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Flexibility of Microgrids with Energy Management Systems

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1 Introduction

In recent years, approaches towards energy transition and sustainable development have been ever-increasing due to the need for mitigating climate change issues and the efficient utilization of existed energy resources. With this regard, state-of-the-art technologies and infrastructures along with active operation and control of different energy resources would become crucial. Amongst all energy resources, microgrids (MGs) are believed to be one of the highly potent resources to deal with the issues of electrical systems. In other words, active operation and control of MGs in which there exist different kinds of demands and energy resources (e.g. energy storages, micro-generation units, etc.) would be beneficial not only for MG stakeholders in terms of cost-benefit efficiency but also for power system operators in terms of MGs' contribution to grid's flexibility.

In order to unlock the active utilization of MGs, cutting-edge technologies along with efficient infrastructure are a necessity. These technologies together in communication with the MGs' energy resources are known as energy management system (EMS). EMSs are intelligent automated systems that contribute to, for instance, lowering/shifting energy consumption in critical moments along with a reduction in the MGs' costs. Although the utilization of EMS might consider other objectives such as CO_2 emission reduction or self-sufficiency, they mostly employ optimization techniques either as single-objective or multi-objective approaches. EMSs can also enable either the bidirectional energy exchange with the network in grid-connected mode, or stand-alone operation of MGs in islanded-mode.

In this chapter, the focus of the study is on the MGs equipped with EMS. There have been introduced several approaches to the energy management of MGs. However, in most of them, economic aspects, i.e. cost reduction, are the top priority desire of the problem from the MG stakeholders' point of view. This could be done in different ways. On the one hand, reducing the total costs of the MGs by maximum utilization of self-production facilities (PV panels, wind turbines, etc.) as well as changing the energy consumption over time from peak hours to off-peak hours during the day. On the other hand, exploiting MGs' flexibility so as to help the upstream grid in critical moments for monetary profits in return. Accordingly, the authors first present an introduction to flexible energy resources (FERs) in MG along with their characteristics in Section 2. Afterward, the MGEM modeling approaches are widely presented in Section 3. In this section, first, the different kind of management method deployed in the MGs are illustrated. Then, various objectives for energy management in MGs will be introduced. Regarding this section, we introduce a number of approaches based on well-known optimization algorithms considering different MG-related as well as grid-related constraints. Microgrids' constraints are related to the physics and limitations of the MG's resources whilst the constraints of the grid are related to the limitation of energy exchange with the upstream grid (e.g. congestion management, emission reduction and/or energy loss reduction). Moreover, the application of the MGEM system in MGs with FERs such as energy storages, electric vehicles (EVs), and thermostatically controllable loads (TCLs) which exchange energy and flexibility with the grid will be discussed as well which is followed by the flexibility services that MGs could provide to the different levels of power system. Finally, the chapter will be summarized and concluded in Section 4.

2 FLEXIBLE ENERGY RESOURCES IN MICROGRID

There could be various types of energy sources in MGs. They might be supplied by either fossil fuels or renewable sources such as wind, solar, etc. [1]. Fig. 1 depicts the most common energy resources in MGs. In general, any energy resource that is located in the MG's demand-/generation-side, and enables the MG's reacting to the needs, could be defined as flexible energy resources. However, based on the amount of flexibility, these energy resources could be divided into two main categories namely high-flexible energy resources and low-flexible energy resources.

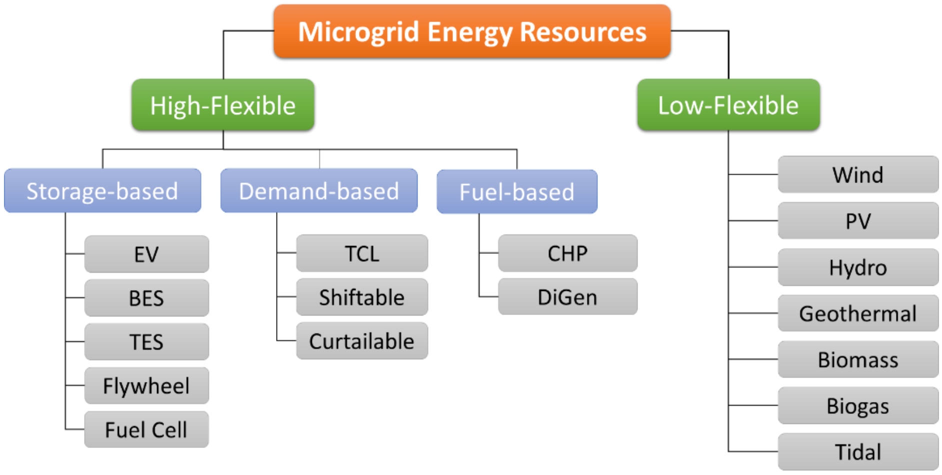

Fig. 1. An overview of microgrids' energy resources

The low-flexible energy resources in the MG consist of renewable generation units which their output power is not fully controllable. This originates from the fact that renewable energy sources such as wind, solar radiation, etc. depending on meteorological conditions. In certain situations, the only way to take action for low-flexible energy resources is to curtail their generation from MG's generation side. Therefore, in MGEM systems, they could be entitled to low-flexible energy resources.

On the contrary, there might be some flexible energy resources in MGs which could help to increase the flexibility of the MG. These types of energy sources could be entitled to high-flexible energy resources. The high-flexible resources could be utilized either in demand-side or generation-side of the MG. In other words, they might be among the consumers' assets, consumers' load, or as a part of a bulk PV system. Having employed the high-flexible energy resources in MGs, the MGEM system could take advantage of them to enhance the flexibility of MG by the active utilization of these resources. Therefore, the focus of this section is on the high-flexible energy resources in MGs. In the following subsections, the explanation about the characteristics of the high-flexible energy resources in MGs is presented.

2.1 Storage-based Flexible Resources

The storage-based FERs refers to the devices that could store the energy in different shapes (i.e. electrical, thermal, mechanical, etc.) in order to utilize it when there is a shortage or in critical moments. Energy storages could help the MGs to enhance their flexibility by injecting the power back to the MG, especially in islanding situations. Storage-based energy resources could be mostly categorized as electric vehicles, battery energy storages, thermal energy storages, flywheels, fuel cells, etc. In the following subsections, the most common storage-based flexible resources are illustrated.

2.1.1 Electric Vehicle (EV)

Electric vehicles as one of the ever-increasing types of flexible energy resources in future smart grids are believed to be among the potential solutions to systems' flexibility. These FERs are adjustable, shiftable, and fast-response which could considerably enhance the MG's flexibility in flexibility services provision. Moreover, EVs could be charged when the prices are at the lowest level meaning that they could be contributing to the cost-reduction target at all system levels. Although the EVs act as the load consumption when they are in charging mode, the recent version of EVs with new charging facilities makes the EVs capable of injecting power back to the grid (i.e. vehicle-to-grid mode) when it is needed. The equations related to the EV's operation are defined as follows. Eq. (1) presents the energy stored in the EV's battery at time *t*:

$$E_t = E_{t-1} + \begin{cases} \eta^{ch} P_t^{ch} \Delta t & \text{charging} \\ \dfrac{P_t^{dis}}{\eta^{dis}} \Delta t & \text{discharging} \\ 0 & \text{unplugged} \end{cases} \tag{1}$$

Where η^{ch}/η^{dis} are the charging/discharging efficiency and P_t^{ch}/P_t^{dis} are the power of charging/discharging, respectively. Δt is the duration time at which the EV is being charge or discharge. According to this equation, the energy of EV's battery depends on its current level of energy as well as its current mode of charging. The EVs' battery are mostly chosen from Li-Ion technology batteries since they are highly efficient compared to the other types of batteries. However, the capital cost of these batteries is nowadays high. Therefore, it is recommended to restrict the lower and upper levels of the battery's stored energy in MGEM systems. This restriction could be considered as a constraint in MGEM problems as in (2) which helps to reduce the number of charging or discharging cycles over a time span.

$$E^{min} \leq E_t \leq E^{max} \tag{2}$$

$$0 \leq P_t^{ch}, P_t^{dis} \leq P^{max} \tag{3}$$

Another constraint related to the EVs' battery could be found in (3). This one similarly helps to limit the charging/discharging power of the battery to avoid the battery from early depreciation. Note that, in order to take advantage of flexibility provision by EVs, the EVs, as well as the charging facilities, must have the capability of working in the vehicle-to-grid mode.

