Energy Management in Multi-Microgrid Systems — Development and Assessment

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***Abstract*— The optimal management of energy generation-/consumption in modern distribution systems has gained attention in the smart grid era. This paper presents optimized and coordinated strategies for performing and assessing energy management in multi-microgrid systems. The energy management process is formulated for multi-microgrid systems that simultaneously incorporate several energy generation/consumption units, including different types of distributed generators (DGs), energy storage units, electric vehicles (EVs) and demand response. Due to the probabilistic nature of some loads (e.g. EVs) and generators (e.g. wind turbine and photovoltaic (PV) modules), a novel probabilistic index is defined to measure the success of energy management scenarios in terms of cost minimization. Moreover, by using the new index, common types of energy controllers, such as DGs, storage units, EVs and demand side management are implemented simultaneously and individually, in a system, and the effect of each addition on the defined index and on operational costs is investigated. Finally, the robustness of the process to the load and generation prediction errors is investigated.**

***Index Terms*— Energy management, distributed generation, storage units, electric vehicles, demand response, Tabu search.**

I. Introduction

THE structure of conventional distribution systems is changed significantly over the past decades [1]-[2]. The introduction of distributed energy resources, along with advanced metering, communication and control technologies at the distribution level, has changed the conventional distribution systems into multi-microgrid systems which are usually faster, more controllable and reliable. Potentially, there are several types of energy resources and energy consumers in multi-microgrid systems. The presence of energy resources, (from fixed and dispatchable power to probabilistic and intermittent nature DGs), and energy consumers, (from fixed and non-controllable to hourly and probabilistic variable loads), in the system, have manifested the need for optimal management of energy in multi-microgrid systems.

Energy management in modern distribution systems has been an interesting research area for the past decades. Several papers have been published on different energy management options in smart grids, from optimal scheduling of energy resources [3]-[6] to demand-side energy management [7]-[10]. With the increasing capacity and variety of them, electric storage units have been an appealing subject for performing energy management [11]-[14]. Moreover, the number of electric vehicles is increasing in distribution systems, which also raised several research opportunities, especially in terms of energy management [15]-[19].

Some researches have also been published in energy management on microgrids [20]-[26] with multi-agent and/or multi-level control structures. For example, the authors in [20] proposed a two-level architecture for distributed energy resource management for multiple microgrids using multi-agent systems. A symmetrical assignment problem based on naive auction algorithm is used in their paper in order to match the buyers and sellers in the energy market. Reference [21] proposes a decentralized optimal control algorithm for distribution management systems by considering distribution networks as coupled microgrids using the coordinated information and strategies of different microgrids. In [22], the authors present a multi-agent based, three-level, hierarchical energy management strategy by combining the autonomous control of local distributed energy resources at the local level with coordinated energy control at the central level of the microgrid. The authors in [23] propose a multi-level energy management system for dc microgrids operations to ensure system reliability, power quality, speed of response, and control accuracy with system distributed control scheduled as the primary control.

Although the results of several interesting research projects have been published in the energy management area [3]-[26], the literature does not report the development of a systematic approach for combining and comparing a variety of energy management options in a multi-microgrid system, where each microgrid, simultaneously, has different types of DGs, storage units, EVs and demand responses. Moreover, the issue of assessing different energy management scenarios in distribution systems in order to provide insights that will contribute to the success of different available energy management programs is not resolved yet.

Given the importance of energy management in smart grids, this paper formulates a day-ahead planning strategy for performing optimized and coordinated energy management in multi-microgrid systems. As shown in Fig.1, such planning will simultaneously supervise several energy resources and energy consumers in multi-microgrid systems that include dispatchable and non-dispatchable intermittent nature DGs, energy storage units, large numbers of electric vehicles and demand response. With this plan, all the controllable generation/consumption devices in different microgrids are controlled by a central energy management system and operate in accordance with each other (either in the same or in different microgrids) to minimize operational costs. Due to the presence of probabilistic nature DGs and loads in the system, to calculate the total operational costs and show how an energy management scenario will affect operational costs, a new probabilistic index is defined to measure the success of energy management process. A case study is also presented to compare and decide between different options for performing energy management in a multi-microgrid system. Energy management is then performed for different energy generation/consumption units individually and collectively.

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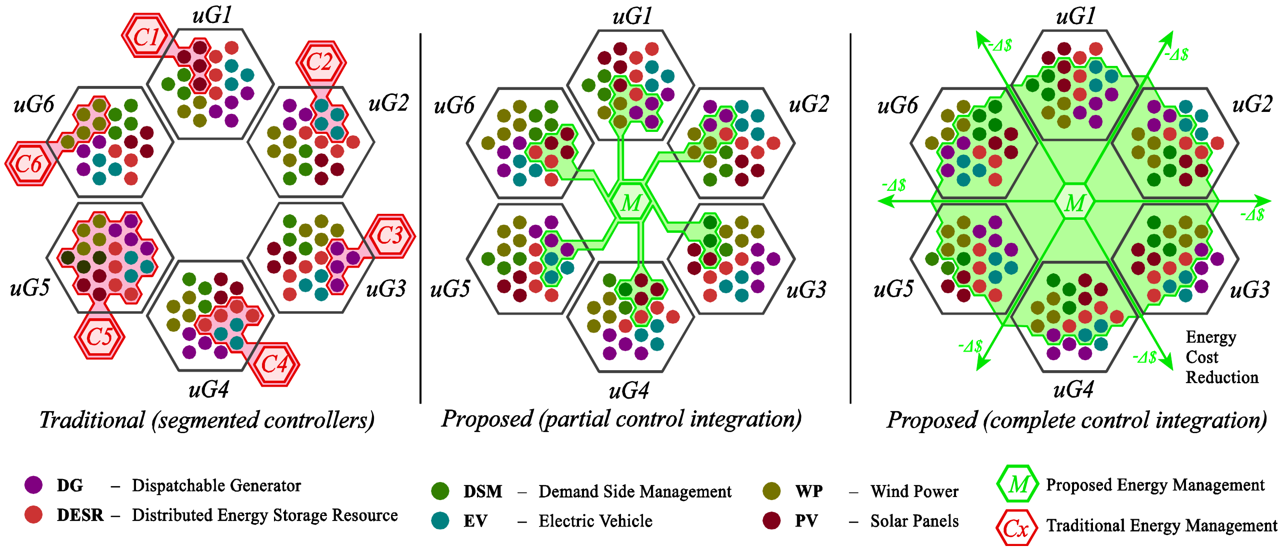

Fig. 1. Proposed versus existing energy management scenarios.

The effect of increasing the number and capacity of generation/consumption units under control on the total costs is shown and the defined index is provided for different energy management scenarios. Moreover, the impact of prediction error on the total daily costs and the defined index is investigated. The PG&E 69-bus system is used for the case studies, and several sensitivity studies are presented to assess different energy management scenarios. The main contributions of the paper can be summarized as follows:

- Formulating the day-ahead optimized energy management problem for a multi-microgrid system that incorporates different types of energy resources, (e.g., wind turbine, PV modules and biomass generators), as well as considering different probabilistic models of EVs for performing energy management,
- Comparing individual and collective energy management options for a multi-microgrid system,
- Defining a new probabilistic index for measuring the success of energy management processes in smart grids under probabilistic load/generation conditions, namely, the energy management success index (EMSI),
- Assessing different energy management scenarios, separately and collectively, in terms of their impact on operational costs and the success of the energy management processes.

