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Two-stage stochastic programming formulation for optimal design and operation of multi-microgrid system using data-based modeling of renewable energy sources

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ABSTRACT

Microgrid (MG) is intended to accommodate distributed renewable energy sources and manage the generated electricity using a dispatch and storage system to satisfy the demand of a local region over time. Main challenges associated with operating such a system stems primarily from the intermittent and uncertain nature of renewable energy sources causing the energy generation to be highly irregular and less predictable. Multi-microgrid (MMG) systems with flexibility to trade energy between individual MGs can alleviate the demand–supply mismatch problem, but its design and operation become more complicated. Previous studies on MMGs addressed only the case where all the MGs are fully connected to share electricity. However, the installation of electric cable connections over the full network can be costly and is often unjustified. To address the question of how to best achieve a tradeoff, this work proposes the use of a two-stage stochastic decision-making approach for designing and operating an MMG considering both the capital cost for installing the electric cables and operating cost. First, real weather data are used to develop stochastic models that describe the uncertain, intermittent nature of energy production through renewable sources over a day. Then, in the first stage, design-level decisions regarding the installation of the electric cable between individual pairs of the MGs are to be determined to achieve the best tradeoff for the modeled system and weather pattern. In the second stage, the optimal energy dispatch planning for each individual MG including the energy trading between the MGs is carried out based on a particular realized scenario of the renewable energy production.

1. Introduction

Microgrid (MG) is a small-scale, community-level grid, which is thought to be the main building block of a future smart grid system [1, 2]. MG is designed to generate electrical energy based on distributed energy resources (DERs) including renewable energy sources (e.g. wind and solar energy) and supply it mainly to a local region. Though it can be connected to the central grid for enhanced robustness and flexibility, it is largely intended to operate independently, so as to lessen the load of the central grid which is becoming more and more strained as the energy demand continues to rise [3]. In general, there are several common components that comprise a MG: distributed renewable energy generation units (e.g. wind turbines and solar panels), energy storage system (ESS) (e.g. batteries), energy consumers with demands (e.g. industries, residents, and electric vehicles), and connection to a main grid (i.e. central grid, utility grid) [4–6].

MG provides some important benefits compared to central grid [4]. First, it enables a faster demand response and reduces the power transmission loss since it is located physically closer to energy consumers than the central grid. More importantly, MG can easily incorporate renewable energy sources into the grid to reduce the carbon footprint of electricity [7–9]. This is particularly relevant today as many countries around the world are trying to raise the portion of renewable energy in total energy generation [10–12]. Despite the benefits, there are also challenges associated with accommodating renewable sources in the grid, primarily due to the intermittent and uncertain nature of these sources. It causes energy generation to be more irregular and less predictable, making the demand response task quite challenging. Therefore, it is necessary to develop strategies to address their intermittency and uncertainty in managing MG systems.

When a demand–supply mismatch occurs in a single MG due to reasons such a shortage of the renewable energy generation, energy

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needed can be drawn from the ESS and/or purchased from the main grid. However, this may be insufficient or very expensive. In the case of a multi-microgrid (MMG), which comprises many such MGs, the MGs may have the additional flexibility of trading energy with other constituent MGs of the MMG under some prior negotiated contract [13–16]. In this case, each MG acts as a prosumer that can trade the produced energy with other MGs in a peer-to-peer fashion without central intermediaries [17–19]. As this can lead to better handling of local variabilities in demand and in renewable energy generation, it can provide an important flexibility needed for managing MGs effectively. In a cooperative MMG system that this study focuses on, constituent MGs trade energy based on a common objective, e.g., minimizing the overall cost of energy dispatches for the entire MMG system [20]. The cooperative operation of MMGs can improve the energy supply balance and the economics of the operation at the same time as shown by several studies. Certainly, it can lower the operating cost compared to the system with no cooperation between the MGs [21]. In addition, [22] and [23] proposed an optimal energy management of a cooperative MMG system where energy can be cooperatively utilized among the MGs. Recently, novel approaches based on multi-agent system (MAS), game theory, and a coalitional operation model have appeared for the problem of operating MMGs [24–26].

Recent studies on MMG have focused on energy trading (i.e. sharing, exchange) among the constituent MGs and addressed decision-making tools for optimal energy supply planning and operation of MMGs with the aim of managing the demand–supply imbalance under uncertainties and lowering the overall cost [1,6,13,27–30]. Some limitations still remain, however. Most studies have addressed the situation where design is already set and all MGs in the MMG system are fully connected through electric cables for transferring energy among them. However, installing electric cables among all pairs of the MGs to have a fully connected MMG system can be costly. There is a lack of studies that take into account the capital cost and the design-level decisions even though the capital cost can account for a major portion of the total cost and therefore optimal network design (i.e. topology) can be an important issue in building MMG systems.

