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# Bi-Level Optimization of Multi-Microgrids: A Review Considering Demand Response Aggregators

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**Abstract**

The increased penetration of renewable energy sources (RES) and electric vehicles (EVs) in addition to the non- renewable energy sources such as microturbine (MT), combined heat and power (CHP) and diesel generator (DEG) must have a coordinated operation for achieving optimal energy management system (EMS) and operation of microgrids. The demand side management (DSM) can be utilized using demand response program (DRP) becomes essential work to deal with distribution generation (DG) that are integrated with distribution grid to minimize the cost of operation and maximize the profit of microgrids owners (MGO), this can be achieved by exchanging data between MGO and distribution system operator (DSO). The optimal operation of microgrid is subject to various constraints that must not be violated. The complication of the energy management is due to the uncertainties of RES, electricity prices and EVs state of charge (SoC) and arrival/departure time, have to be solved with stochastic based modeling. The demand response aggregator (DRA), electric vehicles aggregator (EVA) and energy storage system (ESS) are important players in microgrid optimization that have to be studied thoroughly as they participate in DSM to modify the load demand pattern. The review assists the authors in finding the latest achievements in microgrids management.

## 1. Introduction

In recent years, by growing load consumption and the force to minimize pollutant emissions. Microgrids (MGs) have increasingly become a hot research subject in distribution networks [1, 2]. They have the ability to transform the existing power grid into the modern smart grid [3]. The microgrid (MG) can be defined as a groups of controllable loads, local dispatchable and non-dispatchable DGs, battery energy storage systems (BESSs) and various types of power electronic equipment as a single controllable unit [4]. MGs can be operated in both grid-connected and islanded modes [5]. From the load point of view, consumers obtain incentives to collaborate with the operator of the MG. Flexible load demands shift or decrease their demands during peak times to guarantee MG reliability through DRP [6, 7]. DRP is the amendment of consumer's demand for energy using different approaches like financial incentives and behavioral change through education [8]. Two types of DRP including price-based demand response (PBDR) and incentive-based demand response (IBDR) are used for peak shaving [9, 10]. The use of DRP in MG can minimize price volatility [11]. Moreover, with rising environmental worries all over the world, conventional internal combustion engine (ICE) based vehicles are gradually being substituted by plug-in electric/plug-in hybrid electric vehicles (PHEV) [12]. The existence of the PHEVs presents a novel type of load demand. The growing integration of EVs in distribution networks has also contributed to the development of MGs because of the suitable power dispatch of the vehicle to grid (V2G) mode, which allows two-way power flow between EVs and MGs [13]. The optimal operation of MGs is one of the main challenges that needs to be resolved before they become commonplace [14]. In other words, the management of several renewable and non-renewable sources to supply loads with high reliability and low cost is a very challenging issue. This review assists the authors to find the latest achievements in microgrids management.

## 2. Demand Side Management (DSM)

The modern DSM using both of the consumer electricity prices and the power generation ruled by a contract between the supply side and demand side to switch the load smartly, the objective is to modify load curve to be flattened [17]. The balance between the generated power and the consumer load varying must be kept in all times of operation, for this and to get a good response from the consumer incentives are offered to the consumer to be an active partner in achieving the balance of power. In energy management there must be data exchange between the supply and consumer, the consumer can participate in DSM in three ways [16]. One of the most preferable to be implemented as a DSM program is the peak shifting, which is shifting a percentage of the consumed load from peak load time to off peak load time. Much literature has studied optimization programs to implement peak shifting. In [19] peak shifting is implemented using hybrid approximate dynamic programming. In [18] a technique of a two stage DADR with two players consumer centric and utility centric and the appliances scheduling is decided by CC-DADR based on the smart home measurements depending on appliance adjustment factor and appliances index factor and if CC-DADR is failed in reducing the demand to the scheduled level of load which is decided by the utility a penalty will be paid by the utility for consumer sacrificing. For minimizing the power system transmission losses and improving the reliability of the electricity supply DG near the consumer is of great benefit for both of the consumer and the utility and can support DSM. The different DSM implementations have been tabulated in Table 1.