The paper is organized as follows: Section II explains the energy management concepts and models of system components. Section III presents the problem formulation, and the solution algorithm is explained in Section IV. The energy management process for a multi-microgrid system is presented in Section V, and the performance of different energy management options are investigated in Section VI. The robustness of the process is studied in Section VII, and the paper is concluded in Section VIII.

II. The Concepts and System Components

The balance between the generated electric energy and the consumed electric energy in a multi-microgrid distribution system should always be maintained. Two different approaches can be followed in a multi-microgrid system to perform energy management. The first approach is to let each microgrid operate individually, regardless of the power balance in neighboring microgrids. In this approach, there should be individual energy management centers for each microgrid to control the generation/consumption of the devices inside them. Some neighboring microgrids may have excess power and some may have power deficits that will not be considered in the operation of devices inside the microgrid under control. The other approach is to have a central energy management center that can control all the devices inside all the microgrids simultaneously. This approach can be beneficial in terms of creating a more efficient balance of energy between different generation/consumption devices inside microgrids and between microgrids themselves. Both approaches are investigated in more detail in Section V. Due to the continuous and probabilistic variation of load and generation capacities in the microgrids as well as timely variation of energy price, such generation/consumption balance can be achieved with different methodologies. Thus implementing certain measures to manage the generation/consumption devices can enormously reduce the costs for reaching the balance. In this paper, the load-generation balance in a multi-microgrid system is achieved with the objective of minimizing the utility costs. For this purpose, as demonstrated in Fig. 2, the load and generation uncertainties in the microgrids are predicted for the next 24 hours and by considering the hourly price of electricity, the optimum state and amount of power generation/consumption by the controllable devices are determined. Regardless of which energy management approach is selected for a multi-microgrid system, the process can be performed hourly or in shorter periods, e.g., every 10 minutes, in order to achieve more accurate and continuous results. Moreover, if the predicted data is not available for 24 hours, the same approach can be implemented for a shorter period of time as well (e.g. 10 hours). The following subsections explain the models of typical energy generation/consumption units in a multi-microgrid system and how they can be managed in order to reduce the utility costs.

A. Distributed Generation Units

The DG units are essential components in microgrids and are modeled in this paper as a combination of PV modules, wind turbines and biomass generators, which are the typical components of the most commonly used DGs in distribution systems.

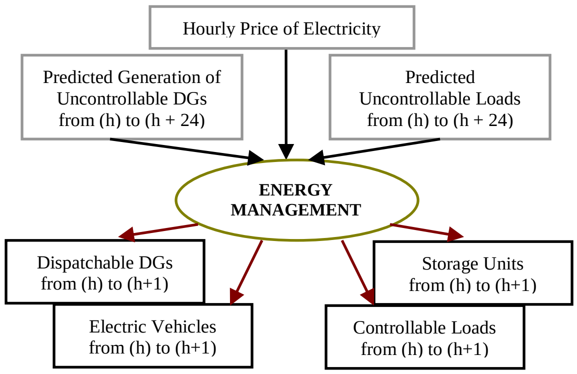

Fig. 2. The day-ahead energy management process at hour *h*.

The DG types presented in this paper have probabilistic, intermittent probabilistic and constant power natures, which mathematically covers the models used for all types of DGs. Therefore, any other type of DG, such as CHP, etc. can be modeled using a similar approach. The output of each PV Module depends on the amount of solar irradiance, the ambient temperature and the characteristics of the module itself. The output power of wind turbines depends on the wind speed and the parameters of the turbine's wind-power conversion curve. Detailed approaches for modeling such DGs are explained in [27]. The biomass generators provide stable firm generation with constant but controllable output powers, and are not affected by uncertainty. In case of uncertainty in the factors that affect the availability of biomass, such as rain, the biomass DGs' output powers can be modeled in a similar way to those of wind turbine generators. For the purposes of energy management, the wind turbine and PV modules output powers are predicted for the next 24 hours by using the short term forecast data for weather conditions. Using such data and the price of electricity for the next 24 hours, the optimum output power of the biomass DGs is predicted hourly for up to the next 24 hours.

B. Energy Storage Units

The energy storage units in microgrids are modeled as active power consumers during the charging period and as generators during the discharging period. The characteristics of these units will be totally different during the charging and discharging time periods. The optimal schedule for the operation of the storage units will be determined in this research based on the cost of energy, the cost of operating storage units, etc., for the next 24 hours. A constraint has been introduced on the amount of power generated by the storage units, which should be less than total loads at anytime. This constraint ensures that, even during off-peak hours, the real power of storage units is less than total demand and guarantees that the reverse power flow, if any, can be modified by controlling the DGs' output power only.

C. Electric Vehicles

Electric vehicles (EVs) add enormous uncertainty to the analysis of microgrid systems. EVs can be considered as loads during charging periods or as loads/generators if they are participating in V2G programs. From a different point of view, EVs can be charged at home in residential areas or be connected to aggregate EV charging stations. As shown in [28], during charging periods, the EVs can be modeled as probabilistic loads with a Normal distribution function in residential communities, while in EV aggregate charging stations they can be modeled probabilistically using the Weibull distribution function. In this research, all four scenarios are considered, which are

- EVs being charged in residential areas, modeled as probabilistic loads with Normal distribution,
- EVs being charged in aggregate EV stations, modeled as probabilistic loads with Weibull distribution,
- EVs being discharged through V2G program in residential areas, modeled as probabilistic generators with Normal distribution,
- EVs being discharged in V2G program in aggregate EV stations, modeled as probabilistic generators with Weibull distribution.

The first two scenarios are modeled as controllable loads for which we can determine the time of charging based on a specified time period, e.g., night hours. The last two scenarios are considered as controllable loads/generators for which we can determine the timeframe and amount of their consumption/generation depending on the selected energy management strategy. In order to determine the probability density functions of EVs, the probability distribution parameters (normal or Weibull) of the EVs can be assumed to be constant (as shown in [28]) or, similarly to the peak EV load pattern, can be predicted by using the historical data.

D. Loads

The loads in microgrids are modeled considering the IEEE-RTS [29]. In this system, the hourly peak load is presented as a percentage of the daily peak load. In order to gain more accurate energy management results, the prediction techniques could also be used for modeling the loads probabilistically or hourly. Some of the loads are assumed to be controllable and available for demand side management purposes. Such loads are considered as transferable from time to time, e.g., from on-peak to off-peak hours.

TABLE I. SELECTION OF NUMBER OF STATES FOR THE PROBABILISTIC STUDY

# of States	2	6	10	12	14	16	20
Objective Function (%)	83.4	91.7	97.4	100	100.1	100.3	100.4
Processing Time (%)	16.67	50	83.33	100	116.67	133.3	166.7

III. PROBLEM FORMULATION

The probabilistic representation of load-generation states and the steps for formulating the proposed energy management success index are presented in this section.

