuel, and Appaswamy, Kaviya. (2016). Integrated energy management of micro-grid using multi agent system. *IEEE*.

[46] Marzband, M., Yousefnejad, E., Sumper, A., and Dominguez-García, J. L. (2016). Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization. *International Journal of Electrical Power and Energy Systems*, 75, 265–274.

[47] Talari, S., Yazdaninejad, M., and Haghifam, M. R. (2015). Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads. *IET Generation, Transmission and Distribution*, 9(12), 1498–1509.

[48] Farzan, F., Jafari, M. A., Masiello, R., and Lu, Y. (2015). Toward optimal day-ahead scheduling and operation control of microgrids under uncertainty. *IEEE Transactions on Smart Grid*, 6(2), 499–507.

[49] Surender Reddy, S. and Momoh, James A. (2015). Realistic and Transparent Optimum Scheduling Strategy for Hybrid Power System. *IEEE Transactions on Smart Grid*, 6(6), 3114–3125.

[50] Lan, Yu, Guan, Xiaohong, Wu, Jiang. (2016). Rollout strategies for real-time multi-energy scheduling in microgrid with storage system. *IET Gener. Transm. Distrib.*, 10(3), 688–696.

[51] Luna, A. C., Diaz, N. L., Andrade, F., Graells, M., Guerrero, J. M., and Vasquez, J. C. (2015). Economic power dispatch of distributed generators in a grid-connected microgrid. In *Power Electronics and ECCE Asia (ICPE-ECCE Asia), 2015 9th International Conference on* (pp. 1161–1168). IEEE.

[52] Changsong, C., Shanxu, D., Tao, C., Bangyin, L., and Jinjun, Y. (2009). Energy trading model for optimal microgrid scheduling based on genetic algorithm. In *Power Electronics and Motion Control Conference, 2009. IPEMC'09. IEEE 6th International* (pp. 2136–2139). IEEE.

[53] Liua, G., Starke, M., Xiao, B., Zhang, X., and Tomsovic, K. (2017). Microgrid optimal scheduling with chance-constrained islanding capability. *Electric Power Systems Research* 145, 197–206.

[54] Cao, Y., et al. (2016). Parallel algorithms for islanded microgrid with photovoltaic energy storage systems planning optimization problem: Material selection and quantity demand optimization. *Computer Physics Communication*.

[55] Bahramara, S., Parsa Moghaddam, M., and Haghifam, M. R. (2016). A bi-level optimization model for operation of distribution networks with micro-grids. *Elsevier, Electrical Power and Energy Systems* 82, 169–178.

[56] Peng, Feijin, Su, Hongzhi, Li, Peng, Song, Guanyu, and Zhao, Jinli. An interactive operation strategy for microgrid cooperated withdistribution systems based on demand response. *International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*.

[57] Nguyen, T. A. (2014). Optimization in microgrid design and energy management.

[58] Nikmehr, Nima and Ravadanegh, Sajad Najafi. (2016). Reliability evaluation of multi-microgrids considering optimal operation of small scale energy zones under load-generation Uncertainties. *Elsevier, Electrical Power and Energy Systems*, 78, 80–87.

[59] Wang, D., Parkinson, S., Miao, W., Jia, H., Crawford, C., and Djilali, N. (2013). Hierarchical market integration of responsive loads as spinning reserve. *Elsiever, Applied Energy* 104, 229–238.

[60] Williams, Trevor, Wang, Dan, Crawford, Curran, and Djilali, Ned. (2013). Integrating renewable energy using a smart distribution system: Potential of selfregulating demand response. *Elsevier, Renewable Energy*, 52, 46–56.

[61] Mohamed, Faisal A. and Koivo, Heikki N. (2012). Online management genetic algorithms of microgrid for residential application. *Elsevier, Energy Conversion and Management*, 64, 562–568.

[62] Lazaroiu, G. C., Dumbrava, V., Balaban, G., Longo, M., and Zaninelli, D. (2016, June). Stochastic optimization of microgrids with renewable and storage energy systems. In *Environment and Electrical Engineering (EEEIC), 2016 IEEE 16th International Conference on* (pp. 1–5). IEEE.

[63] Colson, C. M., Nehrir, M. H., and Pourmousavi, S. A. (2010). Towards real-time microgrid power management using computational intelligence methods. *IEEE.*

[64] Guo, Li, Liu, Wenjian, Jiao, Bingqi, Hong, Bowen, Wang, Chengshan. (2014). Multi-objective stochastic optimal planning method for stand-alone microgrid system. *IET Gener. Transm. Distrib.*, 8(7), 1263–1273.

[65] Khorramdel, B., Khorramdel, H., Aghaei, J., Heidari, A., and Agelidis, V. G. (2015). Voltage security considerations in optimal operation of BEVs/PHEVs integrated microgrids. *IEEE Transactions on Smart Grid*, 6(4), 1575–1587.

[66] Carpinelli, Guido, Mottola, Fabio, Proto, Daniela, and Russo, Angela. (2016). A multi-objective approach for microgrid scheduling. *IEEE Transactions on Smart Grid*.

[67] Wu, Hongbin, Zhuang, Huaidong, Zhang, Wei, and Ding, Ming. (2016). Optimal allocation of microgrid considering economic dispatch based on hybrid weighted bilevel planning method and algorithm improvement. *Elsevier, Electrical Power and Energy Systems*, 75, 28–37.

[68] Wang, Yubo, Wang, Bin, Zhang, Tianyang, Nazaripouya, Hamidreza, Chu, ChiCheng, and Gadh, Rajit. (2016). Optimal energy management for microgrid with stationary and mobile storages. *IEEE.*

[69] Ren, Qiangguo, Bai, Li, Biswas, Saroj K., and Ferrese, Frank. (2016). Energy saving in Microgrid with Tree Configurations Using Nash Bargaining Solution. *IEEE.*

[70] Panwar, Mayank, Suryanarayanan, Siddharth, and Hovsapian, Rob. (2017). A multi-criteria decision analysis-based approach for dispatch of electric microgrids. *Elseveir, Electrical Power and Energy Systems*, 88.

[71] Li, P., Li, R., Cao, Y., Li, D., and Xie, G. (2018). Multiobjective sizing optimization for island microgrids using a triangular aggregation model and the levy-harmony algorithm. in *IEEE Transactions on Industrial Informatics*, 14(8), 3495–3505.

Biographies

C. Suchetha is a Ph.D. student at Amrita School of Engineering Bangalore, Amrita Vishwa Vidyapeetham, India since August 2016. She has completed BTech in Electrical and Electronics Engineering from SKIT, Jawaharlal Nehru Technological University, Hyderabad, India. She obtained MTech in Power Electronics from RGMCET, Jawaharlal Nehru Technological University, Hyderabad, India. She has worked as an assistant professor from 2007. Her Ph.D work is to improve the operation of Microgrids by using adaptive optimization Techniques.

J. Ramprabhakar currently serves as Assistant Professor (S G) at the department of Electrical & Electronics, Amrita School of Engineering, Bangalore campus. He completed his Ph.D. from Indian Institute of Technology, Gandhinagar. He has 9 years of Teaching Experience, 3 years of Industrial Experience.