**Table 1** *Demand response*

| Ref. No. | DRP | Optimization Objectives | Type of Control | Type of Load |
|---|---|---|---|---|
| [15] | IBDR | Profit of shared energy storage provider, User level social Cost | Centralized | Residential |
| [22] | RTP | Profit, Investment | Decentralized | Commercial, Industrial |
| [16] | RTP, IBDR | PAR, Average waiting time, Cost with user comfort | Decentralized | Residential |
| [20] | DLC | PAR, Dissatisfaction level at user end | Centralized, Decentralized | University campus |
| [21] | RTP | Peak demand, Electricity bills | Centralized, decentralized | Residential |

## 3. Microgrid Energy Management

The implementation of the microgrids have to address two main aspects, the first one is energy management, and the second one is the control [23]. Energy storage systems such as batteries are widely used because of high energy density and do not need a lot of maintenance. EVs are utilized with RESs in MGs as they have a major effect to improve the cost, minimizing the utilization of thermal generation plants, load curve shifting and increasing of using the RESs [24]. In [25] showed the multiple features of EVs for the point of view of economic. Energy management must optimize the distribution of energy, which is modelled as objective functions subject to constraints such as voltage, frequency and power flow and these are the variables of the control aspect [26]. The microgrid energy management optimization modelling may be of single objective or multiple objectives, for the single objective optimization functions the cost is frequently taken which includes cost of buying electricity, cost of fuel, cost of maintenance and operation, cost of energy storage systems, cost of investment, cost of components, cost of exchanging of power, cost of cost of reserve, cost of load curtailment, cost of commitment, cost of consumer comfort violation, cost of energy not supplied, cost of electric vehicles charging /discharging, transmission losses cost and cost of incentive consumer, Table 2 summarize the researches that studied a single objective problem. Optimization problems of power system are complex which needs a multi-objective modelling to solve such problems, researchers in literature who studied the multi-objective problems considered two or more of other objectives with or without cost objective such as the pollution of environment, losses of power, voltage profile, expectation of load loss, reliability, peak shaving, sizes of PV/WT and efficiency. Table 3 summarize the literatures of multi-objective problems.

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**Table 2** *single objective optimization*

| Ref. No. | Objective Function |
|---|---|
| [27] | Cost |
| [28] | Losses |
| [29] | Operation Quality |
| [30] | Frequency |
| [37] | Voltage |
| [38] | Smooth Transition |
| [40] | Charging/Discharging |

Table 3 summarizes the literature of multi-objective problems.

**Table 3** M*ulti objective optimization*

| Ref. No. | Objective Functions |
|---|---|
| [34] | Cost, Adequacy |
| [41] | Cost, Losses, Voltage, Security, Peak Shaving |
| [35] | Losses, Reliability |
| [36] | Voltage, Frequency |
| [39] | Frequency, Power Sharing |

## 4. Microgrid Construction

The enhancement of electrical apparatuses and new technology used in manufacturing power system equipment which includes the generation, transmission, distribution and loads alongside with microgrids equipment of new features that are integrated with the main grid of power system, this leads to different microgrids configurations be used. The microgrids components are the resources, load, energy storage system and electric vehicles, the most important part of the electrical power system is the resources, they may be classified as conventional and renewable sources or may be classified as dispatchable and non - dispatchable resources. Generally, the resources must be studied from different aspects such as the fuel consumption, carbon emission, operational cost, efficiency, reliability and investment cost. The diesel generator and microturbine which are of conventional resources are still used in large percentage among the other conventional resources whereas the PV and WT are used more than other renewable resources due to low cost, but they have the uncertain nature because the depend on irradiance and wind speed which they are uncertain. Table 4 presents the research that are included different types of resources. In DR program the load is the main player to achieve the energy management in microgrid, in this concept at peak load time the consumer is shifting their consumption to the off- peak time and this issue is ruled by a contract between the consumer and the microgrid owner. There are three major groups of loads, consumption, important and responsive. Types of loads is presented in Table 5. EV aggregators (EVAs) have been implemented to control the charging/discharging of EVs based on the analysis of the Vehicle to Grid (V2G) capabilities Table 6 presents energy storage systems used in research.