A. Probabilistic Representation of Load-Generation States

In order to integrate the uncertainties mentioned above into the optimization process, such uncertainties are modeled as multi-state variables. For this purpose, the continuous probability density function of the output power of the wind turbines and PV modules, and the EVs charge/discharge pattern for each hour of the day, is divided into a number of states. The selected number of states affects the accuracy and complexity of the formulation. Selecting a small number expedites the calculation process but lowers the quality of results, while selecting a large number increases the quality of results at the expense of calculation time. As shown in Table I, for a simple optimization problem with the objective of optimizing EMSI (Section V-C), increasing the number of states up to twelve will improve the objective function. However, further increases will not have a significant impact on the objective function and will adversely affect the processing time. This table shows that using 12 states provides high quality results. Since the objective function and the processing times will be different depending on the problem and the processing unit, they have been normalized with the 12-state values. Therefore, for each hour of the day we select 12 wind-speed states (N_W), 12 solar-irradiance states (N_S), and 12 EV charge/discharge states (N_{EV}). In this research, the wind speed and solar irradiance and the EVs' behavior are modeled independently for each hour based on their historical distribution; therefore, the inter-temporal or any other correlations are not considered. Assuming that solar irradiance, wind speed and the EVs' charge/discharge states are independent, the probability of any combination of load and generation is obtained by multiplying all the probabilities. Therefore, for each hour, the number of load-generation states will be calculated by multiplying all the states and for a 24-hour period (H=24), the number of load-generation states (N_{state}) is calculated as shown in (1).

$$N_{state} = H \times N_W \times N_S \times N_{EV} \tag{1}$$

Each load-generation state has its own probability of occurrence. If the inter-temporal correlations of wind speed and solar irradiance are to be considered, the probability of each state cannot be calculated by simply multiplying the probability of each state of wind speed and solar irradiance. In fact, the only difference between considering or not considering the correlations will be in the method of calculating the probability of each load-generation state. In the former scenario, the probability of each generation state should be calculated by convolving the two probabilities of wind speed and solar irradiance; however, in the latter scenario, the probability of each state can be calculated by simply multiplying the two probabilities. This may slightly affect the computational tractability in terms of the calculation of probabilities; however, since the formulations of the problem and solution algorithms will remain the same, the proposed method is still practical and useful in high-renewable systems. In order to determine the energy losses or the costs, the AC forward-backward power flow is run for the microgrids for every load-generation state, considering fixed power factor for the loads and generation devices, and the results are accumulated considering the probability of each state.

B. Energy Management Objective Function

The aim of performing energy management in a multi-microgrid system is mainly to reduce operational costs. This section explains the calculation of total operational costs and introduces an index to show how an energy management scenario affects operational costs in a microgrid full of probabilistic parameters. For this purpose, the probabilities in loads and generation units are modeled as deterministic load-generation states, as explained in Section III-A. The overall costs or EMSI is then calculated by deterministically calculating the costs or EMSI for each load-generation state and its accumulation considering the probability of the states. The proposed energy management success index (shown in (2)) is calculated by using the operational costs before and after the energy management process,

$$\text{EMSI} = \sum_{j=1}^{N_{state}} \left(\frac{TC_{j\_Before} - TC_{j\_After}}{TC_{j\_Before}} \times p_j \right) \times 100 \tag{2}$$

where TC_j is the total operational costs at j^{th} load generation state; N_{state} is the number of load-generation states and p_j is the probability of j^{th} load-generation state. The steps to calculate the operational costs and the EMSI for the simultaneous consideration of all energy management options, as well as for the individual consideration of each energy management scenario, are explained in the following. It should be noted that, since the purpose of this paper is to assess different energy management scenarios, only the costs that will be affected by energy management process (operational costs) are investigated, and other costs, such as planning costs, are not considered in this research.

For the dispatchable biomass DGs, the total operational benefits/costs of the DGs (TC_{DG_j}) at j^{th} load-generation state, before and after energy management, can be calculated from (3). In this case, the total costs of the utility include the cost of lost power purchased from the upstream system (first part of (3)) and the cost of DGs for the generation of P_{DG} amount of power (second part of (3)). On the other hand, installing DGs provides benefits for the system, which will reduce costs. These benefits come from DGs supplying power (P_{DG}) to a number of loads instead of purchasing power from the upstream system (third part of (3)). The upstream system is part of the system that supplies each microgrid. It could be the grid itself, if the microgrid is directly connected to the distribution substation, or it could be another microgrid that connects the specified microgrid to the network.

$$\begin{aligned} TC_{DG\_j} = \sum_{h=1}^{24} P_{Loss\_h} \times C_{E\_h} + \sum_{k=1}^{N_{DG}} \sum_{h=1}^{24} P_{DG\_kh} \times C_{DG} \\ - \sum_{k=1}^{N_{DG}} \sum_{h=1}^{24} P_{DG\_kh} \times C_{E\_h} \end{aligned} \tag{3}$$

where P_{Loss_h} is the total system losses at time h; C_{E_h} is the cost of energy at time h; P_{DG_kh} is the output power of k^{th} DG at time h; C_{DG} is the cost of generation for the biomass DGs and N_{DG} is the number of dispatchable DGs in the system. In this paper, the dispatchable DGs are set as biomass-based and the cost of generation is assumed to be the same for all generators. The electricity generated by such DGs is usually more costly than that generated by large power plants; therefore C_{DG} could be larger than C_{E_h}. It is assumed that, before energy management, the DGs are working at nominal power and, after that, the output powers of DGs are determined through an optimization process.

The total operational benefits/costs of storage units (TC_{ESS_j}) at j^{th} load-generation state, before and after energy management, can be calculated from (4), which is different for the charge and discharge period of the storage units.

$$TC_{ESS\_j} = \begin{cases} \sum_{h=1}^{24} \left(\sum_{k=1}^{N_{ESS}} P_{ESS\_kh} + P_{Loss\_h} \right) \times C_{E\_h} + \\ \qquad \sum_{k=1}^{N_{DG}} \sum_{h=1}^{24} P_{ESS\_kh} \times C_{ESS} \qquad \text{if Charging} \\ \sum_{h=1}^{24} \left(-\sum_{k=1}^{N_{ESS}} \eta_{ESS} P_{ESS\_kh} + P_{Loss\_h} \right) \times C_{E\_h} + \\ \qquad \sum_{k=1}^{N_{ESS}} \sum_{h=1}^{24} \eta_{ESS} P_{ESS\_kh} \times C_{ESS} \qquad \text{if Discharging} \end{cases} \tag{4}$$

where P_{Loss_h} is the total system losses at time h, C_{E_h} is the cost of energy at time h, P_{ESS_kh} is the real power (charge or discharge) of k^{th} storage unit at time h, C_{ESS} is the cost of charge/discharge for the storage units, η_{ESS} is the efficiency of the storage units and N_{ESS} is the number of storage units in the system. It is assumed that, before energy management, the storage units are not in service and, after energy management, the charge/discharge amounts and periods are determined by the optimization process.

The total operational benefits/costs of performing demand side management (TC_{DSM_j}) at j^{th} load-generation state, that will be affected, arise from energy losses, which cost different amounts at different hours and are calculated as shown in (5).

$$TC_{DSM\_j} = \sum_{h=1}^{24} P_{Loss\_h} \times C_{E\_h} \tag{5}$$

where P_{Loss_h} is the total system losses at time h; and C_{E_h} is the cost of energy at time h. In a long-term vision, the demand side management may postpone some system upgrades that should be performed by the utility and will reduce the utility costs. In the energy management research presented in this paper, it is assumed that the change in the price of electricity will be reflected in the customers; therefore, from the utility's point of view, the benefits of demand side management at the operational stage will be only the reduction of energy losses. The change in the price for different hours that the load is shifted in between will only be reflected into the cost of energy losses that utility covers. Therefore, for this energy management scenario, the losses before and after demand-side management are used to calculate the EMSI. It should be noted that the demand-side management process has mutual benefits for the customers and the utility. The customers will benefit from paying less to the utility due to the lower price of electricity, and the utility could benefit from load balancing and from reducing the stress of transmission and distribution systems. In this research, since the other benefits of DSM are case-specific and should be calculated based on specific system conditions, they are excluded and, if needed, can easily be added to the total costs function.