2.1.2 Battery Energy Storage (BES)

Battery energy storages are one of the best solutions for future smart grids. They could be centrally controlled, they have very rapid response, and also they could be useful in remote local energy systems, islanded MGs, or in power shortage situations. Moreover, they could effectively help the grid in terms of stability, resiliency, and flexibility. BESs could be found in different sizes, from domestic level to MG level or even grid levels. There have been introduced several materials used in manufacturing BESs such as Li-Ion, Vanadium Redox Flow, etc. The equations related to BES are similar to those mentioned in the previous subsection. However, all the BESs support the bidirectional power flow since they are meant to be discharged when it is needed.

2.1.3 Thermal Energy Storage (TES)

Thermal energy storages are used to store the thermal energy and utilized it when it is required. These storages could be beneficial in MGEM systems in order to store the heat in off-peak low-price times over night for using in high-price moments. The heat might be coming from combined heat and power (CHP) units, the waste heat from biomass/biogas units, or the exhausting heat from industrial units. They can be also beneficial not only for storing heat in summers but also for preserving the cold in the winters and reverting it to the MG's facilities in summers (i.e. seasonal TES). Thermal storages could be various in size and also in response time. Table I presents the typical types of thermal storages with their characteristics [2].

Table I. The typical types of thermal storages with their characteristics

Technology	Capacity (kWh)	Power (kW)	Efficiency (%)	Cost (€/kWh)	Storage Time
Sensible	10-50	1-10000	50-90	0.1-10	days-month
Phase-change	50-150	1-1000	75-90	10-50	hours-month
Chemical	120-250	10-1000	75-100	8-100	hours-days

2.1.4 Flywheel

Flywheel is a mechanical energy storage which consists of a rotational part and other facilities for connecting to the system. In charging mode, flywheel is speeding up to its nominal rotational speed and store energy as kinetic type. Afterward, the stored kinetic energy is preserved in standby mode. When energy is required, the flywheel starts to discharge the stored energy back to the grid [3].

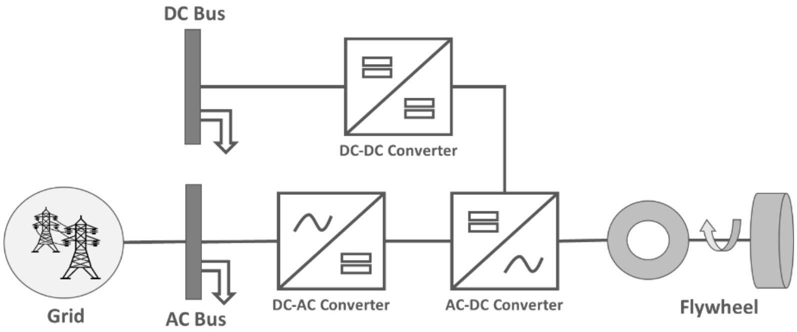

Fig. 2. Flywheel storage utilization in a hybrid grid-connected MG

Fig. 2, depicts a flywheel storage utilization in a hybrid grid-connected MG. In order to calculate the energy of a flywheel storage the following well-known formula is [3]:

$$E = \frac{1}{2} m r^2 \omega^2 \qquad (4)$$

In (4), E is the kinetic energy stored in the flywheel and m, r and ω are the mass of cylinder, radius and rotational speed, respectively.

2.1.5 Fuel Cell (FC)

Fuel cell (FC) as another high-flexible energy resources could also be utilized in MG applications. FCs can produce electricity by converting the chemical energy originating from hydrogen-oxygen reactions into electrical energy. The capacity of FC could be different based on their applications from 100 kW to 100 MW [4]. In solid-oxide FC, for example, anode supplies hydrogen and catalytically split it into a number of protons and electrons. The electrons are then flowing towards the positive side (i.e. the cathode) by flowing through the external circuit. The oxygen then reacts with the protons and also the electrons flowing in the circuit, forming water formula [5]. Solid-oxide FC can operate in parallel with MG's PV panels, meaning that it can be integrated with solar power as a hybrid PV system since they can store the produced energy for hours [4]. Therefore, in the night time, when PV panels cannot produce electricity, the FC could be employed to supply the demand. This could help the MG to have the flexibility to reduce the power exchange with the connected grid aiming at a generation cost reduction or provision of flexibility to the grid for monetary profits in return.

2.2 Demand-based Flexible Resources

The demand-based FERs refers to the devices that only consume energy. In residential MGs, for example, they might be found in the residential home appliances [6]. In other types of MGs, they might be in the shape of an industrial unit's demand or a commercial building's load. In general, all the devices in demand-side that their consumption power could be controlled, are considered as demand-based FER. Since a great number of demand-based FERs are widely being utilized in residential/commercial units, it would be beneficial for MGs to unlock the flexibility that could be emerged from these resources. Thereby, the demand-based FERs in the consumers' premises that are capable of controlling, changing, or shifting are at the center of attention for MGs' manager/operator. Note that, the demand response programs [7] could be a key factor for incentivizing small-scale consumers in MGs for flexibility provision. In the following subsections, some of these demand-based FERs that could enhance the flexibility of MG are presented.

2.2.1 Thermostatically Controllable Load (TCL)

Thermostatically controllable loads refer to the loads that their power consumption could be adjusted by sending command signals to their thermostat. These loads have a great portion of the total demand. In summers, the power consumption is used for cooling whilst in winters, the power consumption is utilized to heat the internal spaces of houses, offices, etc. For instance, electric water heaters (EWH), heating, cooling, air conditioning systems (HVAC), and refrigerators could be categorized in TCLs. These appliances are closely intertwined with the thermal comfortness and other consumers' preferences. Therefore, in MGEM systems, in addition to the operational constraints of appliances, the constraints regarding TCLs must also be considered. One of these constraints is thermal comfort of the users for HVACs and EWHs which could be found in (5)-(6):

$$\theta_i^{min} \leq \theta_{i,t} \leq \theta_i^{max} \tag{5}$$

$$\theta_i^{w,min} \leq \theta_{i,t}^{w} \leq \theta_i^{w,max} \tag{6}$$

Where θ_i^{min} and θ_i^{max} are the minimum and maximum desired temperature requested by user *i,* respectively. $\theta_i^{w,min}$ and $\theta_i^{w,max}$ are the minimum and maximum desired temperature of hot water requested by user *i,* respectively. Finally, $\theta_{i,t}$ and $\theta_{i,t}^{w}$ is the interior and hot water temperature of user i, respectively.

In order to unlock the flexibility from TCLs in an MG, they must be aggregated. Aggregating several TCLs in an MG could help to reduce or increase the power consumption in certain moments for the provision of upward or downward flexibility services to the connected upstream network. However, it is worth mentioning that the response time of some TCLs is a bit low. Therefore, they might not be suitable for all kinds of flexibility services but still beneficial for those services that have a slow activation time.