This paper provides a novel computational framework for the optimal management of MMGs considering both the operation-level and design-level decisions. To deal with the challenge of uncertainty regarding renewable energy sources, this paper first discusses the development of a stochastic model for the prediction of the wind speed and solar radiation intensity using Markov Chain Monte Carlo (MCMC) and regression, in a similar fashion as [31]. With respect to the level of cooperation in MMG systems, two extreme levels are *fully cooperative* and *strictly individual* (i.e. independent). Under the fully cooperative operation, all the constituent MGs participate in the energy trading unconditionally for the benefit of the MMG system as a whole. Thus, the MGs can trade energy with one another in the most flexible fashion. At the other extreme of the strictly individual operation, there is no energy trading at all among the MGs, meaning each MG is operated independently. In this paper, a level of cooperation considered is somewhere between the two extreme levels. Under this *partially cooperative* operation, each of the constituent MGs takes part in the energy trading if it can reduce its own operating cost, which is practical as constituent MGs in most MMGs are rational decision-makers [21,29]. Under the partially cooperative operation, we address a design-level decision problem (to determine the optimal topology) beyond the usual operation-level ones by proposing a two-stage stochastic programming (2SSP) approach considering both the capital cost for installing the electric cables between the MGs and the operating cost of the entire MMG.

In this work, it is assumed that the location of each constituent MG is fixed, and the optimal topology is obtained to determine how the constituent MGs are connected through electric cables. According to the proposed 2SSP formulation, the decision of whether to install the electric cable between each pair of MGs is determined in the first stage by considering the capital cost and the expected value of the operating cost. Therefore, the first-stage decision is determined once as a 'here-and-now' decision on a larger timescale. With the decision made in the first stage, daily optimal energy dispatch decisions for each individual MG and energy trading between the MGs is carried out in the second stage based on the renewable energy generation as predicted by the developed stochastic model. Therefore, the second-stage decision is a 'recourse' decision for the daily operation of the MMG, which is to be repeated on a daily basis. A schematic structure of the 2SSP formulation proposed in this study is shown in Fig. 1.

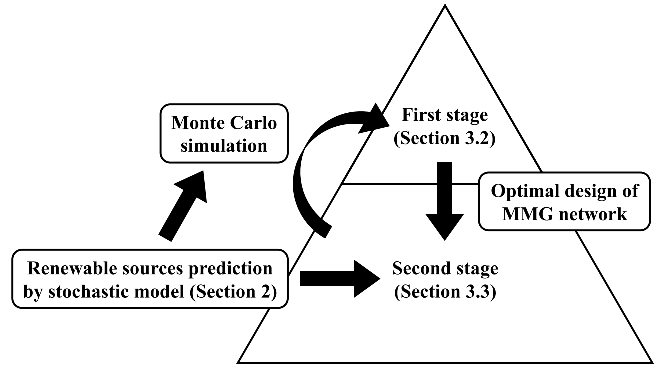

Fig. 1. Schematic structure of the proposed 2SSP formulation.

The rest of this paper is organized as follows. In Section 2, a stochastic model is developed for the daily prediction of the renewable energy sources. The 2SSP approach for the management of MMG systems is presented in Sections 3 and 4. The first-stage here-and-now decision-making on the installation of the electric cables between the MGs and the second-stage recourse decision-making on the energy dispatches and energy trading is described in Section 3. In Section 4, an illustrative example is shown with the results from the two-stage stochastic decision-making. Finally, conclusions drawn from this study can be found in Section 5.

2. Stochastic model development for renewable energy sources

Wind and solar power are considered important renewable energy resources of the future, but it is difficult to incorporate them directly into the grid due to their intermittency and uncertainty. For proper grid management, variabilities in the wind speed and solar radiation intensity need to be considered in the dispatch decisions, for example by modeling them with stochastic time-series models. Based on some available open data, we developed a multi-scale nonstationary stochastic model that can be used to generate time sequences of wind speed and solar radiation intensity as well as to predict their future values. We used a sampling technique of Markov Chain Monte Carlo (MCMC) and regression to develop time-series models with an hourly increment that can capture day-to-day as well as month-to-month variations. The models are developed by a similar method as in [31] and by decomposing the variations into the time scales of day-to-day (for inter-day variations) and hour-to-hour (for intra-day variations) for each month. The same method is used for modeling both the variations of the wind speed and those of the solar radiation intensity.

Once the time-series models are developed, sample data are generated by the following procedure. First, a daily average value for each month m and day d is calculated using the inter-day (i.e. day-to-day) time-series model with a first-order MCMC. MCMC is carried out by sampling from a probability distribution. It is an appropriate method to generate a time series of the daily average value since the collected data of daily average values of the wind speed and solar radiation intensity for each particular month showed fairly stationary behavior.

The prior generated daily average value serves as a bias for an hourly value sequence for the corresponding day, which is generated using the intra-day time-series model. Note that, for the intra-day modeling, regression is used rather than the MCMC sampling.

2.1. Inter-day variation

Inter-day variation, the evolution between two consecutive days, is modeled using the sampling technique of MCMC as in Eq. (2.1a) [31, 32]. The daily average value is evolved based on the first-order Markov Chain, which implies that the average value of a day is dependent only on that of the previous day as represented in Eq. (2.1b).

$$P(a^{day}_{m,d+1} = j | a^{day}_{m,d} = i) = \frac{\pi_{ij}}{\sum_j \pi_{ij}} \text{ for } i, j \in \Omega^a_m \tag{2.1a}$$

$$a^{day}_{m,d+1} = a^{day}_{m,d} + \hat{a}^{day}_{m,d} \tag{2.1b}$$

where a can represent either the wind speed or the solar radiation intensity, and the superscript day signifies that it is a daily average value. $a^{day}_{m,d}$ and $\hat{a}^{day}_{m,d}$ represent the daily average value and exogenous information of the daily average value, respectively. π_{ij} represents the transition probability from ith value to jth value.