The electric vehicles, whether charged through EV aggregate or residential buses, can be treated as controllable loads and storage units simultaneously. However, there are some restrictions that should be considered. Firstly, the behavior of EVs is not deterministic; the charging and discharging scenarios, as well as whether the EVs are parked or on the road, is probabilistic. For this research, it is assumed that 50% of EVs are participating in the V2G program, which means that they can also be considered as generators as long as they are not being charged, and the probability that the car is parked in EV stations or at houses follows the probabilistic model presented in [30]. Therefore, as was done with the formulations regarding storage units, the total operational benefits/costs of the utility that are related to the operation of EVs (TC_{EV_j}) at j^{th} load-generation state, can be calculated as shown in (6). The only difference between EVs operating as storage units and the storage units is that the cost of charging the EVs will be paid by the vehicle owners and not by the utility; therefore, the total cost will equal zero at charging periods and the period of charging for the EVs will only affect the system losses which cost different amounts at different hours. In this research, it is assumed that, with some price incentives, the EV owners are encouraged to participate in V2G program and authorize the utility to take control of the charge/discharge pattern of their vehicles. Also, it is assumed that if the vehicles are participating in V2G program, the utility is already compensating their participation during discharge periods; however, the compensation can also be considered separately for taking control over charging periods, and can be added as a cost for the utility during this period as well.

$$TC_{EV\_j} = \begin{cases} \sum_{h=1}^{24} P_{Loss\_h} \times C_{E\_h} & \text{if Charging} \\ \sum_{h=1}^{24} \left(-\sum_{k=1}^{N_{EV}} \rho_{EV} P_{EV\_kh} + P_{Loss\_h} \right) \times C_{E\_h} + & \\ \qquad \sum_{k=1}^{N_{EV}} \sum_{h=1}^{24} \rho_{EV} P_{EV\_kh} \times C_{EB\_h} & \text{if Discharging} \end{cases} \tag{6}$$

where P_{Loss_h} is the total system losses at time h; C_{E_h} is the cost of energy at time h; P_{EV_kh} is the discharged power of k^{th} EV bus; C_{EB_h} is the cost of buying electricity from EV owners at time h; ρ_{EV} is the percentage of EVs participating in the V2G program, and N_{EV} is the number of EV buses in the system. Before energy management, the EV buses are operating as regular probabilistic loads and, after energy management, the charge/discharge amounts and time periods for the EVs participating in V2G program are determined through the optimization process.

After calculating total operational costs for all the devices including DGs, ESSs, DSM and EVs, the utility's total operational costs for each load-generation state can be formulated as (7).

$$TC_j = TC_{DG\_j} + TC_{ESS\_j} + TC_{DSM\_j} + TC_{EV\_j} \tag{7}$$

The EMSI can then be calculated by using (2) and by calculating the costs before and after performing energy management in (7). Since the EMSI represents the reduction in the total operational costs of the system, by optimizing the EMSI, the total operational cost will be minimized for the system under study. In a case where the energy management is performed for a multi-microgrid system, TC_j can be calculated for each microgrid individually and be summed for all microgrids to obtain a single objective function for performing energy management.

IV. Solution Algorithm

The objective function for performing energy management in a multi-microgrid system was defined in the previous section (EMSI). The goal at this stage is to find appropriate values for the decision variables P_{DG}, P_{ST}, L_{DM} and P_{EV} for the next 24 hours to optimize this objective function. The combinatorial nature of the present problem demands efficient solution algorithms. Heuristic optimization techniques are well suited for such optimization problems. Two types of algorithms are used in this research: Tabu Search (TS), as the main optimization method and the forward-backward-based probabilistic power flow method. TS is a heuristic search algorithm that uses different memory structures to intelligently and effectively guide the search to a good solution. As with other optimization methods, there are both advantages and disadvantages to using TS. The advantages of TS are that it allows a non-improving solution to be accepted in order to escape from a local optimum, it can be applied to both discrete and continuous solution spaces, and, for larger and more difficult problems

TABLE II. SELECTION OF NUMBER OF ITERATIONS

# of Iterations	20	50	100	150	200	250	300
Objective Function (%)	66.2	74.3	86.1	95.4	97.3	100	100

TABLE III. SELECTION OF PERCENTAGE OF COMPONENTS TO BE CHANGED

% of components	5	10	20	30	40	50	60
Objective Function (%)	62.3	85.1	93.0	100	97.2	96.1	91.8

(such as the problem formulated in this research), Tabu Search obtains solutions that rival and often surpass the best solutions previously found using other approaches [31]. There are also some disadvantages, e.g. many parameters must be determined to reach the global optimum and the number of iterations could be large. Considering the advantages and disadvantages of TS and the nature of the formulated problem, TS will be an appropriate and efficient solution algorithm. The steps needed to solve the optimization problem using the TS algorithm are shown in Fig. 3 and explained in the following sub-sections.

A. Neighborhood Definition in TS

The first step in TS is to select the starting point, and the process continues iteratively until a certain criterion, which is usually the maximum iteration numbers, is reached. Selecting a small number as the maximum number of iterations will affect the final results. However, if the maximum number of iterations is selected properly, the whole search space will be covered and examined.

The maximum iteration number depends on the nature of the problem and decision variables. One approach to setting the maximum iteration number is to increase it continuously until there is no improvement in the objective function value, as was done in the research described in the . Table II shows the effect of selecting different maximum number of iterations on the objective function for a simple optimization problem with the objective of optimizing EMSI (Section V-C). It is seen that, by increasing the number of iterations, the objective function will improve up to a certain value.

The starting point can be selected as a decision variable with arbitrary but feasible values. For example, the values of P_{DG}, P_{ST}, P_{DM}, and P_{EV} could be all set as zero or 0.5 p.u. to start the process. The interesting fact about the Tabu search is that the final solution is not dependent on the starting point at all and, by using long-term memory (as will be shown in Section IV-C), the search process jumps into new regions whenever no improvements is seen in a specific region. Therefore, it will be possible to select any value as the starting point without leading to different solutions. The decision variables for performing energy management by using the k^{th} system component for the next 24 hours can be shown as the following vectors:

$$P_{DG\_k} = [P_{DG\_k1} \;\ldots\ldots\; P_{DG\_k24}], \quad (8)$$

$$P_{ST\_k} = [P_{ST\_k1} \;\ldots\ldots\; P_{ST\_k24}], \quad (9)$$

$$L_{DM\_k} = [L_{DM\_k1} \;\ldots\ldots\; L_{DM\_k24}], \quad (10)$$

$$P_{EV\_k} = [P_{EV\_k1} \;\ldots\ldots\; P_{EV\_k24}], \quad (11)$$

where the components of P_{DG_k}, P_{ST_k}, L_{DM_k} and P_{EV_k} represent the output power of DGs, output/input power of storage units, load percentage to be supplied and charge/discharge power of EVs for the next 24 hour time period, respectively. The next step is to make sets of neighbors for all the starting points. Each neighbor is selected by changing a number of components of each vector and checking its feasibility in terms of the constraints which are voltage and current limits and DGs capacities. This number is chosen based on the size of the decision variable vectors. A small number will make the neighborhood more homogeneous and a large number makes it more diverse. Table III shows how changing different percentages of the components, used to create the neighborhood list, affects the objective function. It is seen that, by increasing the percentage of components that are changed, the objective function will improve up to a certain value and then will worsen. The reason for this is that changing a large percentage of components will prevent the search from concentrating in a specific region to find the local optimum, which could result in locating the global optimum.