2.2.2 Shiftable Load

Shiftable loads are those that their consumption power cannot be controlled, however, the operating time could be shifted from high-price to low-price hours. These loads also need to work for a constant cycle and they could not be disconnected once they started which means shiftable loads must run a cycle completely. Therefore, the MGEM system can only schedule the related start time. Dishwasher, washing machine, and clothes dryer, as the devices which might be found mostly in residential households in the MG, could be grouped in shiftable loads' category [8]. A MG operator could take advantage of shiftable loads for energy scheduling during a day considering the consumers' comfortness constraints.

2.2.3 Curtailable Load

The power consumption of curtailable loads could be adjusted, usually without any significant effect on consumers' comfortness. These adjustments limit the energy consumption of devices by changing the settings thorough a command signal, without any consequences. As an example, lighting devices could be curtailed by a command during the day or as an automated function of natural daylight [8].

2.3 Fuel-based Flexible Resources

The fuel-based FERs are those that could be categorized in the generation side. Naturally, these FERs produce power by using fossil fuels as input energy sources. However, their output generating power could be regulated according to the system's needs. The output power generation of fuel-based FERs could be adjusted by changing the amount of intake fuel. Therefore, these FERs could contribute to increasing the MG's flexibility. Although these resources could not be categorized as a totally sustainable energy resource, their power production could be controlled in critical moments for flexibility provision targets. In the following subsections, a brief overview of the most important fuel-based FERs are provided.

2.3.1 Combined Heat and Power (CHP)

The most famous fuel-based flexible resource in MGs is combined heat and power (CHP) unit. A CHP unit is generally a power generation unit which combines the heat production with electricity generation. CHPs could be regarded as a decentralized distributed generator located at the MG level. This DG has the ability to produce heat and electricity simultaneously which could be beneficial in increasing the efficiency and flexibility of the MG. The exhausted heat from the power generation cycle in the CHP could be utilized to provide the required energy for the heating load as well as hot water within the MG internal network. In the MG level, the size of the CHPs depends on the size of the MG which could be found up to 20 MW. CHPs, however, could also be installed in customer-level applications with a maximum capacity of 15 kW [9]. Although the energy efficiency of the CHP unit can be assumed to be constant, the CHP unit's efficiency practically differs with dynamic operation due to the variation of output power. This could help the MGs to enhance their flexibility or providing flexibility services to the upstream grid. Note that, ramping constraints need to be considered in MGEM problems since the CHP unit requires some time to reach the steady-state condition after changing its set point [10].

2.3.2 Diesel Generator (DiGen)

Diesel generator as one of the fuel-based FERs could be beneficial in MGEM. This FER may be utilized when there is a power shortage in the MG. They could also be considered as flexibility sources when upward flexibility is needed from the upstream network. However, the sizing of the diesel generators in the MG is quite crucial since the ramping rate of the generator should be adequate for fulfilling the MG's/network's need. In fact, diesel generators play a quite important role when, for example in an islanded MG, the power generation is not enough and the energy storages are almost discharged. Therefore, these FERs are also called backup units in local energy systems. They could be different in size from 5 kW to 5 MW or more. The equation regarding fuel consumption of the diesel generator can be calculated from (7) that should be considered in MGEM optimization problems [11].

$$Cost = c_1 \times P^{DG} + c_2 \times P^n \qquad (7)$$

In (7), P^{DG} and P^n is the produced power and the nominal power of the generator, respectively. c_1 and c_2 are the coefficients related to fuel consumption's curve which typically considered $c_1 = 0.246$ l/kW and $c_2 = 0.08145$ l/kW, respectively [12].

3 MODELLING THE MICROGRID ENERGY MANAGEMENT

Microgrid, as one of the potential solutions to the future smart grids, usually confronts the lack of power generation. This is due to the variability and intermittency both from generation and demand sides [13]. Energy management methods have been believed as one of the solutions to this issue. The most important target of energy management is to find the optimal operation point of different kinds of energy resources in order to supply the requested demand constantly and efficiently [14]. It should be mentioned that the main objective of these studies is reducing consumption costs whilst taking advantage of the MGs' flexible capacity for the provision of energy and flexibility services. However, there might be various approaches and tools towards this target. Before discussing the MGEM tools and techniques, the MG management methods are briefly illustrated in the next subsection.

3.1 Microgrid Energy Management Methods

The approaches toward the control and operation of MG resources as well as dispatchable loads are known as MG management methods. These management method could be deployed by having an agreement between the MG operator and the MG's members/stakeholders. The microgrid energy management (MGEM) could be defined in two perspectives [15]:

1) Decentralized energy management
2) Centralized energy management
3) Distributed energy management

In decentralized MGEM, the control and operation of FERs located at the MG have more degree of freedom. This means the FERs' adjustability in this management method helps more to meet the preferences of the stakeholders/consumers. In centralized MGEM, however, a central controller decides how the FERs and generation units should be operated. It has to be mentioned that in both centralized and decentralized management methods, the technical constraints of the MG must be taken into account. The most important constraint would be the balance between load and production within the MG [16].

Distributed MGEM as another management method in MGs is presented in the literature as well. This type of management method is mostly based on game-theoretic approaches. In distributed MGEM, game players, as the agents in the MG, seek the best management method for their own objectives taking into account the overall goal of the MG regarding energy management considerations [17].

Having mentioned the above approaches, the MGEM problems generally aim at scheduling the operation of generation units, storage systems, and even controllable loads in the MG [18]. These problems have been presented with various objectives. In the following section, some of these objectives with the related considerations are elaborated.

3.2 Microgrid Energy Management Objectives

3.2.1 Cost Reduction / Profit Maximization

One of the most important objectives of energy management is reducing the total operation cost of MGs' components. This operational cost includes, for instance, the fuel cost, cost of purchasing energy from the grid, degradation cost of battery energy storages, etc. [19]. The cost reduction in an MGEM could be over different time spans from real-time to daily, monthly, or even yearly periods. However, energy management sometimes might be defined for real-time operation. In this case, the real-time operational cost of MG is the objective of the problem. Accordingly, the generation and demand as well as the scheduling of the FERs should be in a way that the overall cost of the MG tends to be minimized in real-time [20]. Accordingly, the MGEM system is in charge of scheduling the generation and flexible loads so that the total cost of energy purchasing from the grid as well as the operational costs of the DGs become minimized as in (8).

$$\min \quad \mathrm{Cost}^{\mathrm{MG}} = \sum_t \left(Cost_t^{EN} + \sum_i Cost_t^{DG_i} + \sum_j Cost_t^{BES_j} + \sum_j Cost_k^{EV_k} \right) \tag{8}$$

$$\text{Subject to:} \quad \text{Constraint}\ \{\text{DGs, FERs}\}$$

In (8), $Cost_t^{EN}$ is the cost of purchasing energy from the grid at time *t*. Accordingly, the total temporal operational cost of DGs, BESs and degradation cost of EVs that must be paid to the EV owners for vehicle-to-grid contribution, are $\sum_i Cost_t^{DG_i}$, $\sum_j Cost_t^{BES_j}$ and $\sum_j Cost_k^{EV_k}$, respectively.

