# Optimal Operational Management of Open-Market Community Microgrids

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# Optimal Planning and Operational Management of Open-Market Community Microgrids

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**Abstract**

In this article, a new business model comprising multiple stakeholders is proposed to develop a frame for future flexible retail energy market in community microgrids. The microgrid comprises multiple and different distributed energy resources (DERs) such as renewable generation units, battery energy storage systems (BESSs), and micro diesel engines (MDE), to minimize daily operational costs of the system. To solve the defined complex optimization model, some operational strategies are proposed and then genetic algorithm is adopted to determine the hourly optimal power dispatch. The case study shows that the proposed model minimizes the daily operating cost of the community system effectively.

*Keywords:* Artificial intelligence; battery energy storage system; genetic algorithm; microgrids; renewables;

## 1. Introduction

The increasing global energy crisis, greenhouse gas emission, and limiting conventional energy resources are proliferating the integration of renewables in modern power systems. Furthermore, the huge investment and right-of-way problems of high voltage transmission lines in vertically integrated traditional power system have prompted restructuring and deregulation of modern power industry. Nowadays, various distributed energy resources (DERs) are integrated into distribution systems in order to achieve various techno-economic and social benefits. The commonly accepted DERs can include distributed generations (DGs), battery energy storage systems (BESSs), electric vehicles, superconducting magnetic energy storage systems etc. The optimal integration of DERs minimizes power/energy loss [1, 2, 3], emission [4, 5], node voltage deviation [2, 3], cost of network up-gradation, investment and various operating costs while improving reliability [6] and stability [1, 2, 3] of the system.

The growing interest in renewables, controllable loads & switches, and BESSs along with several advancements in information and communication technologies have led to the concept of microgrid. The microgrids can be designed, with the inclusion of local available energy resources, in order to improve the efficiency, reliability and resiliency of distribution systems [7, 8]. The increasing possibilities of revenue generation from microgrids, beyond reliability and resiliency, is contributing to the rise of third-party and mixed-ownership models in distribution systems. The electricity regulators from all across the globe are promoting the mixed models while ensuring that the electricity retail market works in the interests of consumers [9]. Generally, they are doing this by monitoring the market and, where necessary, taking action to strengthen healthy competition or enforce the rules with which suppliers must comply. These models have prompted the growth of prosumers (producer and consumer) in community microgrids in which consumers can also participate into retail electricity markets in order to optimize their energy bills.

In literature, various community microgrid models [7, 10, 11] and optimization frameworks [8, 12, 13] have been developed, aiming to maximize the techno-economic benefits of different stakeholders. Some energy prosumers based business models are also developed [14]. In order to optimize the local energy generation among consumers, some peer-to-peer energy trading models are also suggested in [15, 16, 17, 18]. Generally, various planning and operation management models have been proposed in existing literature assuming that initial investments are done either by utilities/consumer or sometimes third parties. However, a combined business model of community microgrid retail energy market, comprised of multiple stakeholders facilitating time of use (ToU), feed-in tariff (FIT), and fixed price (FP) has to be investigated.

In this paper, a new optimization framework is developed for optimal planning and operational management of community microgrids. Multiple DERs, managed by different stakeholders, has been considered such as roof-top solar panels (RSPs), BESSs, and MDE, to minimize daily operating costs of community microgrid. A combined model considering ToU, FITs and FPs is proposed in which each DER owner will sell the power to community microgrid either on FP, FIT, or as per the ToU. In this open market model, each customer would have an opportunity of cost effective and reliable supplier selection. To solve the proposed complex optimization model, genetic algorithm (GA) is adopted to determine the hourly optimal supplier selection followed by power dispatch. The case study shows that the proposed model minimizes the daily operating cost of the community system effectively while maximizing the benefits of multiple stakeholders.

## 2. Proposed optimization framework for retail energy market in community microgrids

In the existing deregulated environment of the power systems, the direct involvement of power consumers is rather limited due to technical and economic barriers. Generally, distribution network operators (DNOs) are the primary energy distributors therefore most end users have no sight on the actual Distribution Use of System (DUoS) and incurred costs are not reflected in electricity bills. The Office of gas and electricity market (Ofgem) in the UK is facilitating the openness of retail electricity market by introducing competitions [9]. Each customer has freedom of switching energy supplier as per the individuals' requirements and costs.