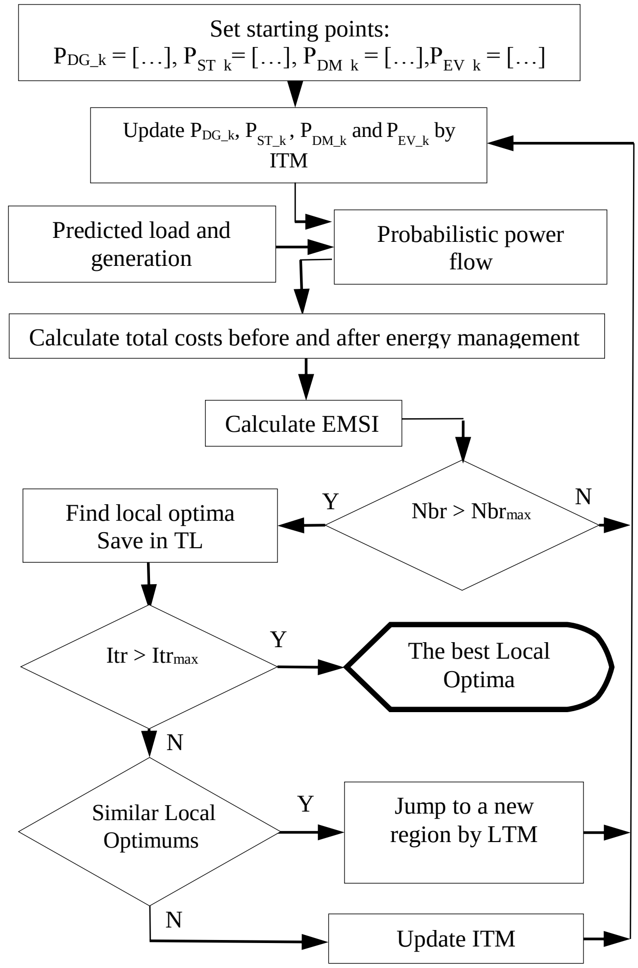

Fig. 3. Flowchart of energy management in Multi-microgrid system, *Nnbr* is number of neighbors and *Itr* is the iteration number.

In this research 30% of the components of each decision variable vector are changed in creating the neighborhood list. For example, if the length of the decision vector is 10, changing three components to make a new neighbor is appropriate. Selecting the maximum number of neighbors will affect the final results. The effect of selecting a different number of neighbors on the objective function for the same case study (Section V-C) is shown in Table IV. It is seen that, by increasing the number of neighbors, the objective function will improve up to a certain value.

TABLE IV. IMPACT OF NUMBER OF NEIGHBORS ON THE OBJECTIVE FUNCTION

# of Neighbors	5	10	25	30	35	40	45
Objective Function (%)	89.5	88.3	100	100	100	100	100

TABLE V. IMPACT OF LENGTH OF TABU LIST ON THE OBJECTIVE FUNCTION

TL	2	5	8	10	12	15	20
Objective Function (%)	64.3	86.2	92.8	100	99.1	97.3	96.4

Next, the best neighbor is set as the new starting point and the process continues until the maximum number of iterations is reached. Different memory structures, such as short-term (Tabu list), intermediate-term and long-term memories, are implemented to diversify and intensify the search process and reach the global optimum more effectively.

B. Tabu List and Aspiration

To avoid stopping in a local optima, and to prevent cycling around it, some Tabu restrictions should be imposed by using a short-term memory called Tabu List (TL). This list, which has a FIFO (first in first out) structure, keeps track of the best solutions that have been visited in previous moves, or the moves that have resulted in the optimum point in previous regions, and avoids revisiting them. The length of TL depends on the size of the problem and is usually determined experimentally. In our problem, we have made the TL from the best recently visited solutions. For this purpose, a quantity, which is unique for each set of parameters, is saved in the TL as shown in (12).

$$\sum_{i=1}^{n} Z(i)\times 2^{i} \qquad (12)$$

where Z is a vector that is created by placing the components of all decision vectors (including P_{DG_k}, P_{ST_k}, L_{DM_k} and P_{EV_k}) together.

Table V shows the effect of selecting different TL values on the objective function for a simple optimization problem with the objective of optimizing EMSI (Section V-C). It is seen that, by increasing the TL, the objective function will improve up to a certain value and then will worsen. The reason again is that selecting a large number as TL will prevent the search from concentrating in a specific region to find the local optimum (potentially global optimum).

An aspiration criterion is a rule that releases the valuable members of Tabu list. This relaxation is allowed when the newly met solution point has better properties than the optimum point reached so far. This phenomenon will make the search process more intelligent and prevent it from missing higher quality results.

C. Intensification and Diversification in TS

Two memory structures are used in TS to avoid random search, namely, Intermediate-Term Memory (ITM) and Long-Term Memory (LTM). The ITM memorizes the common features of sub-optimal solutions for a number of iterations and then tries to search for the optimum point with similar features in that region. This intensification process will guide the search in each region to identify the high quality solutions rather than to make random undirected movements. During the search process, the LTM is used to diversify the search by jumping to a new region and allows the algorithm to go through all the possible solutions to find the global optima. This long-term memory will keep track of the common features of all initial starting points in different regions to

TABLE VI. SELECTED BUSES FOR INSTALLING ENERGY RESOURCES

Energy Resource	Locations (Buses)	Capacities (kW/kVAr)
Wind Turbine	13,16,19,43,49,52	50,25,50,50,50,25
PV Module	17,23,41,50,53,56	25,25,25,25,25,25
Biomass DG	15,22,27,41,42,54	100,100,100,100,100,100
Storage Units	11,27,31,48,52,64	50,50,50,50,50,50
Reactive Sources	5,19,26,33,52,65	50,50,50,50,50,50

TABLE VII. EVS AND CONTROLLABLE LOADS

Load Type	Locations (Buses)	Rated Powers (kW/kVA)
Residential EVs	4,11,22,43,57,62	15,15,15,15,15,15
Aggregate EVs	5,12,24,44,53,63	25,25,25,25,25,25
Controllable Loads	11,12,38,39,48,54	(145+j104),(145+j104),(128+j91), (128+j91),(100+j72),(59+j42)

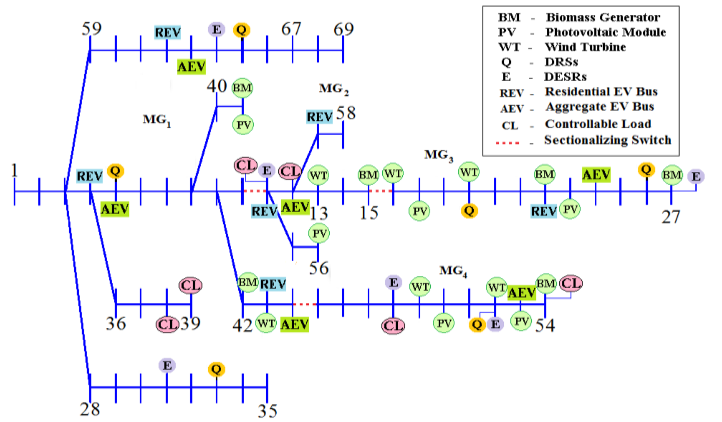

Fig. 4. Multi-microgrid system and the location of components.

avoid restarting from similar, previously used starting points. To summarize, as shown in Fig.3, the TS will search all regions and finds the local optima in each neighborhood, and when all the regions have been searched by the algorithm, the best local optima will be the global optima. If the maximum number of iterations is selected properly, the whole search space will be covered and examined.