**Table 6** *List of topic in energy storage system*

| *Types of Sources* | | *Types of Loads* | | *Energy Storage* | |
|---|---|---|---|---|---|
| Ref. No. | Resources | Ref. No. | Loads | Ref. No. | Energy Storage |
| [27] | DEG, FC, PV, WT, CH | [26] | RE, NCR, NRL | [27] | BESS |
| [40] | PV, WT | [34] | RE, NCR, RL | [34] | BESS, HCES |
| | | [32] | RE, NCR, RL | [31] | BESS, $H_2S$ |
| | | [33] | CO, NRL | | |

## 5. Bi-level Optimization

Bi-level optimization is a multi- follower problem where the constraints of the upper level or leader include another optimization problem of the lower level or follower, the solution of the bi-level optimization problem can be of two types: classical methods and evolutionary methods. Table 7 show the divisions and sub-divisions of bi-level optimization solutions with [41] with research that implemented these methods for solving the bi-level problems. In bi- level optimization problems each level is affecting the other level despite that the objective function of each level is optimized by its own level independently [42], in this research a bi- level optimization model is implemented to solve the studying of performance optimization of a multi decision maker in a smart distribution network that consists of three players with win-win game. Table 8 presents the implementation of bi-level for optimizing MGs in literature. The DSO is the major player in power system distribution, it is optimizing the maintenance and operation and planning of the distribution grid [50]. In unidirectional or conventional distribution grid which has the power flow from the generation plants to the consumers i.e the power is flowing in only one direction, the DSO is buying the energy from the supplier and sell it to the consumer On integrating of DERs which consists of RES, DGs and ESSs to compose a grid connected MGs there was a need to use communication facilities in distribution grid, the DSO tasks have widely expanded because the energy flow can be bidirectional as the consumer can be supplied from the MGs and there is an energy exchange between the distribution grid and MGs. The DSO tries to optimize its cost of operation and buying energy from the energy supplier and also the DSO optimize the energy exchange between the other actors such as microgrid owner (MGO), demand response aggregator (DRA) and Electric vehicles aggregator (EVA). For enhancing the performance of DR program and increasing the effectiveness of the DR program, the DRA popped up as one of the actors of the SDN which tries to optimize its profit by exchanging data with DSO and controllable consumers to submit bids to DSO to sell/buy electricity in higher /lower price respectively [51]. The EVA is a connecting link between the DSO and EVs, it estimates SoC of EVs and offer energy to participate in electricity market. The EVA contributes in day ahead (DA) of energy scheduling and inform the EV owner (EVO) the energy prices to optimize the profit. In [52] various methods that are suggesting enhancing the decision -making of EVA for participating in electricity market. In[53] a stochastic optimization algorithm bidding model of EVA is designed to participate in DR and reserve markets. In [54] the impact of V2G features is addressed by implementing a stochastic EVA model for exchanging of energy and the reaction to the stochastic equilibrium is designed. Since the EVA can compensate the stochastic behaviour of renewables or load forecasting errors, a cooperative game model has been presented in [55] to capture the interactions between utilities and parking lots in the spinning reserve market, considering the V2G scenario. EVA could also form a non-cooperative game where they try to maximize their own profit in a competitive environment. EVA is a bi-level optimization problem which consists of two levels. The upper level is EVA trying to optimize its profit from exchanging energy in DA market. The lower level is represented by the EVOs which try to buy the energy from EVA or other rivals in optimum price. The complexity of the decision-making problem is because of the uncertainty in DA and balancing market prices and EVs' demand. Actually, EVA buy energy from DSO and sell it to the EVO to optimize its profit. EVA has to offer electricity prices to retain EVOs from changing to other EVAs with a reasonable profit.