In using Eq. (2.1a), it is assumed that the wind speed (or solar intensity) data take on a discrete set of values in order to circumvent the need to employ an infinite dimensional transition matrix Π. Therefore, the real wind speed and solar radiation data are assigned to the nearest discretized values, which are stored in the discretized space of states, Ω^a_m for month m. Each component of the set Ω^a_m corresponds to each row and each column of the transition matrix Π. Then the component of Π for the ith row and jth column, π_{ij}, represents the probability of transitions from state i to j between two days determined by the frequency of such transition found in the collected past data. Eq. (2.1a) can be used directly for sampling a new daily average value of the wind speed or solar radiation intensity given the value of the previous day.

2.2. Intra-day variation

Intra-day variation, the evolution within each day, is modeled with a parametric time series model with its parameters determined using regression. An error term, which is assumed to be an independent sequence, is used to recursively generate the values of the wind speed and solar radiation intensity for 24 hourly instances [31]. As shown in Eq. (2.2a), an hourly value at (m, d, h), i.e., month m, day d, and hour h, is obtained based on the daily average value at (m, d) obtained from the inter-day model and the hourly value at the previous hour $(m, d, h-1)$ with an error term, which is assumed to be an independent, identically distributed sequence sampled from a normal distribution [31,33]. Eq. (2.2b) represents the probability density function of the error term $e^a_{m,h}$ in Eq. (2.2a), which follows a normal distribution.

$$a_{m,d,h} = \theta^{a,h}_{m,h} + \theta^{a,d}_{m,h} a^{day}_{m,d} + \theta^{a,h-1}_{m,h} a_{m,d,h-1} + e^a_{m,h} \tag{2.2a}$$

$$P(e^a_{m,h}) = \frac{1}{\sqrt{2\pi {\sigma^a_{m,h}}^2}} \exp\left(-\frac{(e^a_{m,h} - \mu^a_{m,h})^2}{2{\sigma^a_{m,h}}^2}\right) \tag{2.2b}$$

where the first, second, third, and fourth terms in the right-hand side in Eq. (2.2a) represent the bias term for the deterministic hourly profile over a day, the effect of the daily average value, the effect of the previous hour value, and the normally distributed noise term on the hourly value in (m, d, h), respectively. The parameters $\theta^{a,h}_{m,h}$, $\theta^{a,d}_{m,h}$, $\theta^{a,h-1}_{m,h} a_{m,d,h-1}$, $\mu^a_{m,h}$, and $\sigma^a_{m,h}$ are obtained using regression based on the collected past data.

To sum up, the values of $a_{m,d,h}$ represent the hourly data in month m, day d, and hour h for the wind speed and the solar radiation intensity, which the developed multi-scale stochastic model generates. Since they have direct implications on the renewable energy generation, it can be an important factor in the decision-making of the MMG operation, which will be described in Section 3.

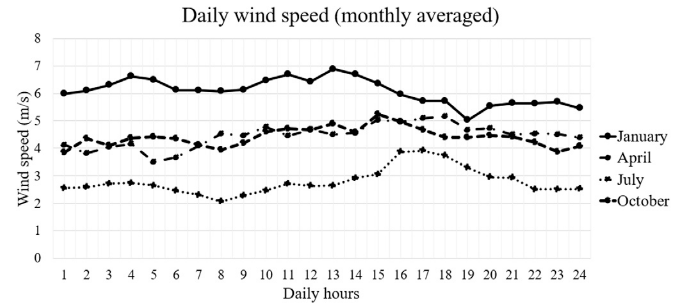

Fig. 2. Sample result of wind speed modeling for representative months.

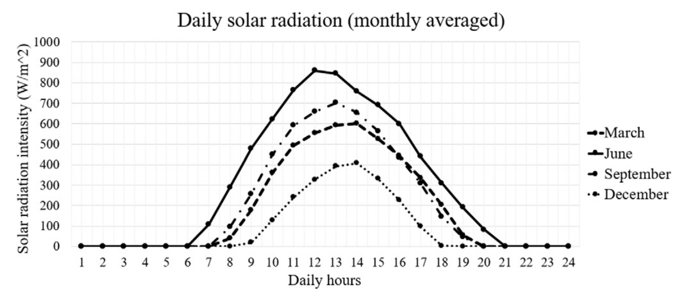

Fig. 3. Sample result of solar radiation modeling for representative months.

2.3. Results of uncertainty modeling

Using the above data-fitted models, sample sequences for the hourly values indexed with time stamp of (m, d, h) can easily be generated, starting from an independent, identically distributed sequence of $e^a_{m,h}$ sampled from a normal distribution. Figs. 2 and 3 display sampled hourly sequences of the wind speed and solar radiation intensity for four representative months. Shown are the average values of the samples for a particular hour of a day over all days of the month. The generated wind speed data shows the expected behavior of being high in winter months and low in summer months, whereas the solar radiation samples show the opposite trend.

3. Problem formulation as a two-stage stochastic program

3.1. Two-stage stochastic programming

This work proposes a two-stage decision-making approach for managing MMG systems considering both the capital cost for the electric cables connecting the MGs and the operating cost of the entire MMG. First, the decision on whether to install an electric cable between each pair of MGs in the MMG has to be made. Since this decision precedes the daily operation of the MMG, we formulate the decision-making problem in the framework of two-stage stochastic programming (2SSP). In 2SSP, the first-stage decision should be based on data available at the time of the decision-making.