The two types of memories have been implemented for each decision vector by using two sets of vectors with the same length as the decision variables. Each component of the ITM vectors will represent the number of times the associated component has been changed in the sub-optimal solutions. The larger each component is, the lower the chance is that the value is the optimum. Thus, the next movements or neighborhoods will be selected so that the components that are thought less likely to be the optimum have a higher chance of being changed. The long-term memory is also implemented in a similar way. More details on definition and implementation of the memory structures can be found in [32]-[33]. As a sub-program, the forward-backward power flow algorithm is also a well-known method used for power flow calculations in radial distribution systems [34]. During the optimization process, the AC forward-backward power flow is run for each load-generation state and the results, such as energy losses or EMSI, are accumulated by considering the probability of the states. It should be noted that in this paper, it is assumed that the distribution system is radial; therefore, the best option for performing power-flow would be the forward-backward method. However, selecting a different power flow method will not affect the proposed energy management scheme. The same goal can be achieved by using other methods, such as Newton – Raphson, which is more appropriate for solving meshed networks.

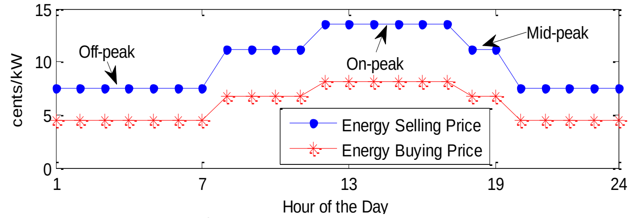

Fig. 5. The hourly price of selling and buying electricity.

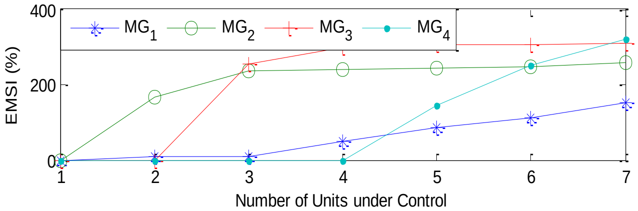

Fig. 6. Variation of EMSI by changing the number of controllable units.

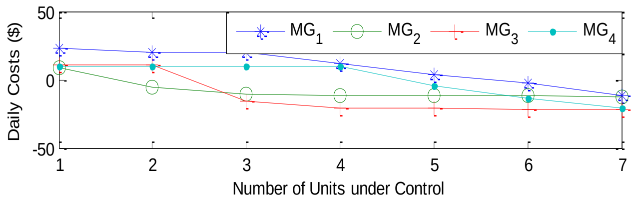

Fig. 7. Daily costs by changing the number of controllable units.

V. Energy Management in Multi-Microgrid Systems

The system under study and the energy management approaches proposed for a multi-microgrid system are presented in this section.

A. *The System under Study*

The well-known PG&E 69-bus distribution system is selected for the implementation and sensitivity studies. The system's modified load data can be found in [35]. This system is divided into four microgrids by locating three sectionalizing switches in the system, and different types of energy resources are added to the microgrids, with the capacities shown in Table VI. During normal operation of the system, the microgrids are connected together and to the grid. Therefore, the grid power is also covering part of the energy required by the loads inside the microgrids. However, the same formulations and approach can be used in cases where the microgrids are operating in islanded or off-grid mode. The reactive sources are modeled as fixed generation installed on specific buses. The reactive sources could be fixed capacitors (e.g. bus 5) or an auxiliary service provided by the DG unit, such as wind turbines (e.g. bus 19), and their location and capacity are predetermined based on the construction of the microgrid. In cases where there are variable reactive sources, they may also be used for voltage/line loading control. In such cases, the generation capacities of reactive sources can be considered as decision variables for optimization problems, in a similar approach to that taken with active power. The EV aggregate charging stations and areas with residential EV charging capabilities, as well as controllable loads for performing demand side management, are listed in Table VII. The locations of energy generation-/consumption units and the sectionalizing switches are shown in Fig. 4. The price of electricity is chosen from Hydro One Company in Ontario, Canada. There are three price levels, for on-peak, mid-peak, and off-peak periods, as shown in Fig. 5.

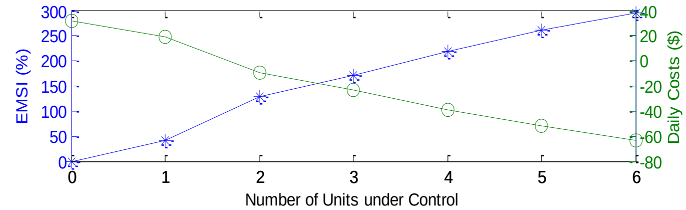

Fig. 8. EMSI and daily costs by changing the number of controllable units.

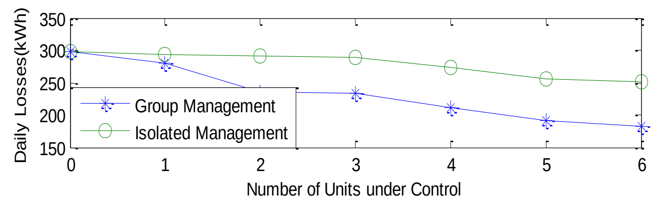

Fig. 9. Daily energy losses by changing the number of controllable units.

In this figure, the hourly price of buying electricity from the customers participating in the V2G program is also shown, and is proportionate to the selling price. In the following, the two energy management options for a multi-microgrid are implemented in the system under study and are compared in terms of their successfulness.

B. *Multi-Microgrid Isolated Energy Management*

At this stage, the holistic energy management process covering all generation/consumption devices is implemented for each microgrid separately, and the results are presented. The operational costs for each generation/consumption unit are explained in details in Section VI. The variation of EMSI and daily costs for different microgrids with different numbers of controllable units (0 to 6) are shown in Fig. 6 and Fig.7. It is seen that for all microgrids, having more units under control will result in larger EMSI index and less operational costs. For some microgrids, increasing the number of controllable units in the system does not affect the EMSI because the controllable unit is not located in that microgrid. For this system, the summation of daily costs related to energy management in microgrids are reduced from \$32 to \$-51 per day. The negative values mean that performing energy management will not only reduce the costs, it will also benefit the system. It should be noted that the costs that are considered in this research are only those that will be affected by performing energy management scenarios, such as costs of losses or operation of DGs, storage units and purchasing electricity from EV owners. Other costs related to the system, including all planning costs, are not considered here.

C. *Multi-Microgrid Group Energy Management*

In this section, the proposed energy management process is implemented for the whole multi-microgrid system. The total operational costs for each load-generation state are calculated using (7), and the EMSI for the system is calculated by substituting (7) in (2). It is assumed that, at each stage, one unit from all controllable devices comes under control. The EMSI and daily costs reduction for increasing the number of units under control from 0 to 6 are shown in Fig. 8. It is shown that by increasing the number of units under control, the EMSI increases from 0 to 298%. Moreover, the daily costs related to energy management will be reduced by increasing the number of units under control.

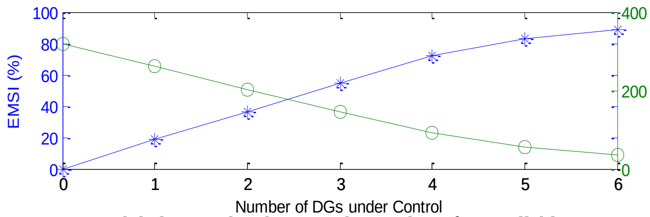

Fig. 10. EMSI and daily costs by changing the number of controllable DGs.

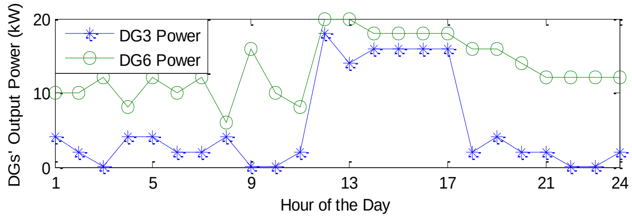

Fig. 11. Hourly variation DG3 and DG6 output powers.