This objective could also be considered in a different shape which says the MGEM objective is to maximize the total profit of the MG instead of operational cost. The monetary profit for a MG mostly comes from selling energy to the grid or providing flexibility services to balancing responsible parties. Accordingly, the objective function of the MG could be defined considering the following formulation:

$$\max \quad \mathrm{Profit}^{\mathrm{MG}} = \sum_t \left(P_t^{sell} \lambda_t^{sell} - P_t^{buy} \lambda_t^{buy} - Cost_t^{MG} \right) \tag{9a}$$

$$\max \quad \mathrm{Profit}^{\mathrm{MG}} = \sum_t \left(F_t^{up} \lambda_t^{up} + F_t^{dn} \lambda_t^{dn} - P_t^{EN} \lambda_t^{EN} - Cost_t^{MG} \right) \tag{9b}$$

$$\text{Subject to:} \quad \text{Constraint}\ \{\text{DGs, FERs, Grid Limits}\}$$

Eq. (9a) indicates the objective function of MGEM problem for a grid-connected MG which only exchange energy with the grid while the (9b) presents the objective for a flexibility provider MG. In (9a)-(9b), P_t^{sell} and λ_t^{sell} are the exported power to the grid and the price of selling to the grid, respectively. P_t^{buy} and λ_t^{buy} are the imported power from the grid and the price of energy to the grid, respectively. F_t^{up} and F_t^{dn} are the upward and downward flexibility provided to the network, respectively. λ_t^{up} and λ_t^{dn} are the price of upward and downward flexibility, respectively. P_t^{EN} and λ_t^{EN} are the quantity and price of purchased energy from the grid, respectively. Finally, $Cost_t^{MG}$ refers to the total operational cost of the MG which includes degradation cost of energy storages, EVs as well the operational cost of generation-side resources. Note that, in both definitions, the constraints related to the operational consideration of the assets as well as members' comfortness must be taken into account in MGEM problem.

3.2.2 Self-sufficiency

One of the important targets of MGEM in MG is self-sufficiency. A MG is self-sufficient when there is a balance between the generation and consumption within the MG. In other words, the power produced by the MG's resources could fulfill its demand over a period of time. This objective becomes pivotal mostly when an islanding situation is predictable since, in that case, the MG becomes disconnected from the grid and the stability of the MG becomes critical. The MGEM with an objective of self-sufficiency could be tackled by reducing the peak demand, load shedding as well as discharging the storage-based flexible resources. In this way, based on the level of emergency, the MGEM should define a priority for the utilization of fast-response FERs located in the MG. However, this objective could have other targets inside itself. For example, the self-sufficiency of MG in moments at which the renewable energy resources have production and the energy storages have a sufficient level of charge could be deployed to reduce energy purchasing from the grid. Therefore, fewer greenhouse gases emission as well as cost reduction could also be considered as the results of self-sufficiency objective. The objective function regarding the self-sufficiency in MGEM systems must satisfy the following constraint:

$$G_t^{MG} \geq D_t^{MG} \tag{10}$$

$$G_t^{MG} = \sum_i P_t^{DG_i} + \sum_j P_t^{dis_j} \tag{11}$$

$$D_t^{MG} = P_t^{BL} + \sum_i P_t^{FL_i} + \sum_j P_t^{ch_j} \tag{12}$$

In the above equation, G_t^{MG} is the MG total generation and D_t^{MG} is the MG total demand at time *t*. In (10)-(12), the $P_t^{DG_i}$ is the production of DG *i* at time *t*. P_t^{BL} and $P_t^{FL_i}$ are the baseline load and power consumption of flexible load *i* in the MG at time *t*, respectively. $P_t^{dis_j}$ and $P_t^{ch_j}$ are the discharging and charging power of storage-based resources *j* at time *t*, respectively. It has to be mentioned that the other constraint regarding the simultaneous charging/discharging limitation and the operational constraints of DGs also must be taken into account.

3.2.3 Flexibility Provision

As the traditional power systems have been experiencing a fast and vast transition to the smart, local, and decentralized ones, the flexibility services concept has been introduced in order to cover the whole system-related issues. In this light, MGs as the local energy systems is believed to be a suitable choice in providing local and system-wide flexibility. Flexibility services could be provided by MGs through the effective utilization of FERs and also distributed energy resources in MG by using MGEM systems. However, before mentioning the flexibility services provision by the MGs, the definition of flexibility in an electrical system should be clarified. A comprehensive definition of the flexibility of electrical systems could be the ability of the system to adjust its operating point continuously and also to resist the predicted and unpredicted differentiations happening in operating conditions. Accordingly, a flexible electrical system must adapt to the possible changes both in generation and consumption in a temporal manner [21]. Therefore, another possible objective of MGEM might be providing flexibility services by MGs to the connected upstream networks. These services could appear in different shapes. An overview of the flexibility services (e.g. in Nordic countries [22]) that MG can provide to other entities are presented in Fig. 3.

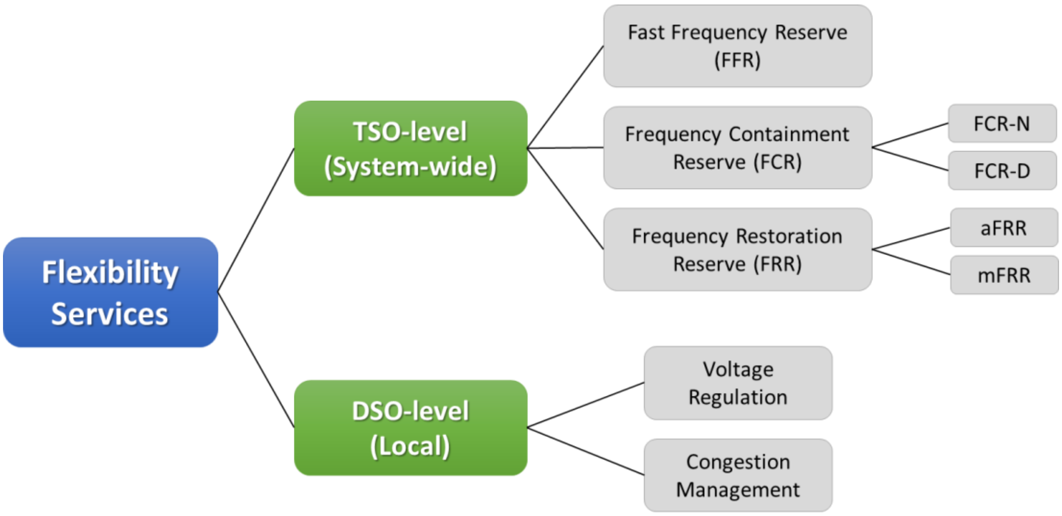

Fig. 3. An overview of the flexibility services (in Nordic)

3.2.3.1 TSO-level Flexibility Services

The transmission system operator is the responsible party for TSO-level balancing issues which could be addressed by the contribution of all system-level flexible resources, e.g. MGs. There are three types of services that local energy systems can contribute to flexibility provision to transmission-level needs, which are fast frequency reserve (FFR), frequency containment reserve (FRR), and frequency restoration reserve (FCR). TSO-level flexibility services have been the conventional generation units' responsibility. However, recently and more increasingly in future power systems, MGs as the potent sources of flexibility, would be among the flexibility service responsible parties. Depending on the size of grid-connected MGs and the flexibility needs of the upstream entities, MGs could contribute to one or more specific flexibility services in singular or aggregated manners. The TSO-level flexibility services (e.g. in Finland [23]) with their characteristics are summarized as in the Table II. The flexibility services in this table are categorized as reserve product services [23].