In the proposed community microgrid model, some of the ongoing policies of Ofgem, UK are adopted. The regulatory framework allows multiple stakeholders to participate in community based retail electricity markets by investing in different DERs such as RSPs, MDE and BESSs. A sample prototype of proposed model is shown in Fig. 1. Each DER owner and grid are selling energy to the community under one of the tariff structures among ToU, FITs and FPs. The smart energy management systems (SEMSs) deployed in each house has opportunity of switchover to any supplier as per the customer need and economics. All the SEMSs are having access to real-time or ToU energy price of utility. Similarly, the BESS owner is also having the option to charge the battery either from grid or RSPs based on the availability and tariffs. The objective of proposed model is to minimize the operating cost of residential

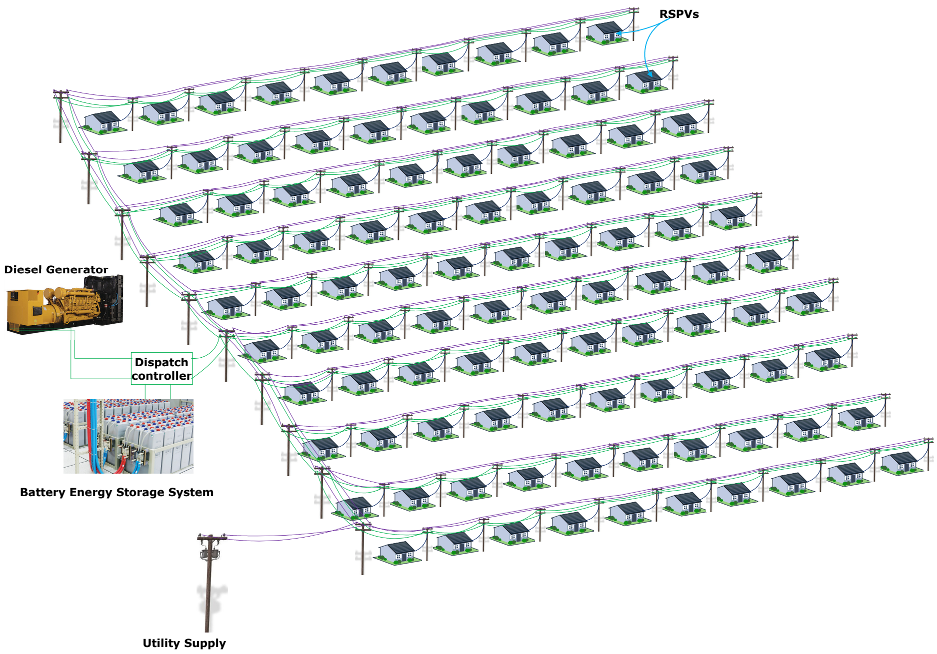


Figure 1: Prototype of proposed community microgrid

community microgrids for a time-frame $T$, can be expressed as

$$F = \sum_{t=1}^{T} \left[\alpha(t)C_{grid}(t) + \beta(t)C_{der}(t)\right] \tag{1}$$

where,

$$C_{der}(t) = \gamma(t)C_{rsp}(t) + \xi(t)C_{bess}(t) + \chi(t)C_{de}(t) \tag{2}$$

*subjected to*:

$$p_{grid}(t) = \sum_{i=1}^{n_H} p_i^d(t) - p_{rsp}(t) + p_{bess}^{ch/disch}(t) - p_{de}(t) \qquad \forall\ t \tag{3}$$

$$0 \leq p_{de}(t) \leq p_{de}^{rat} \qquad \forall\ t \tag{4}$$

$$p_{bess}^{disch}(t) \leq p_{bess}(t) \leq p_{bess}^{ch}(t) \qquad \forall\ t \tag{5}$$

$$\underline{E} \leq E(t) \leq \overline{E} \qquad \forall\ t \tag{6}$$

$$E(t) = E(t-1) + \eta_{bess} p_{bess}^{ch/disch}(t) \Big/ W_{bess} \qquad \forall\ t \tag{7}$$

Equations (3)–(7) are expressing the power balance, diesel generator limits, BESS charging/discharging limits, SOC limits, and SOC balance constraints respectively. where, $C_{grid}(t)$, $C_{rsp}(t)$, $C_{bess}(t)$, and $C_{de}(t)$ are representing the cost of power purchase from utility grid, RSP, BESS, and MDE respectively at time $t$. $\alpha(t)$, $\beta(t)$, $\gamma(t)$, $\xi(t)$, and $\chi(t)$ are the binary decision variables of power transaction from grid, microgrid, RSPs, BESS, and MDE respectively at time $t$. Here, $p_i^d(t)$, $p_{rsp}(t)$, $p_{de}(t)$, $p_{bess}(t)$, $p_{bess}^{ch/disch}(t)$, and $E(t)$ are denoting the power demand of $i$th house, dispatch of RSPs, MDE, BESS, available limits of BESS dispatch, and available SOC at time $t$ respectively. The parameters $p_{de}^{rat}$, $\underline{E}$, $\overline{E}$, $\eta_{bess}$, $W_{bess}$, and $n_H$, are the rated capacity of MDE, minimum & maximum SOC limits of BESS, efficiency & rated capacity of BESS, and total number of houses in community respectively.