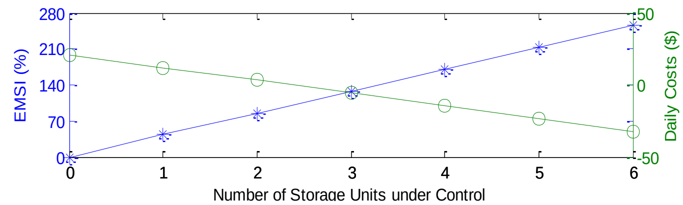

Fig. 12. EMSI and daily costs by changing number of controllable storage units.

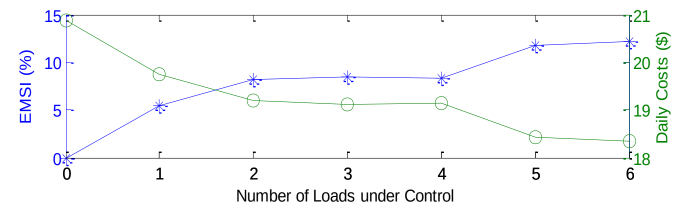

Fig. 13. EMSI and daily costs by changing the number of controllable loads.

D. *Results Comparison*

The two proposed scenarios for performing energy management for a multi-microgrid system, isolated and group, seem to be efficient for a multi-microgrid system. In this section, they are compared in terms of daily energy losses as a considerable operational cost. The variation of daily energy losses for the two scenarios is shown in Fig. 9. It is seen that daily energy losses are reduced in both energy management scenarios by increasing the number of units under control. The daily energy losses for the isolated microgrid energy management are reduced from 297 kWh to 252 kWh; however, when energy management is performed for the whole system, the daily energy losses are reduced from 297 kWh to 183 kWh, which is a much larger reduction. Also, the total daily costs (benefits) of operating microgrids in group management is $-63, while in isolated management, the cost is $-51. Clearly, this difference in the operational costs and daily energy losses, if accumulated over a year or over several years, will add up to a huge amount and, in addition to providing environmental benefits, will benefit both utilities and customers and will affect the price of electricity. In practice, although each microgrid may tend to operate independently and have discrete energy management systems, this study shows that performing energy management for the whole system of multiple microgrids simultaneously will be more beneficial and cost effective than performing it for each microgrid individually. In fact, the multi-microgrid group energy management approach avoids the tragedy of the commons. In other words, it prevents individual microgrids from acting independently and rationally according to their own self-interest and from behaving contrary to the best interests of the whole system by depleting common resources.

VI. Assessment of Energy Management Options

At this stage, each energy management scenario is applied in the multi-microgrid system individually for different cases, and the results in terms of EMSI and total operational costs are investigated.

A. *Energy Management via Dispatchable Biomass DGs*

The biomass DGs are considered to be dispatchable in this research. It is assumed that the cost of operating such DGs is 0.12$/kW. In this section, only the dispatchable DGs are considered as control variables for performing energy management. The EMSI and the daily costs for the utility are calculated for different cases where the energy management is performed for different numbers of DGs, and the results are presented in Fig. 10. It is seen that optimally controlling the biomass DGs with capacities ranging from 0 to 600 kW, can increase the EMSI from 0 to 88.91%. When all the DGs are optimally controlled for energy management purposes, the daily costs for the utility of operating the DGs only, will be reduced from $319.69 to $35.44, which is a considerable reduction for a single day. If we assume almost the same amount of savings for a period of a whole year or more, we can see that the savings will be great. In order to see how the output of DGs varies during 24 hours in the optimum energy management scenario, the output power of the third and sixth generators are plotted in Fig. 11 as samples for a case where all six generators are optimally controlled. It is an interesting point that, although the cost of the energy generated by biomass DGs is much higher than the price of electricity during off-peak hours, owing to the amount of loss reductions, it is still more beneficial to run the DGs at some buses than to energize the loads from the network. This fact further emphasizes the need to perform optimum energy management for the modern distribution systems.

B. *Energy Management via Storage Units*

In this section, only the storage units are considered as control variables to perform energy management. It is assumed that the efficiency of the storage units is 80%, with one charge/discharge cycle occurring every 24 hours at a cost of 0.005$/kWh. It should be noted that, since the purpose of this research is to assess different energy management scenarios, only the costs related to the operation of the devices are minimized and other costs, such as replacements, fixed O&M, etc., are not considered. As shown in Fig. 12, by increasing the number of controllable storage units, the EMSI increases from 0 to 255%. Moreover, the daily costs related to operate the storage units is reduced from $20.89 to $-32.53. The negative cost shows that when the storage units are optimally controlled, they do not merely cover their own operational costs, but provide financial benefits for the utility as well, which may cover the installation costs over a longer time.

C. *Energy Management via Demand Side Management*

The demand-side management is considered as a control option in this section. It is assumed that up to 30% of the loads connected

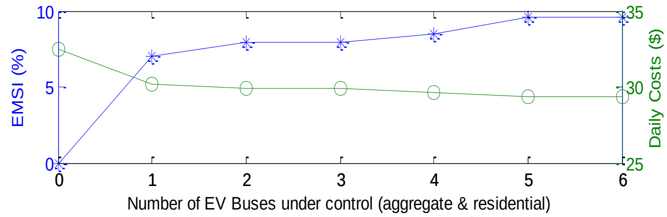

Fig. 14. EMSI and daily costs by changing the number of controllable EV buses.

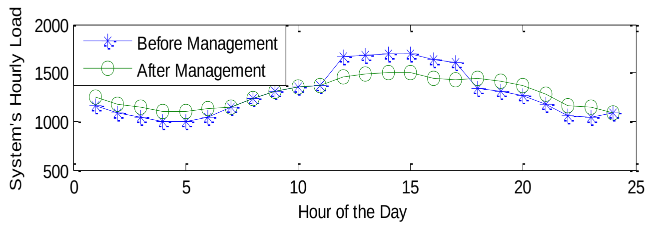

Fig. 15. Variation of loads at bus 48 before and after demand side management.

TABLE VIII COMPARING DIFFERENT ENERGY MANAGEMENT OPTIONS

Control options available for energy management				Daily Costs
DGs	DESRs	EV	DSM	Reduction ($)
X				41.9
	X			53.4
		X		3.4
			X	2.1
X	X			88.6
X		X		43.8
X			X	42.1
	X	X		55.7
	X		X	54.2
		X	X	5.2
	X	X	X	57.9
X		X	X	45.8
X	X		X	91.4
X	X	X		92.2
X	X	X	X	95.3

to buses mentioned in Table VII are controllable and can be shifted for up to 6 hours. At each stage, one of the loads is added to the controllable loads, and its impact on the EMSI is shown in Fig. 13. It is seen that by increasing the number of controllable loads, the EMSI increases from 0 to 12.1%. The total daily costs related to the shifting of loads are also reduced from $20.48 to $18.37. The reduction in daily costs is related to the costs that the utility has to pay and clearly the customers' saving at the controllable buses will be much greater due to the difference in the price of electricity during off-peak and on-peak hours.