Table II. The characteristics of the Nordic flexibility services

Service	FFR (new)	FCR-D	FCR-N	aFRR	mFRR
Application	In very low-inertia situations	In big frequency deviations	Always in use	In certain hours	Incidents/imbalances of balancing parties

Activation	1 sec.	Less than 1 min.	1-5 min.	5 min.	15 min.
Min. Bid Size	Not defined yet	1 MW	0.1 MW	5 MW	5 MW

- **FFR:** The FFR service as the recently introduced flexibility service in Nordic will be utilized in extremely low-inertia situations when there are ±0.5 Hz frequency fluctuations. The maximum amount of FFR services need in Nordic is estimated 300 MW.
- **FCR-D:** The FCR-D service is needed in huge frequency deviations which at least 50% of it needs to be activated in 5 seconds and the rest is required to be activated in 30 seconds. The system's need in this service is only for under-frequency situations (i.e. increase in generation or decrease in demand)
- **FCR-N:** The FCR-N service is for normal operation of the system and is being activated all the time. The system's need in this service is only for both under-frequency and over-frequency situations (i.e. increase/decrease in generation or demand). Note that, this service is symmetrical which means the flexibility providers like MGs must be able to provide the flexibility needs equally for upward and downward flexibility.
- **aFRR:** The aFRR service is activated when . In this service, unlike FCR, the asymmetrical bids are also accepted which means the upward and downward flexibility bids could be submitted separately. Note that, the activation price to the service providers will be paid according to the price of balancing energy market.
- **mFRR:** The mFRR service is activated manually in 15 minutes. Bids are needed to be delivered 45 minutes prior to activation hour. In this service, like aFRR, the upward/downward flexibility bids are being submitted separately. Note that, in this service, the prices are constantly greater than day-ahead energy prices so that it is quite beneficial for flexibility providers like MGs.

3.2.3.2 DSO-level Flexibility Services

There are two types of flexibility services that are introduced in the electrical systems namely voltage regulation and congestion management in which MGs can contribute as DSO-level flexibility providers. Voltage regulation services could be provided by MG's power electronic devices like FERs' converters and also by injected active power control through the point of common coupling (PCC) with the distribution grid. The power electronic devices are able to control the reactive power which is effective in voltage regulation applications. Similarly, congestion management services could be provided by the mentioned FERs. In DSO-level flexibility provision by MGs, along with the MG-related constraints, the distribution network's limitations such as active and reactive power and injected current should also be taken into account.

3.3 Microgrid Energy Management Tools and Techniques

There have been introduced various types of MGEM modeling techniques in the previous literature. These techniques include the optimization approaches along with intelligence control tools such as model predictive control, game theory methods, etc. In the following subsections, some of the most popular tools and methods will be introduced.

3.3.1 Optimization Methods

The basic approach to energy management problems would be based on optimization algorithms. This originates from the nature of the energy management since it is supposed to minimize or maximize an objective depending on the targets of MG's stakeholders as well as the method of asset management [24]. There have been introduced many optimization techniques which could be employed correctly depending on the type of the problem. In general, the optimization techniques could be split into two main categories, convex and non-convex. Fig. 4, presents a general overview of the proposed types of optimization problems [25].

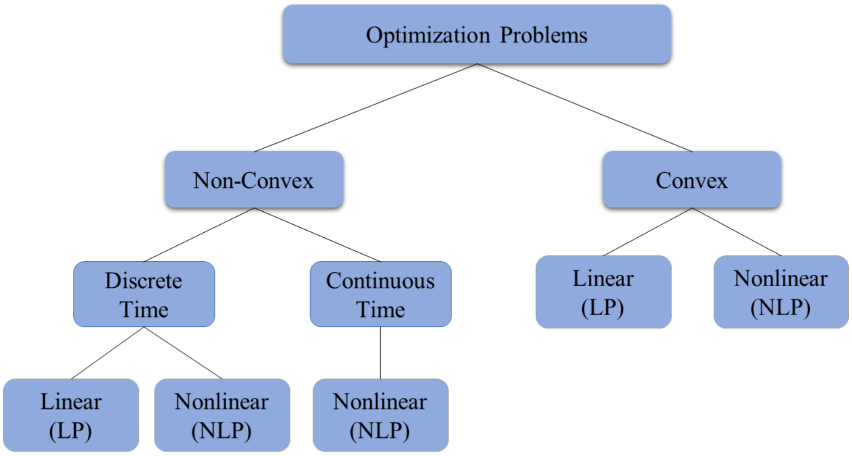

Fig. 4. General categorization of optimization problems

The type of optimization technique could be chosen correctly depending on the problem's characteristics. In MGEM, the type of problems mostly are convex or the problems are defined in a way that they could be solved with convex techniques (i.e. convex relaxation). This is due to the fact that the convex problems give better convergence compared to the non-convex ones [25]. Furthermore, there could be many uncertainties in MG operation due to the nature of MG components. For instance, the intermittent renewable components such as wind turbines, photovoltaic units, and on the top of them, the unpredictable demand could create the mentioned uncertainties [26]. These uncertainties, however, could be addressed by means of some well-known mathematical and statistical techniques during the definition of optimization problems for MGEM. In order to analyze the impact of uncertainty of data, the following three types of optimization methods have been proposed:

- Deterministic Optimization
- Stochastic Optimization
- Robust Optimization

Although the deterministic approach for defining an optimization problem could be beneficial for comparing the results of the problem with other approaches, robust and stochastic optimization solutions are believed as the most effective techniques in energy management problems which are illustrated in details in the following subsections [27].

3.3.1.1 Deterministic Optimization

Deterministic problems are those that have a unique output for any kind of input [25]. As an example, wind speed or solar radiation which are variable over a time span could directly affect the output power of wind turbines or PV systems. Therefore, for different values of wind speed and solar radiation, the power generation of these renewable units would change. However, the power generation function of these renewable units could be defined deterministic meaning that, for any wind speed and solar radiation, the output power of wind and PV units are considered as certain values. This type of problem formulation would not take place in reality, however, there are some applications for deterministic approaches. Furthermore, this method could be beneficial when the aim is to have an idea about the overall operating points of the system in a certain condition. In MGEM problems, there is some component in the system that has strong stochasticity (e.g. renewables, demand, etc.) and could not be modeled as deterministic functions. Consequently, the other types of optimization techniques (i.e. stochastic and robust) are usually recommended that will be introduced in the following subsections.

3.3.1.2 Stochastic Optimization

In stochastic optimization, the problem of energy management could be presented by a statistical objective function. In this light, the uncertain parameters of the problem such as the output power of renewable energy units could be modeled as the well-known probability distribution functions. These distribution functions might be different due to the difference in the nature of renewable sources such as solar irradiation or wind power. They also might be different due to the uncertainties stemming from the stochastic behavior of consumers such as the behavior of EV owners and the pattern of charging their vehicles. However, all these uncertainties are can be considered as the most popular distribution functions since their sources mostly follow a predictable pattern. The general formulation of a stochastic optimization problem could be found in (13):

$$\min_{x \epsilon \chi} \sum_{\omega \epsilon \Omega} \pi(\omega)\, F(x,\omega) \quad (13)$$

In (13), $\pi(\omega)$ is the probability of scenario ω, Ω is the set of scenarios, χ is the set of decision variables. The function $F(x,\omega)$ could be different based on the objective of the MGEM problem. According to the stochastic optimization method, the main objective function of the problem could be written as the sum of the objective function of each scenario multiplied by the scenario probability. In this method, the value of uncertain variables in the system is considered by defining several possible scenarios. Note that, for each scenario, a probability of occurrence should be considered in a way that the summation of the probability of all scenarios must be equal to one as follow:

$$\sum_{\omega} \pi(\omega) = 1 \quad (14)$$

There have been presented a number of computational methods for generating the above scenarios. Amongst these methods, one of the most popular scenario generation techniques is the Monte-Carlo method which is widely employed in the literature [28]. The number of the considered scenarios for the problem has a direct impact on the accuracy of the problem. In other words, by increasing the number of these scenarios the result would be more accurate. However, a large number of considered scenarios for the stochastic optimization problems could result in a huge computational cost. In order to reduce the computational cost of solving, the number of scenarios should be reduced. Therefore, one could use a mathematical method to limit the possible scenarios. For instance, the K-means clustering technique is proposed in order to tackle a large number of scenarios [29]. In the following sub-sections, uncertainty modeling methods for different sources of stochasticity are illustrated.