General 2SSP is formulated as follow.

$$\min \{g(x) = f(x) + E_\xi[q^*(x, \xi)]\} \tag{3.3a}$$

where x is the first-stage decision variable, $f(x)$ is an objective function which is dependent only on the first-stage decision, ξ is a random parameter vector, which contains data that would be revealed only for the second-stage decision, and $q^*(x, \xi)$ is the optimal value of the objective function of the second-stage decision-making problem which is generally given as follow.

$$\min \{q(y, \xi) \mid T(\xi)x + W(\xi)y = h(\xi)\} \tag{3.4a}$$

where y is the second-stage decision variable.

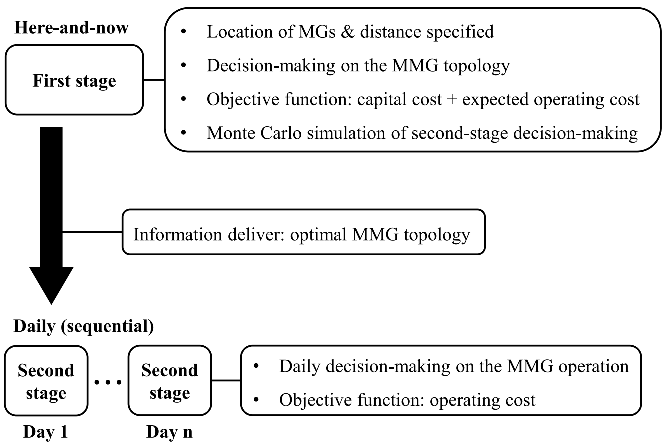

Fig. 4. Framework of two-stage stochastic programming structure.

Under the above formulation, the first-stage decision variable x is determined before the realization of the uncertain vector ξ because it is a random vector of which realization is not revealed at the time the first-stage decision is made. However, the objective function of the second-stage decision-making problem is taken into account as the expectation value with respect to ξ. After the first stage decision is made, the second-stage decision-making problem can be solved based on specific realized parameter values at each time instance.

In this study, based on the 2SSP formulation, the first-stage here-and-now decision is to select the pairs of MGs which would be connected via electric cables. Hence, the objective function of the first stage is the capital cost for installing the electric cables plus the expected value of the operating cost of the MMG following the first-stage decision. After solving the decision-making problem in the first stage, daily decision-making on the optimal energy dispatches in each individual MG and energy trading between the MGs through the first-stage decision is solved in the second stage based on the renewable energy generation realized each day. Fig. 4 shows the schematic structure of the 2SSP decision-making formulation this study adopts.

3.2. Problem formulation of the first stage

The objective of the first-stage decision-making is to minimize the capital cost for installing the electric cables between MGs plus the expectation of the minimum operating costs in the second-stage decision-making as represented in Eq. (3.5a).

$$\min \{ (\sum_{i}^{n} \sum_{j \neq i}^{n} C_{EL} Dist_{ij} b_{ij}^{EL}) + E_{\xi}[q^{*}(b^{EL}, \xi)] \} \tag{3.5a}$$

where b^{EL} is an $n \times n$ matrix that contains the binary decision variables representing whether or not to install an electric cable between the respective nodes and is to be determined by the optimization, and n is the number of MGs in the MMG. C_{EL} is the unit installation cost (UIC) for installing a unit length of an electric cable, and $Dist$ is a matrix of a same size as b^{EL} (i.e. $n \times n$) and contains the distance information between the respective pairs of the MGs in the MMG. Therefore, the first term in Eq. (3.5a) represents the total capital cost for installing the electric cables in the MMG. Once the cable connection is set up between a pair of MGs, it will be kept in place for the lifetime of the cable. Thus, the installation cost of the cable should be weighed against the benefit brought by the energy trading between the MGs over its lifetime. ξ is the random vector containing the uncertainty information and is realized in the second stage of the decision-making. q^{*} is the minimum operating cost obtained from the second-stage optimization. The expectation of the minimum operating costs in the second stage, $E_{\xi}[q^{*}(b^{EL}, \xi)]$, is obtained by averaging the results from the Monte Carlo simulations of the second-stage decision-making problem, which will be explained later. More detailed definitions of all the decision variables and input parameters are explained in the Nomenclature section.

The decision variable in the first-stage decision-making problem is b^{EL}, which is a matrix of binary variables. If the electric cable is not to be installed between a pair of MGs, say MGs i and j, the corresponding element of the decision variable matrix, b_{ij}^{EL}, is equal to 0, whereas it being equal to 1 implies the decision of installing a cable between the MGs i and j. The decision variable matrix must always satisfy $b_{ij}^{EL} = b_{ji}^{EL}$ for $\forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, n\} \backslash i$.

The first-stage decision must be made before the second-stage operation-level decisions such as the optimal energy dispatches in each MG and optimal energy trading amounts between the selected MG pairs. The unknown data and the optimal operation-level decisions not available at the time the first-stage decision-making are handled through sample average calculation. Each Monte Carlo simulation of the second-stage decision-making randomly generates different realized sequences for the renewable energy generation and energy demand from consumers. For the given data, the optimal intra-MG and inter-MG decisions are found through the second-stage optimization. Accordingly, the optimal value achieved (i.e. minimum operating cost of the MMG) for the given data can also be obtained and serve as a sample. We repeat this many times to generate enough samples to ensure that the average value property represents the expectation of the minimum operating cost, $E_{\xi}[q^{*}(b^{EL}, \xi)]$, of the second-stage optimization, which is incorporated into the objective function of the first-stage decision-making problem as shown in Eq. (3.5a).