D. Energy Management via Electric Vehicles

In this section, only the electric vehicles charging and discharging periods for the V2G program are considered as control variables. The V2G program cannot be successful without the active participation of vehicle owners, and the active participation of vehicle owners cannot be obtained without reasonable price incentives. The hourly prices for purchasing electricity from vehicle owners are as shown in Fig. 5. Through the application of the V2G program, the EVs can be ordered to act as generation sources and/or as responsive loads depending upon the state of the power system and of the EVs battery storage systems. Fig. 14 shows the variation of EMSI as well as daily costs for the utility for several scenarios. It is seen that by taking more EV buses (aggregate and residential) under control, the EMSI increases from 0 to 9.7%. Moreover, the daily cost is reduced from $32.5 to $29.1. It is shown that due to the lower capacity of EVs compared

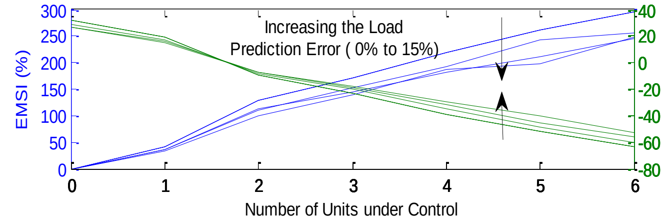

Fig. 16. EMSI and daily costs by changing the load prediction error.

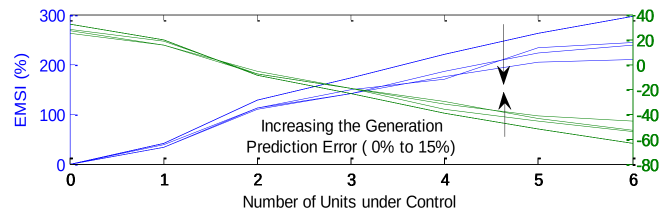

Fig. 17. EMSI and daily costs by changing the generation prediction error.

to that of biomass DGs and storage units, the cost reduction is relatively lower. The hourly variation of total system loads before and after performing energy management for a case in which six aggregate and six residential EV buses are under control is shown in Fig. 15. As explained before, depending on their availability, the state of charge and the system's condition, EVs can be instructed to be generators or responsive loads. For this study it is assumed that the charging period can be delayed by up to 12 hours.

E. Summary and Comparison

The different energy management scenarios are compared in this section to investigate the effectiveness of considering all generation/consumption devices in the energy management process. For this purpose, the results of several case studies in terms of daily costs reduction are presented in Table VIII. In all case studies, it is assumed that all six controllable devices from each group (DGs, DESRs, DSM and EVs) are covered by the energy management system. The letter X in the table shows that the related device is controlled in all microgrids for the purpose of energy management. It is seen that by including more devices in the control zone of the energy management system, the EMSI will be larger and the total operational costs will be reduced. It should be noted that the cost reduction amount and the calculated values depend significantly on the rated power of the controllable devices and the results could be different for different selections of such values. The purpose of generating this table is to demonstrate that considering all controllable devices in the energy management process will be more cost effective and beneficial.

VII. ROBUSTNESS OF THE ENERGY MANAGEMENT PROCESS

The day-ahead energy management plan, proposed in this paper, used the predicted values of loads and generation for the next 24 hours to plan for the generation and consumption of devices in the multi-microgrid system. This section investigates the sensitivity of the plan in terms of the EMSI and total costs to the prediction error. The prediction error occurs when the actual load/generation data for the next 24 hours differs from what we predicted. For instance, if we assume the load will be 1pu in hour H but it is actually 1.05%, we have a 5% error in load. Therefore, an increase in load/generation prediction error is modeled by increasing-/decreasing the actual load/generation by X% from the predicted

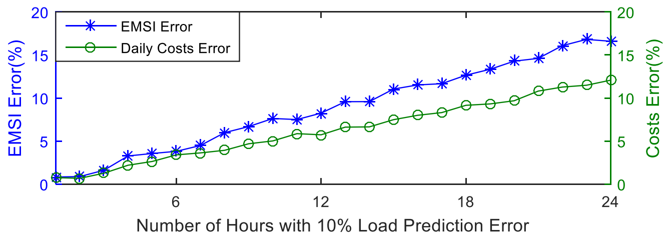

Fig. 18. EMSI and daily costs by changing the number of hours with 10% load prediction error.

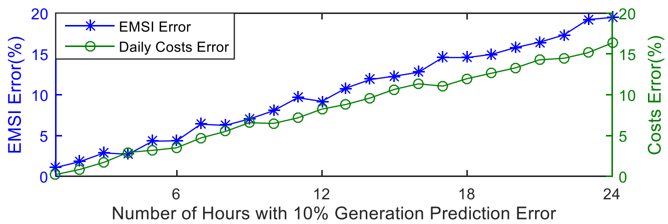

Fig. 19. EMSI and daily costs by changing the number of hours with 10% generation prediction error.

load/generation data for each system component. The EMSI is then calculated by using the settings of load/generation devices derived from predicted data by using the actual load/generation data. The EMSI and total costs for the cases that we have examined (5%, 10% and 15% prediction error in load and generation level) are plotted in Fig. 16 and Fig. 17, respectively. The prediction error is considered as both excess and deficit (up or down shift) compared to predicted values of all loads and generation units in the system, and the EMSI and daily costs for the worst cases are plotted in the figures. As shown in Fig. 16, by increasing the load prediction error from 0% to 15%, for the case that all the units are under control, the EMSI is reduced from 298% to 246%. Also for the same case, by increasing the load prediction error, the total daily costs are increased from $-63 to $-52. The impact of generation prediction error on the EMSI and daily costs are plotted in Fig. 17. It is seen that by increasing the generation prediction error from 0% to 15%, the EMSI reduces and the daily costs increase. For the case that all devices are under control, the EMSI reduces from 298% to 239%, and the total daily costs are increased from $-63 to $-45 per day. To better illustrate the impact of hourly basis prediction error on the EMSI and total costs, several case studies are run and the results are presented in Fig. 18 and Fig. 19. In these figures, it is assumed that the prediction error is 10% and this error exists for predicted load and generation for the next X hours, where X ranges from 1 to 24. It is seen that, by increasing the number of hours that have 10% prediction errors for load and generation, the calculated error for EMSI and daily costs will increase. Moreover, the error in calculated EMSI and daily costs is slightly larger if the error is in the amount of power predicted to be generated by the DGs. This study shows that although some benefits are lost due to the prediction error, the benefits in terms of the EMSI and daily costs are still considerable to justify energy management implementation in smart distribution grids.

VIII. Conclusions

In this paper, an optimized strategy for performing energy management in multi-microgrid systems is presented. The research paper makes new contributions to the field in terms of defining a new probabilistic index (EMSI) to assess the success of energy management options, considering all energy management options (including probabilistic DGs, DESRs, DSM and EVs) simultaneously for the purpose of energy management, solving the energy management problem for multi-microgrid systems and performing assessments for different energy management scenarios.

A case study is presented to compare two different energy management options for multi-microgrid systems. It is shown that in a multi-microgrid distribution system, performing energy management for the whole system simultaneously would be more beneficial compared to performing it separately for each microgrid. It is shown that the total system's energy losses will be much lowered when energy management is performed collectively.

Furthermore, through several sensitivity studies, it is shown that in most cases, performing energy management in a multi-microgrid system does not merely cover the controlled devices' operational costs, but also provides the utility with financial benefits that may cover the installation costs over a long period of time. Moreover, by simultaneously performing different energy management scenarios (e.g., controlling all generation-/consumption units), the EMSI will increase further and the operational costs will be reduced significantly.

The case studies presented in this paper provide an insight for utility engineers to 1) compare the different energy management scenarios in a multi-microgrid system, and 2) select the appropriate energy management option, based on their requirements, for implementation in a multi-microgrid distribution system.

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