**Table 7** *Bi- level optimization methods*

| I. Classical | | | | II. Evolutionary | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| (a) | (b) | (c) | (d) | (A) | (B) | (C) Meta-modelling – based Methods | | | |
| Single Level Redu-ction | Descent Method | Penalty Function Method | Trust - region Method | Nested Method | Single -level Redu-ction | (1) Reaction Set Mapping | (2) Optimal Lower - level Value Function | (3) By passing Lower-level Problem | (4) Auxiliary bi-level Meta-model |
| [56], [57]. [58], [59] | [60], [61] | [62], [73], [74] | [63], [64] | [65], [66], [67], | [68], [69], [70] | [71] | [72] | | |

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**Table 8** *Bi-level optimization of MGs*

| Ref. No. | Leader | Leader Optimization | Followers | Followers Optimization | Application |
|---|---|---|---|---|---|
| [67][43] | Electricity/ Natural gas HUBs | Deviation of final schedule of hubs, forced load shedding | DSO | Limitations of power/gas shortage during emergency conditions | 69- bus electricity network, 14-node gas network |
| [44] | EMS | Cost | MGs | Cost | Two MG system |
| [45] | MG | Operation cost, carbon trading cost | MG | Operation cost, carbon trading cost | MMG system |
| [46] | DSO | Cost | PLO | Profit | IEEE-15 bus |
| [47] | MG Planner/ designer | Investment, emission cost | EMS | Cost | Typical MG |
| [48] | DSO | profit | MGs | Cost | Market structure |
| [49] | DSO | Profit | DGO | Cost | Market structure |
| [50] | Transmission planner | Investment cost | Pool trading | Social welfare | Garver's six-bus test system. |

## 6. Conclusion

MGs are the greatest solution to integrate renewable energy resources in power systems for technical, economic and environmental reasons. With the fast integration of renewable energy resources, the number of MGs in the power system has been considerably increased consequently, the optimal management of each MG, interaction and energy exchange among various MGs is a serious challenge. The benefit maximization for MG systems is an important issue because of numerous sophisticated factors comprising the stochastic nature of renewable energy resources (photovoltaic and wind turbine), random behavior of loads and time-varying electricity prices. The use of EVs and storage systems in MGs has presented an unprecedented complexity into the energy supply system because of the uncertain nature of these vehicles. The uncertainty of arrival and departure times, as well as the state of charge (SOC) in the arrival and departure of the EVs, is a big challenge in the entry of such vehicles and their facilities into energy networks. With high integration of MGs in distribution networks as independent entities are added into distribution networks MGs are in charge of scheduling their DERs, storages and etc. with considering several objectives such as minimizing their operating costs, maximizing their benefits and enhancing resiliency. In addition, with the development of new technologies such as DR and EVs, the role of load demands is altered from unresponsive consumers towards more active participants in the system operation. For achieving the highest advantages from the mentioned privileges and enabling the interaction between end-users and the system, the existence of aggregating entities is needed. DRA and EVA act as a connector between the system and some consumers and pursues particular objectives. Reviewing the recently published papers show that DR and EVs are taken into account as a dependent tool by the Distribution System Operators (DSO) and their financial considerations are not considered. Moreover, some limited papers have introduced the DRA and EVA concepts for providing financial identity. With the introduction of such aggregators, DSOs are faced with many problems in case energy management and scheduling. Recent published papers have shown that the optimal operation of MGs in the presence of such entities with various functions has not been studied so far. DSO needs to trade with such kinds of actors in an effective and economic way. Therefore, it is needed to propose an effective method to coordinate the DSO and various aggregators in MGs and achieve win-win conditions among all contributors to the distribution network. A review of recent papers also shows that various uncertainty modelling can be used for the MGs. Scenario-based approach is commonly applied for uncertainty modelling of MGs. This method leads to an expensive solution process owing to all the variables are multidimensional, having the equal size to the number of scenarios generated. Furthermore, this approach needs a priori knowledge about the probability functions of uncertain parameters. Other references, however, proposed robust optimization, which normally needs complex formulations or multi-stage processes that could provoke intractability issues as well.

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## Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

## Author Contribution

*The authors confirm contribution to the paper as follows:* ***study conception and design:*** *Adel R. O, Ziyodulla Y. Muhammet T. G.;* ***data collection:*** *Adel R. O, Ziyodulla Y. Muhammet T. G;* ***analysis and interpretation of results:*** *Adel R. O, Author Ziyodulla Y. Muhammet T. G;* ***draft manuscript preparation:*** *Adel R. O, Ziyodulla Y. Muhammet T. G. All authors reviewed the results and approved the final version of the manuscript.*

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