### 2.1. *Cost of power purchase from main-grid*

Traditionally, the utility grid is found to be the main source of power supply to the communities. The proposed residential community is also fed by a common distribution transformer. The cost of power purchase from the grid is expressed as

$$C_{grid}(t) = p_{grid}(t) \times e_{grid}(t) \tag{8}$$

here, $p_{grid}(t)$ and $e_{grid}(t)$ are denoting the power transaction and its price at time $t$ respectively.

### 2.2. *Cost of power purchase from diesel generator*

The diesel or gas generators are considered as one of the alternatives during power outages, in-spite of high emission and running costs. However, it requires a small space and cost of installation with high ramp rate. Therefore, one MDE is also considered in proposed model and its running cost is expressed as

$$C_{de}(t) = (a_0.p_{de}^{rat} + a_1.p_{de}(t)) \times e_{de} \tag{9}$$

where, $a_0$, $a_1$, and $e_{de}$ are the intercept coefficient of fuel curve (units/hr/kW), slop of fuel curve (units/hr/kW), and per-unit diesel price respectively. The fuel price will vary with amount of power dispatch.

### 2.3. *Cost of power purchase from roof-top solar photovoltaics*

In proposed schemes, the RSPs are being deployed on the roofs under some agreements between house owner(s) and investors. A long-term FITs plans are adopted for RSPs, cheaper than the utility grids [19]. The cost of power purchase from RSPs is expressed as

$$C_{rsp}(t) = p_{rsp}(t) \times e_{rsp} \tag{10}$$

$$p_{rsp}(t) = \begin{cases} p_{rsp}^{rat} & \text{if } s(t) \geq s_{rat} \\ p_{rsp}^{rat} . \frac{s(t)}{s_{rat}} & \text{if } s(t) < s_{rat} \end{cases} \tag{11}$$

here, $e_{rsp}$, $p_{rsp}^{rat}$, $s(t)$, $s_{rat}$ are the price of per unit power purchase from RSPs, rated capacity of RSPs, solar irradiation at time '$t$' and rated solar irradiation of RSPs respectively.

### 2.4. *Cost of power purchase from battery energy storage systems*

The optimal deployments and operational management may generate enormous amount of benefits for utilities, consumers, BESS owners [20, 21]. In proposed model, BESS is also assumed to be deployed by third-party who sells power to community microgrids under FP contract subjected to SOC availability. The cost of power purchase from BESS is defined as

$$C_{bess}(t) = p_{bess}(t) \times e_{bess} \tag{12}$$

The optimal dispatch of BESS, $p_{bess}(t)$ is determined in each hour between available, $p_{bess}^{ch}(t)$ and discharging, $p_{bess}^{disch}(t)$ energy limits, as suggested by [20] and, expressed in (13) and (14) respectively.

$$p_{bess}^{ch}(t) = \begin{cases} 0 & \text{if } E(t) = \overline{E} \\ \overline{p_{bess}} & \text{if } E(t) + \frac{\eta_{bess}\overline{p_{bess}}}{W_{bess}} \leq \overline{E} \\ (\overline{E} - E(t)).W_{bess} & \text{if } \overline{E} - E(t) < \frac{\eta_{bess}\overline{p_{bess}}}{W_{bess}} \end{cases} \tag{13}$$

$$p_{bess}^{disch}(t) = \begin{cases} 0 & \text{if } E(t) \leq \underline{E} \\ -\underline{p_{bess}} & \text{if } E(t) - \frac{\eta_{bess}\underline{p_{bess}}}{W_{bess}} \geq \underline{E} \\ -(E(t) - \underline{E}).W_{bess} & \text{if } E(t) - \underline{E} < \frac{\eta_{bess}\underline{p_{bess}}}{W_{bess}} \end{cases} \tag{14}$$

where, $e_{bess}(t)$, $\overline{p_{bess}}$ and $\underline{p_{bess}}$ is the cost of power purchased from BESSs in $t$th hour, maximum charging and discharging power limits of BESS or converter in an hour respectively.