3.3.1.3 Robust Optimization

The robust optimization method was first introduced in 1973 [30]. This method has been introduced and employed in many research as one of the most powerful approaches towards energy management in order to act as an alternative for modeling the problems with uncertain parameters. The robust optimization is employed when the energy management problems confront a limited amount of data but at the same time several uncertainties. In this optimization method, unlike the stochastic optimization with many possible scenarios, we consider only one scenario which means this optimization does not need any kind of probability distribution function [31]. This scenario is assumed to be the worst-case regarding the uncertain situations in the optimization procedure. In energy management problems, the worst-case scenario is the one that is believed to have the most severe outcome that happens in the real situation. In other words, in this method, it is assumed that the uncertain parameters are in their worst condition [30]. This could help to have a realistic paradigm towards the occurring scenario and if possible, it could improve the results of the optimization in comparison with stochastic methods [32].

In this method, the optimal result of the optimization has two features. First, less data is needed for uncertain parameters here which means only minimum, maximum, and mean of the uncertain parameter is required. Second, the optimal solution of the problem is feasible for all conditions which could be quite beneficial in decision making.

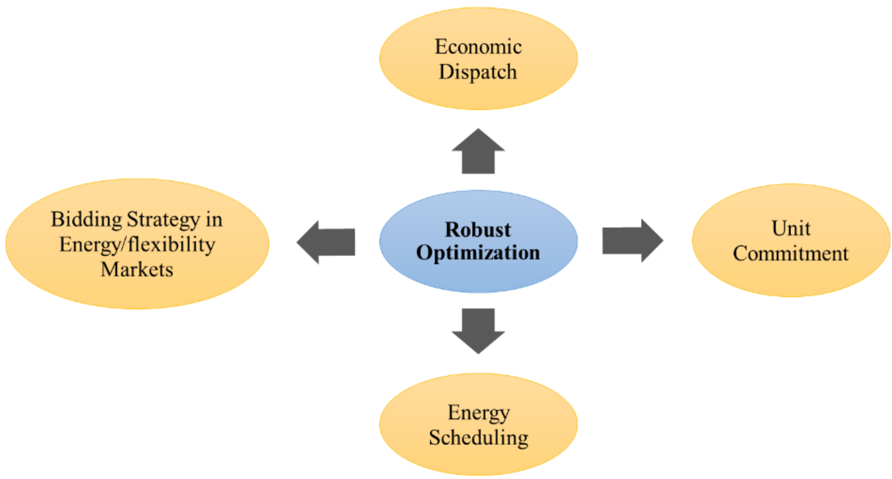

Fig. 5. Applications of the robust optimization

The robust optimization approach has many applications in MGEM such as bidding strategy [33]. These applications could be dealing with the uncertainty of renewable energy units' generation, consumers' load, and energy/flexibility market prices. Fig. 8, provides a summarized overview of the most important applications of the robust optimization techniques in MGs.

In general, the basic formulation of a robust optimization problem would be as follow:

$$\min_{x\epsilon\chi} \max_{\omega\epsilon\Omega} \mathbb{C}(x,\omega) \qquad (27)$$

Where χ is the set of uncertainties and Ω is the decision variables' space [34]. In MGEM problems, for instance, the robust optimization technique could be employed in order to minimize the cost function of MG (i.e. $\mathbb{C}$) while the baseline demand of the MG is at the highest possible value. In the following subsection, the uncertainty characterization methods are presented.

3.3.2 Uncertainty Characterization

3.3.2.1 Uncertainty of Wind Units

The uncertainty of the wind power units is due to the variable nature of wind speed in different weather conditions. The uncertainty related to the generation output of wind power units has been specifically studied in the previous works like [35], [36] and [37]. In order to model the uncertainty of wind power production the well-known Weibull distribution function is proposed [36]. The introduced formula of Weibull probability distribution function is as follows:

$$f_s(s) = \left(\frac{k}{c}\right)\left(\frac{s}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \qquad k, c > 0 \tag{15}$$

In (15), c and k refers to the scale factor and shape factor, respectively. This distribution function could be divided into N_{sc} scenarios in which the probability of occurrence of each scenario could be defined and written as follows:

$$\pi_\omega = \int_{S_\omega}^{S_{\omega+1}} f_s(s)\, ds \qquad \omega = 1,2,\dots,N_{sc} \tag{16}$$

In (16), the S_w denoted the wind speed of the scenario w. Accordingly, the output power of the wind, P^{WT}, unit could be obtained by using the following equation:

$$P^{WT} = \begin{cases} 0 & 0 \le S_\omega < S_i \\ P_r(A + S_\omega B + S_\omega^2 C) & S_i \le S_\omega < S_r \\ P_r & S_r \le S_\omega < S_o \\ 0 & S_\omega \ge S_o \end{cases} \tag{17}$$

The power generation curve of wind units could be found in Fig. 5.

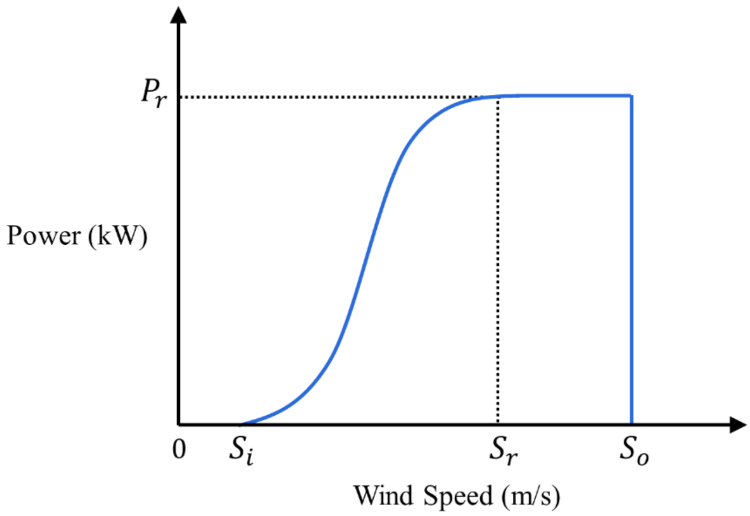

Fig. 6. Output power of wind units based as a function of wind speed

The generation of the wind unit directly depends on the wind speed in a specific time-step. In (17), the constant values A, B and C could be achieved, for example from [38], and are related to the characteristics of the wind turbine. Note that, S_i, S_o, S_r and P_r indicate the cut-in speed, cut-out speed, rated speeds and rated power, respectively.

3.3.2.2 Uncertainty of PV Units

The uncertainty related to the photovoltaic units stems from the variable amount of solar irradiation. Solar irradiation could be different from one location to another which results in the intermittent generation of PV units. The amount of solar radiation is dependent on the weather temperature, weather conditions, and the angle of photovoltaic panels. However, by studying the long-term patterns of solar radiation, for instance, in a specific location, it can be realized that they mostly follow a pattern. These patterns could be modeled as one of the most popular probability distribution functions. The most utilized distribution that is being used to model the generation of PV units would be Beta distribution [39]. This function is introduced as following equation:

$$f_{\mathcal{R}} = \begin{cases} \mathcal{R}^{\alpha+1}(1-\mathcal{R})^{\beta-1}\left(\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\right) & 0 \le \mathcal{R} \le 1\,; \alpha, \beta \ge 0 \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

$$\alpha = \left(\frac{\mu}{1-\mu}\right)\beta \tag{19}$$

$$\beta = \frac{\mu(1-\mu^2)}{\sigma^2} - (1-\mu) \tag{20}$$

In (18)-(20), the parameters α and β denote the features of function which can be obtained by means of (19) and (20), respectively [40]. The Beta distribution curve for different values of α and β is depicted in Fig. 6. The variable $\mathcal{R}$ refers to the solar radiation in kW/m^2. Note that, the Γ refers to well-known Gamma function.