3.3. Problem formulation of the second stage

The second-stage decision-making problem for the optimal operation of MMG is significantly simpler and more straightforward. The MMG operation with an arbitrary number of MGs is studied in this paper. In developing a generalized decision-making model for MMG comprised of an arbitrary number of MGs, some premises are made. First, all MGs include just a single kind of renewable energy generation (i.e. either wind turbines or solar panels, but not both) and energy generation, energy stored in the ESS, consumer demand are all aggregated as single terms at each time instant. In addition, the energy trading with each connected MG at each time instant is to be calculated as a single aggregated amount. Second, all MGs are connected to the main grid to sell or buy electricity as needed (albeit at worst price or cost). Finally, the operation of the MMG considered is partially cooperative which lies somewhere between the two extremes of independent operation and fully cooperative operation. That is, each of the constituent MGs in the MMG takes part in the energy trading only if it can reduce its own operating cost by trading compared to the independent operation without energy trading.

The objective of the second-stage decision-making with the partially cooperative MMG operation is to minimize the sum of operating costs of all MGs from all types of intra-MG and inter-MG decisions over a day. The objective function is represented in Eq. (3.6a).

$$\begin{aligned} \min \ & \sum_{i} (\sum_{h \in H} (c_{p}^{h} p_{i}^{h} - c_{s}^{h} s_{i}^{h}) + \alpha_{i} \sum_{h \in H} (con_{i}^{h} - pcon_{i}^{h})^{2} \\ & + c_{ESS,i} \sum_{h \in H} (ch_{i}^{h} + dch_{i}^{h}) + \sum_{j} c_{trd,ij} tr_{ij}^{h}) \end{aligned} \tag{3.6a}$$

In Eq. (3.6a), the operating cost of each MG over a day is composed of four different terms. The first term represents the cost incurred by the energy transaction with the main grid. The second term stands for the dissatisfaction cost caused by a failure to meet the consumers' preferred consumption where α_i represents the discomfort factor of MG i. The third and fourth terms represent the costs resulting from using the ESS of each MG and trading energy with other MGs, respectively.

Similarly as in the previous work [21], the decision variables in the optimization problem of each constituent MG in MMG under the partially cooperative operation are divided into the intra-MG and inter-MG decision. Intra-MG decision of each MG i at each hour h includes: renewable energy supplied to consumers (g_i^h), energy purchased from the main grid (p_i^h) or sold to the main grid (s_i^h), energy consumption by consumers (con_i^h), and energy charged to (ch_i^h) or discharged from the ESS (dch_i^h). These decision variables are common among all the constituent MGs in the MMG. In addition to these, under the cooperative operation of MMG, inter-MG decision indicating the amount of traded energy between MGs (tr_{ij}^h representing the energy traveled from MG j to i at time h) is included in the decision. All of these decision variables are to be decided together on an hourly basis over a day through optimization, which implies that each variable can take on different values at 24 hourly instances (i.e. from $h = 1$ to $h = 24$). In addition, the decision variables need to be individually determined for all the constituent MGs through the optimization.

Several parameters serve as inputs to the optimization problem. They include information on cost, demand, renewable energy, capacity, and efficiency. Particularly, the amount of renewable energy generated through a renewable energy source is uncertain. Therefore, the stochastic models explained earlier are used to predict the wind speed and solar radiation intensity and get the parameters for the renewable energy generation (G_i^h for MG i and at hour h). These are assumed to be known during the second-stage decision-making.

Constraints for the partially cooperative operation of MMG are formulated similarly to [21] and are listed from Eq. (3.7a) to Eq. (3.7l). Constraints (3.7a)–(3.7f) represent the bounds on each of the decision variables, respectively. Constraint (3.7g) represents the storage dynamics and bounds on the amount of stored energy in the ESS given its capacity and lifetime. Constraints (3.7h) and (3.7i) represent the restrictions on power sold to the main grid and the total energy balance, respectively. In addition, the constraint shown in Eq. (3.7j) represents the traded energy balance between two MGs. The constraint (3.7k) enforces that two MGs i and j can trade energy only if they are connected through an installed electric cable. For the partially cooperative operation assumed, we impose that the sum of the minimum operating cost over the day with the energy trading for each MG must not be higher than the minimum operating cost under the MG's individual operation for the day (C_i^{IO}). The constraint is shown in Eq. (3.7l). Constraints (3.7a)–(3.7i) should be imposed on an hourly basis and for all the MGs (i.e. for $\forall i, h$). Constraints (3.7j) and (3.7k) must hold for $\forall i, j, h$, and (3.7l) for $\forall i$.