## 3. Genetic algorithm

In order to solve the proposed optimization framework, developed in Section 2, a powerful optimization method is required therefore genetic algorithm (GA) is adopted. It has strong exploration ability to search the global optimal solution for real-life engineering optimization problems [8, 20, 21, 22]. The optimization variables considered in this model are optimized in each hour. These can include $\alpha(t)$, $\beta(t)$, $\gamma(t)$, $\xi(t)$, $\chi(t)$, $p_{bess}(t)$, $p_{de}(t)$, and $p_{grid}(t)$. The structure of individual adopted in proposed GA is shown in Fig. 2. The flowchart of proposed approach is also shown in Fig. 3.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\alpha(t)$ | $\beta(t)$ | $\gamma(t)$ | $\xi(t)$ | $\chi(t)$ | $p_{bess}(t)$ | $p_{de}(t)$ | $p_{grid}(t)$ |

Figure 2: Structure of an individual adopted in genetic algorithm

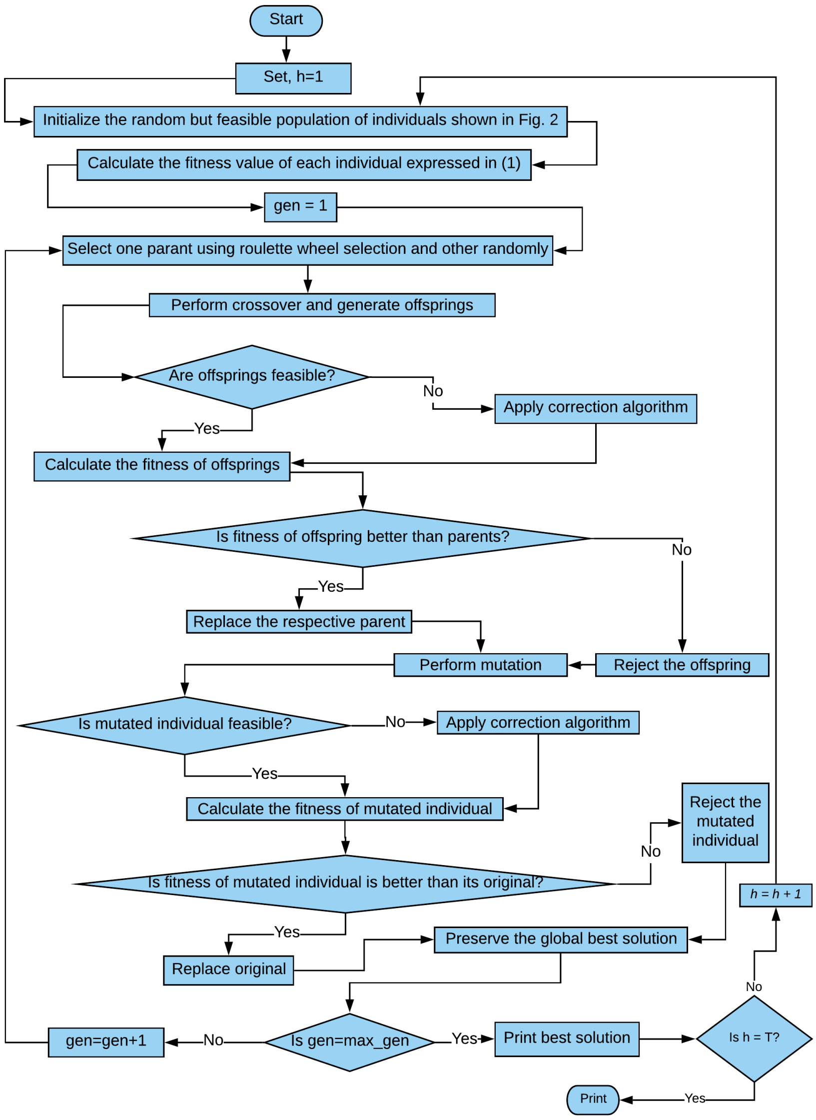


Figure 3: Flowchart of proposed genetic algorithm based optimization model

## 4. Case study

In this study, the demand profile of a residential community with $n_H$=100 houses are considered. The fuel curve characteristic of MDE and hourly multiplying factors of load demand, solar power generation and energy pricing are shown in Fig. 4. The various parameters considered in this case study are as follows: peak demand or total sanctioned load of the community=690kW, diesel price=1.20£/L, intercept coefficient of fuel curve of MDE, $a_0$=0.032L/hr/kW, slop of fuel curve of MDE, $a_1$=0.242L/hr/kW, rated capacity of MDE=100kW, diesel density in UK, $\rho_{fuel}$=832 g/L, average net lower heating value of the diesel, $LHV_{fuel}$=42.6(MJ/kg), rated capacity of RSPs=250kW, rated capacity of BESSs =200kWh, energy price of RSPs=3.93(p/kWh), energy price of BESS, =13.49(p/kWh), maximum charging/discharging of BESS in an hour, $\overline{p_{bess}}/\underline{p_{bess}}$=50/30kW.