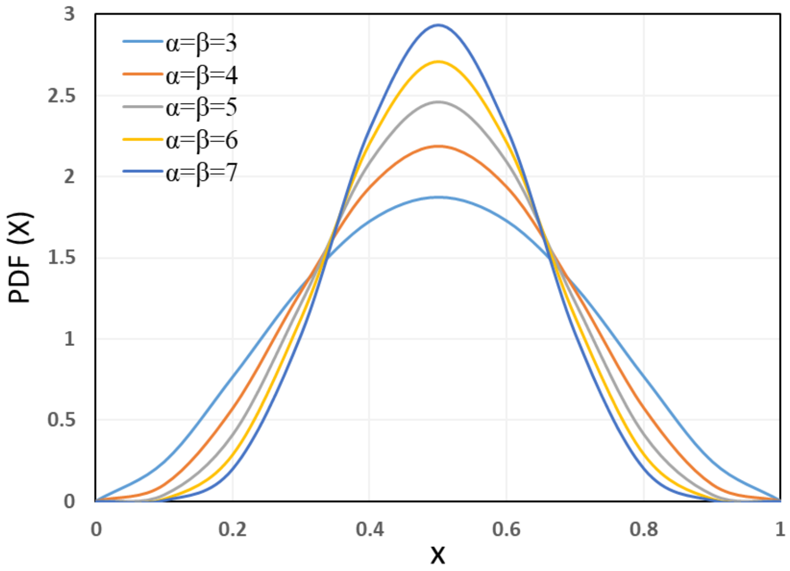

Fig. 7. The Beta distribution curve for different values of α and β

In (19)-(20), the mean and standard deviation of solar radiation could be denoted by μ and σ. Accordingly, the output power of the photovoltaic unit can be calculated using the following equation [39]:

$$P^{PV} = N_p\, \mathcal{R}\, (V_{oc} - k_v\theta_c)(I_{sc} + k_c\theta_c - 25k_c)\left(\frac{V_{mpp}I_{mpp}}{V_{oc}I_{sc}}\right) \tag{21}$$

Where P^{PV} is the power generation of PV system and the parameter N_p refers to the number of panels in the PV unit. $\mathcal{R}$ is the solar radiation at the location of PV unit. The constants k_v and k_c are related to coefficient temperatures of voltage and current, respectively. V_{mpp} and I_{mpp} denotes the respective voltage and current in the maximum power point condition. V_{oc} and I_{sc} refers to the voltage in open-circuit and current in short-circuit conditions, respectively. θ_c is the temperature of solar cells that can be approximated using the following equation:

$$\theta_c = \theta_{amb} + \frac{\mathcal{R}(\theta_n - 20)}{0.8} \tag{22}$$

In (22), the term θ_{amb} is the ambient temperature of PV panels and θ_n is the temperature in nominal operation condition.

3.3.2.3 Uncertainty of EV Owners' Behavior

In order to model the uncertain behavior of EV owners, for example in an MG, a distribution function is needed that could correctly represent the usage pattern of EVs. The most usual probability distribution that is used to model the uncertainty of EVs is truncated Gaussian distribution function [41], [42] and [43]. In the case of an MG, the EVs owned by the MG stakeholder, residential/commercial units, and/or a charging station could be considered in the uncertainty modeling with single or multiple probability distributions. In this light, for every single EV, the initial state-of-charge (SoC) and the availability of the EV in the understudy time horizon could be taken into account.

$$SoC_i^{ini} = f_{TG}\left(x, \mu^{soc}, \sigma^{soc}, SoC_i^{min}, SoC_i^{max}\right) \qquad (23)$$

In (23), the SoC_i^{ini} is the initial SoC of EV i. μ^{soc} and σ^{soc} are the mean and standard deviation of EVs' SoC, respectively. SoC_i^{min} and SoC_i^{max} are the minimum and maximum possible SoC of EVs in the MG. This equation could be utilized to generate the possible scenarios for initial SoC of the EVs.

According to the above equation, the truncated Gaussian distribution that could be used for modeling the initial SoC of an EV is depicted in Fig. 7 [44]. In this exemplary figure, the minimum and maximum SoC for EVs considered 0.3 and 0.9, respectively. In Fig. 7, the value of mean and the standard deviation are considered 0.5 and 0.25, respectively. The exact value of the parameters could be estimated by studying the historical and regular patterns of EVs' behavior.

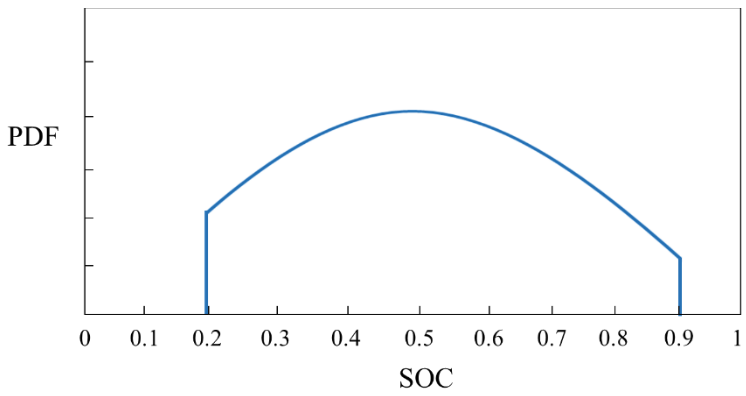

Fig. 8. Truncated distribution of EV's SOC

Moreover, the most probable availability times of each EV have to be in hand for modeling the behavior of EVs. This could happen by considering the historical plug-in and plug-out times of EVs to the grid. Accordingly, the plug-in and plug-out times of EVs in the MG could be modeled with a distribution function as follows:

$$\begin{cases} t_i^{in} = f_{TG}\left(x, \mu^{in}, \sigma^{in}, t_i^{in,min}, t_i^{in,max}\right) & \forall i \\ t_i^{out} = f_{TG}\left(x, \mu^{out}, \sigma^{out}, t_i^{out,min}, t_i^{out,max}\right) & \forall i \end{cases} \qquad (24)$$

In (24), t_i^{in} and t_i^{out} are the times of plug-in and plug-out by EV i, respectively. This equation could be employed to generate several possible scenarios for plug-in and plug-out times of EVs in the MG.

3.3.2.4 Uncertainty of Flexibility Needs

In order to schedule and operate the MG in an efficient manner, the flexibility needs of the system should be predicted in advance. The concept of flexibility needs refers to the amount of regulation up/down needed for maintaining the system's balance in a predefined bandwidth. In fact, the flexibility need for a specific time is determined by the system's operator by the time of activation. However, the MG manager/aggregator should have the idea about the approximate values of flexibility that are supposed to be assigned from the system's operator. The flexibility need is always uncertain due to its dependency on several factors that need to be modeled by stochastic methods.