$$0 \le g_i^h \le G_i^h \tag{3.7a}$$

$$0 \le p_i^h \le P_i^{max} \tag{3.7b}$$

$$0 \le s_i^h \le S_i^{max} \tag{3.7c}$$

$$con_i^{h,min} \le con_i^h \le con_i^{h,max} \tag{3.7d}$$

$$0 \le ch_i^h \le CH_i^{max} \tag{3.7e}$$

$$0 \le dch_i^h \le DCH_i^{max} \tag{3.7f}$$

$$(1 - DoD_i)ESS_i^{max} \le ESS_i^0 + \sum_{h'=1}^{h} (\eta_{ch,i} ch_i^{h'} - \frac{1}{\eta_{dch,i}} dch_i^{h'}) \le ESS_i^{max} \tag{3.7g}$$

$$s_i^h \le G_i^h - g_i^h + ESS_i^0 + \sum_{h'=1}^{h} (\eta_{ch,i} ch_i^{h'} - \frac{1}{\eta_{dch,i}} dch_i^{h'}) \tag{3.7h}$$

$$g_i^h + p_i^h + dch_i^h + \sum_j tr_{ij}^h - s_i^h - ch_i^h - con_i^h = 0 \tag{3.7i}$$

$$tr_{ij}^h + tr_{ji}^h = 0 \tag{3.7j}$$

$$-b_{ij}^{EL} tr_{ij}^{max} \le tr_{ij}^h \le b_{ij}^{EL} tr_{ij}^{max} \tag{3.7k}$$

$$\sum_{h \in H} (c_p^h p_i^h - c_s^h s_i^h) + \alpha_i \sum_{h \in H} (con_i^h - pcon_i^h)^2 + c_{ESS,i} \sum_{h \in H} (ch_i^h + dch_i^h) + \sum_j c_{trd,ij} tr_{ij}^h \le C_i^{IO} \tag{3.7l}$$

In the constraint (3.7l), C_i^{IO} represents the minimum operating cost for the independent operation of each MG. The parameter C_i^{IO} is determined from a preceding optimization minimizing the cost of independent operation of each constituent MG. This optimization is done in another optimization module (i.e. independent-module) before the above optimization to set the value of C_i^{IO}'s for each MG. This optimization module is represented by Eq. (3.8a).

$$\min \sum_{h \in H} (c_p^h p_i^h - c_s^h s_i^h) + \alpha_i \sum_{h \in H} (con_i^h - pcon_i^h)^2 + c_{ESS,i} \sum_{h \in H} (ch_i^h + dch_i^h) \tag{3.8a}$$

Since there is no energy trading under the independent operation, the objective function does not include the term regarding the cost of energy trading. Likewise, variables for the amount of traded energy between MGs are not included. In addition, the constraints (3.7j), (3.7k), and (3.7l) related to the energy trading are not included. Besides, the constraint (3.7i), the total energy balance within a MG under the partially cooperative operation is replaced by the constraint represented in Eq. (3.9a).

$$g_i^h + p_i^h + dch_i^h - s_i^h - ch_i^h - con_i^h = 0 \tag{3.9a}$$

The above-mentioned decision-making problem for the second stage can be directly solved each day. Its Monte Carlo simulation runs also provide the samples for computing the expectation of the objective function needed for the first-stage decision-making. Going further, if the daily renewable energy generation and demand profiles cannot be predicted accurately at the start of each day and need hourly updates, one can always solve the optimization repeatedly at each hour after updating the prediction. Finally, since energy storage is involved, the end effect may be an issue, i.e., the energy stored in the ESS may hold no value at the end of a day leading to a complete drainage. This is because the optimization is performed over a daily window and does not consider the next days. A constraint may be imposed on the storage level or the value function for the stored energy at the end of the day may be constructed to overcome such limitation [31].

4. Illustrative examples

To develop a stochastic model for the prediction of energy harvested from renewable sources (i.e. wind speed and solar light intensity), we used the hourly data for 10 years (2008~2017) in Boulder, Colorado, USA [34,35]. By incorporating the wind speed and solar radiation intensity values predicted by the stochastic model as input parameters to the optimization model, the decision variables of the two stages are optimized. For the previously described 2SSP formulation, the first-stage decisions and the second-stage decisions are determined in sequence, i.e., the decisions regarding the topology of the MMG are made first followed by the operation decisions of the MMG system with the resulting topology. On the other hand, the first-stage decisions must consider the performance of the second-stage decisions for the resulting system and thus cannot be made independently.

The first-stage decision-making incurs a high computational cost caused by the large number of integer decision variables, the nonlinearity, and the need to solve a large number of the daily second-stage decision-making problems generated through Monte Carlo simulations in order to evaluate the expectation of the operating cost in the objective function. We used the genetic algorithm (GA) approach to determine the first-stage decisions since the GA offers many advantages in solving optimization problems that involve a large number of discrete variables and significant nonlinearity in the objective function or constraints [36]. While the first-stage decisions are optimized by the GA, a large number of the second-stage decision problems for different Monte Carlo realizations (providing the data for the amount of the

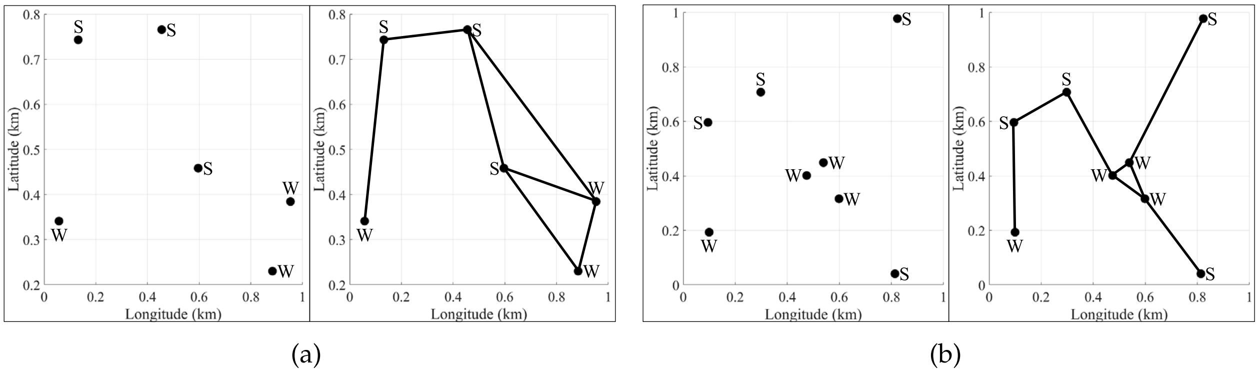

Fig. 5. Location of the MGs in the studied MMG and its optimal topology for (a) case 1 and (b) case 2.