Now, the proposed optimization framework developed in Section 2 is solved by using the genetic algorithm presented in Section 3. The simulation results obtained are presented in Table 1. The table shows the optimal values of

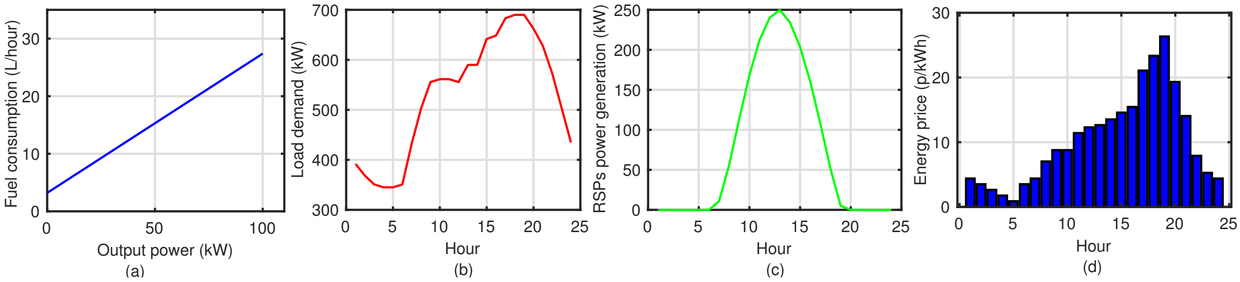


Figure 4: (a) Fuel characteristic of MDE and hourly multiplying factor of (b) load demand (c) solar power generation (d) energy price

optimization parameters such as status of switches along dispatch of MDE and BESS. It can be observed that battery owner charges the BESS either in light load hours or high PV generation. Due to high running charges, community purchases MDE power in peak load hours only, i.e., 17:00 to 20:00. As observed from (9), the MDE requires a minimum running charges of $a_0.p_{de}^{rat} \times e_{de}$=3.84£, even at zero power generation in each hour. The MDE's electrical energy calculated at rated generation is found to be $n_{de}$=37.07% though, the alternator efficiency is = 92.5%. The daily revenue collections by different stakeholders is presented in Table 2. It shows that each stakeholder is able to generate daily revenue by adopting this model. As per the available data and information, the community would be able to save 57.95 £ on each day which roughly estimated to be 21151£/annual at no initial investment.

Table 1: Optimal status of switches and dispatch of community microgrid using proposed retail electricity market

| Hours→ Variables↓ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha \rightarrow$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $\beta \rightarrow$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $\gamma \rightarrow$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $\xi \rightarrow$ | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |
| $p_{bess}$(kW) | -13 | -4 | 0 | -3 | 0 | -44 | 0 | -43 | -30 | 0 | -20 | -14 | 0 | 24 | 30 | 29 | 24 | 26 | 26 | 34 | 0 | -3 | -15 | 0 |
| $\chi \rightarrow$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| $p_{de}$(kW) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 98 | 100 | 100 | 100 | 0 | 0 | 0 | 0 |

Table 2: Daily revenue generation of each stakeholder and profit of the community

| Owner(s) | Revenue before planning (£) | Revenue after planning (£) | Profit of Community (£) |
|---|---|---|---|
| Utility | 1487.30 | 1124.30 | 57.93 |
| MDE owner | – | 207.74 | |
| RSPs owner | – | 71.29 | |
| BESS owner | – | 26.04 | |

## 5. Conclusions

In order to facilitate the competition in power retail with transparent DUoS of distributors, a novel business model is developed in this paper. Under the proposed framework, multiple power suppliers/sellers are placed in front of each customer in-spite of the requirement of additional network assets such as conductors and other equipment. Nevertheless, in the long run, it is beneficiary and necessary at a residential community level, which can avoid a blanket upgrade of the whole network with reduced operational complexity. The proposed study considers some realistic models and ongoing policies of Ofgem, UK, to promote fair third-party involvement in UK distribution systems and to improve customer services and system efficiency. The proposed model is expected to increase the operational and billing flexibility of modern power consumers in a fully deregulated power market. One of the promising feature of proposed model is that it does not require initial investment from customers and help in smart grid policies implementation.

In future, the model can be extended for long-term planning analysis of DERs and EVs owned by different stakeholders. A multiobjective optimization framework may be developed to determine the optimal profit sharing in all stakeholders.

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