In order to model the uncertainty related to the flexibility needs, one can deploy a probability distribution function. It is obvious that the amount of flexibility need from the upstream grid that needs to be activated has a value between zero and the assigned value by the MG. In other words, the minimum activated amount of flexibility is zero when the MG is not supposed to provide any flexibility for a time step, and in contrast, the maximum value of the activated flexibility by the MG when the MG is supposed to provide the entire amount of assigned flexibility to the upstream network. However, the MG aggregator must schedule the demand and generation in a way that provides all the offered flexibility to the upstream network. With this regard, the activated amount of upward and downward flexibility from the system's operator could be modeled as uniformly distributed between zero and its maximum value [44].

$$UF_{w,t} = f(x) = \frac{1}{F_t^{up}} \qquad 0 \leq x \leq F_t^{up} \tag{25}$$

$$DF_{w,t} = f(x) = \frac{1}{F_t^{dn}} \qquad 0 \leq x \leq F_t^{dn} \tag{26}$$

In (25) and (26), the $UF_{w,t}$ and $DF_{w,t}$ are the upward and downward activated flexibility. F_t^{up} and F_t^{dn} refers to the upward and downward assigned flexibility.

3.3.3 Model Predictive Control

Model predictive control (MPC) as a subfield of optimal control has several applications in electrical energy systems operation and control, especially in the energy management systems. Generally, MPC is a technique that makes a decision at a time through solving an approximate model over future horizons. There might be many engineering problems where the model is not in hand. In the MPC method, at least, an approximate model of the system is required. MPC is mostly employed to solve a problem with stochastic parameters which is modeled by means of a deterministic approximation. MPC might also utilize a stochastic model of the system in the future, however, the solution may be hard to converge [34]. In this method, the actions about the future configurations are realized by making the decisions now. Alternatively, it might utilize sampled approximations for the future, introduced as MPC in some literature, which are standard strategies in stochastic programming [45]. The overview of the MPC strategy for more clarification is depicted in Fig. 9. This figure states that how the decision made by MPC at the current moment, could predict the optimal trajectory of the system towards the future changes in the next time steps. This procedure will iterates every time step until the controller find the best solution.

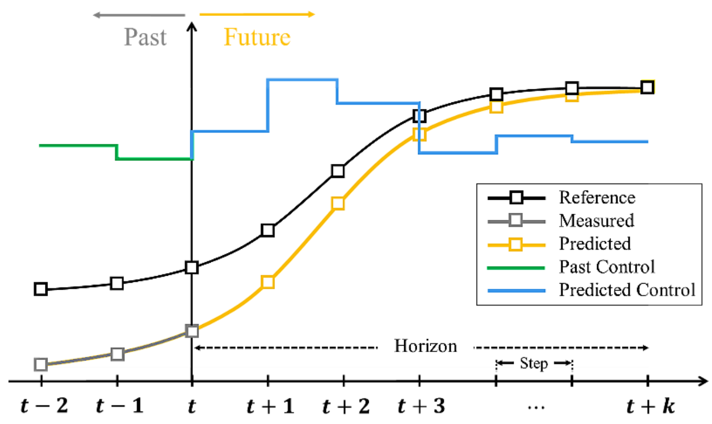

Fig. 9. Model predictive control analogy

The MPC method is believed to be applicable in MGEM systems, especially when there are many stochasticities within the MG. Some of the most important applications of MPC method in MGs could be classified as follows [46]:

- ✓ Providing an optimal solution to control the operation of MG's FERs for different objectives in MGEM systems.
- ✓ Providing a control-based decision making to deal with the intermittency of consumers (demand, EVs, etc.) as well as renewable energy resources (wind, PV, etc.) in the MGEM optimization problems in order to tackle the stochasticity and randomness of these components.
- ✓ MPC is useful in handling some binary variables that need to be considered in MGEM problem. This could be beneficial when the situation of some components (e.g. charging mode of BESs, availability of EVs, ON-OFF mode of flexible loads) might possibly change and the new decisions should be made based on the situation.
- ✓ MPC could be beneficial in dealing with sudden changes in the MG where the new decisions should be made based on the new situation to maintain the MG in its normal operating point. This could help the MG to improve its degree of freedom in unusual conditions.

- ✓ MPC is also helpful when a distributed management method is taken within the MG. In this case, there might be several agents in the MG who make the MGEM problem complicated. Hence, MPC is believed to be a suitable choice in dealing with such problems.

Despite the above advantages and usefulness of the MPC method, it might have a high computational cost due to several optimization problems that need to be run in each time step over a horizon. More information regarding different types of MPC formulation can be found in [46]. In the following subsection, a brief overview of the game-theory application in MGs are presented.

3.3.4 Game-theory

Another potential approach to MGEM problems is game theory. Game theory is believed to be among potential techniques in the operation of MGs due to the capability of enabling distributed management for MGs' resources [47] [48]. In order to implement a MGEM problem as a game theory problem, the resources located at the MG could be considered as game participants. Despite the game theory's shortcomings in problem convergence, it is still a good choice for multi-agent-based decision making studies.

Game theory has many applications from the energy industry to economic studies in complex systems. In general, its concept refers to mathematical techniques that model the interaction between multiple decision-makers [49]. The choice of one decision-making entity could affect the choices of the other entities. One of the applications of game theory could be in distributed management of MGs. In order to implement a MGEM problem as a game theory problem, the resources located at the MG could be considered as game participants. The following four steps should be taken for a game-theoretic problem:

a) Defining players of the proposed game
b) Defining the individual and overall goal
c) Dealing with the coupled constraints
d) Finding the Nash equilibrium

Game theory methods could be split into two categories: cooperative game and non-cooperative game [50]. A cooperative game is the one with a number of entities in which the main goal of these players are in-line with each other. In contrast, the non-cooperative game refers to a game in which the entities are in conflict with each other and they try to act independently regarding their goals [51]. However, the choice of the suitable game-theory approach for MGEM problems directly depends on the method of MG management and the agreements between MG operator and members.

4 SUMMARY AND CONCLUSION

The MG is an autonomous or semi-autonomous system that consists of DGs, RESs, FERs as well as dispatchable loads working together which are able to operate in both grid-connected and islanded mode. MGs as the potential sources of sustainability are designed to expand the decentralization goals along with cooperation with the whole system toward flexible electrical energy systems. However, the increasing penetration of renewable sources and the decentralization in either MG or system-level networks have resulted in several stability and resiliency issues. Consequently, the EMSs are proposed to efficiently control and manage the operation of all energy resources locate in generation-side and demand-side so as to deal with the stochastic outcomes of a deregulated system. Moreover, the smart power systems in the future will confront several uncertainties due to the very low-inertia situations which must be addressed by the EMS as well as the novel control techniques in advance.

In MG concepts, the EMS also could play a pivotal role in dealing with the aforesaid issues since they could be employed to satisfy several objectives in operation and control of the MG. The EMSs could also be beneficial in providing different kinds of services to the national or regional grids. Accordingly, MGEM systems could be designed and planned carefully so that they can take into account all the individual or environmental constraints and limitations of consumers' electrification. Hence, in order to have an efficient and synergetic contribution by MGs, the MGEM problems should be defined by problem formulations in which all the uncertainty, stochasticity, restrictions, and also monetary payback for its stakeholders are considered precisely.

Different types of optimization formulations were used for the MGEM problems. Most of them focused on minimizing MG's operating costs such as fuel costs, maintenance costs, and the cost of imported energy from the grid. These optimization techniques could be categorized based on their optimization types, objective functions, constraints, and also tools that are utilized to solve MGEM problems. The most popular ones include stochastic and robust optimization techniques. Furthermore, there have introduced some tools such as model predictive control, intelligent techniques, and game-theory in order the make the MGEM more efficient and predictable.

To sum up, the utilization of MGs equipped with the MGEM system could be a potential solution to future power systems issues. The control and optimization techniques in MGEM system enable the active and sustainable utilization of energy resources. These energy management systems could help to enhance the flexible utilization of energy resources as well as the flexibility of the whole power system by providing different types of balancing and ancillary services. However, in order to make the most out of these MGEM plans, the smart selection of control and optimization trajectories are of the necessity.

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