renewable energy generation and the demand from the consumers) need to be solved in each iteration. Since the second stage involves a convex programming problem, it is solved using *CVX*, which is a MATLAB code (i.e. package) for specifying and solving a convex programming problem [37,38]. This module requires the user to explicitly specify the variables, objective function, and constraints of the optimization and provides a number of solver options. For the solver within *CVX*, *Gurobi* is used given its capability of handling Mixed Integer Programming [39].

This section presents an illustrative example of solving the 2SSP for the MMG system.

4.1. First-stage decisions

For the illustrative examples, we considered two virtual MMG systems which are comprised of 6 MGs (case 1) and 8 MGs (case 2). We assumed that the rated voltage of the installed electric cables is 69 kV, and the electric cables are installed overhead rather than underground. The installation cost per unit length of the electric cable is chosen as $ 285,000 per mile [40]. The lifetime of an installed cable is assumed to be 80 years. Since the objective function of the first-stage decision-making problem represents a daily cost, the annualized installation cost divided by 365 is used. In addition to the capital cost for installing the electric cables, the expected optimal operating cost of the MMG is considered in the first-stage decision.

Location of the MGs of the two studied systems is shown in Fig. 5 where each dot represents a MG. The letter W or S written next to each dot indicates whether the corresponding MG generates the renewable energy based on wind turbines (W) or solar panels (S), respectively. The axes represent the latitude and longitude of the virtual map (distance in kilometers) of the MMG. Given a decision for the first stage, the topology of the MMG system is set. The optimal topology of the two case studies are also shown in Fig. 5 where each line connecting two dots represents a bidirectional cable installed between two MGs.

The capital cost for the installation of electric cables, the expected operating cost of the MMG as well as their sum (i.e. the total cost) are compared for the optimal topology of the MMG from the first-stage decision-making against those for the independent MMG topology (no connection) and the fully connected MMG topology (full connection) in Table 1. Note that it is impossible to minimize both the capital cost and the expected operating cost at the same time. In the independent MMG topology, electric cables for sharing are not installed between any MG pair, and the MGs operate individually without trading. Hence, the cost of installing electric cables is zero, while the operating cost will be compromised as the MGs must purchase all extra energy needed by the demand of consumers from the main grid. In contrast, the fully connected MMG incurs the maximum capital cost while minimizing the operating cost aided by the flexibility of trading energy with any other MGs in the system. We verify that the optimal topology of the MMG determined by the 2SSP gives a lower total cost than the independent and fully connected MMGs in both case studies, by installing electric cables only for the pairs where the benefit exceeds the cost. The cost incurred for the fully connected MMG is significantly higher, pointing to the benefit of the 2SSP-based formulation proposed in this paper in terms of reducing the total cost.

Table 1
Comparison of the total daily cost of the optimal topology with the independent and fully connected networks for case 1 and case 2.

Case 1	Optimal network	Independent	Fully connected
Capital cost	$ 15.761	$ 0	$ 51.539
Expected operating cost	$ 18.491	$ 41.870	$ 16.166
Total cost	$ 34.253	$ 41.870	$ 67.705
Case 2	Optimal network	Independent	Fully connected
Capital cost	$ 14.027	$ 0	$ 90.281
Expected operating cost	$ 15.702	$ 46.219	$ 13.245
Total cost	$ 29.728	$ 46.219	$ 103.526

4.2. Second-stage decisions

In the second stage of the 2SSP, decisions on the energy dispatches within each MG and decisions on the energy trading between the MGs are made. In other words, a pair of MGs can trade energy only if an electric cable has been installed between them. In this section, example results of the second stage for the case 2 (involving 8 MGs) are presented. The optimal intra-MG decisions in each of the 8 MGs are shown in Appendix. In addition, the daily averaged energy trading decisions between the MGs are shown on a 2-D map in Fig. 6. The thickness and direction of each arrow indicate the degree and direction of the energy trading over a day. The daily average amounts of energy trading between each pair of MGs are written in kWh. Note that only the MGs that are connected with each other through electric cables can trade energy.

4.3. Sensitivity analysis

The formulated 2SSP finds the solution representing an optimal tradeoff between the capital cost and the operating cost of the MMG. However, the UIC of the electric cable can vary region to region by its characteristics and economic circumstance. Specifically, it changes depending on the rated voltage and the installation position, either overhead or underground [40]. Therefore, in this section, a sensitivity analysis with respect to the UIC is carried out, focusing mainly on how the first-stage decisions are affected. In particular, the total cost and the number of connected MG pairs are compared with those of the independent and fully connected MMGs to validate the reliability of the results. The results of the sensitivity analysis on the UIC are shown in Table 2 and Fig. 7. The UIC changes by multiplying a factor

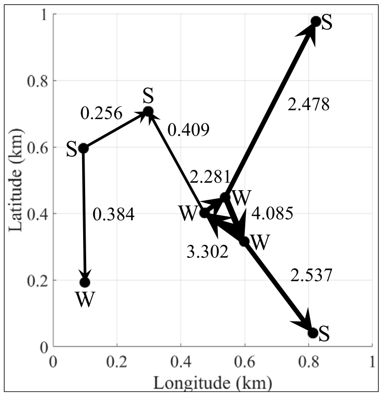

Fig. 6. Second-stage decisions for the optimal energy trading between MGs (for the case 2).

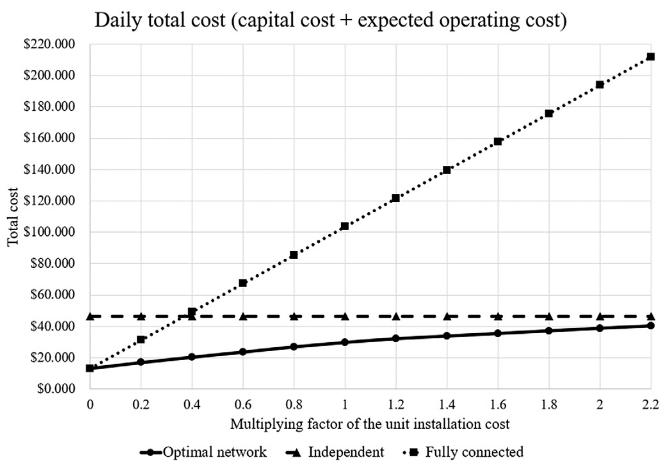

Fig. 7. Total costs of the optimal MMG, the independent MMG, and the fully connected MMG as the UIC changes (for the case 2).

increasing with an increment of 0.2 to $ 285,000 per mile which is used in Section 4.1.

According to the results represented in Table 2 and Fig. 7, the total cost of the optimal MMG increases naturally as the UIC of electric cables increases. Note that the total cost for the independent MMG remains the same (at $ 46.219) regardless of the different cost scenarios because electric cables are not installed at all in this case. The total cost for the fully connected MMG increases in a linear manner as the UIC increases. Thus, there is a point where the total cost for the fully connected MMG becomes lower than that of the independent one if the UIC is sufficiently low (by a factor between 0.2 and 0.4 in this case). Furthermore, we notice that the optimal MMG will converge to the fully connected one as the UIC decreases, becoming identical when the UIC is zero. As the UIC becomes higher, less pairs are connected, with the solution gradually converging to the independent one.

4.4. Discussions

According to the results of the first-stage decisions represented in Table 1 and Fig. 5, the operating cost close to that of the fully connected topology can be achieved by installing just a smaller number of electric cables. This implies that the fully connected case makes connections that are almost never used. By applying the 2SSP decision-making proposed in this paper, the optimal topology of an MMG system encompassing only the critical connections can be found, saving a large amount in the capital cost.

In the optimal MMG network, MGs that are located in the outskirt area of the MMG tend to be connected with just a small number of MGs. In contrast, MGs located in the center of the MMG tend to be connected with more MGs, acting as a hub. Moreover, MGs that are located apart from each other tend not to be connected since it leads to a high cost. However, the nature of renewable energy sources can demand a connection between them since the first-stage decision results from the consideration of the intermittent tendency of the renewable energy source in each MG. Generally, solar energy generation involves a temporal restriction. That is, solar energy cannot be generated during nighttime whereas wind energy can be generated both daytime and nighttime as long as the wind blows at a sufficiently high speed. Thus, it is advantageous that a MG with solar energy is connected beforehand with MGs with wind energy to ensure a more stable supply. As can also be seen in Fig. 5, all MGs that use solar energy are connected with at least one MG using wind energy in both case studies.

5. Conclusion and future work

Multi-microgrid (MMG) systems incorporating the flexibility of trading energy between the microgrids (MGs) can provide several operational and economic benefits. For such systems, the topology decisions are linked to the operation as the general formulation of this study showed. For optimal decision-making, stochastic modeling for the uncertain renewable energy generation (via wind and solar) is first needed so that intermittent and time-varying behavior of the wind speed and solar radiation intensity can be simulated in a realistic manner. To tackle the limitation of the previous studies brought by assuming the fully connected MMGs, this work proposed a two-stage stochastic programming (2SSP) formulation that can consider both the capital cost for installing the electric cables for the energy trading and the operating cost. In the first stage, decisions whether to connect are determined for each pair, by considering the cost of installation vs the savings in the operating cost. Based on the developed stochastic models for the renewable sources and a given network topology, the daily optimal energy dispatch decisions for each individual MG and the energy trading between the connected MGs can be optimized and the expected operating cost can be evaluated. This in turn provides a basis to select the best topology representing the optimal tradeoff between the capital cost and the operating cost. The applicability and reliability of the developed 2SSP decision-making framework were demonstrated by the case studies. The optimal topology obtained by the 2SSP formulation outperformed both the independent and fully connected MMGs in terms of the total cost (the capital cost plus the operating cost) by reducing the installation cost of electric cables compared to the latter and properly managing the energy trading between the constituent MGs to lower the operating cost of the entire MMG compared to the former.

Despite the generality of the formulation, the computational cost for solving the 2SSP is quite high since the first-stage decision involves a large number of binary variables, and a large number of second-stage Monte Carlo simulations need to be carried out to evaluate the expectation. As the number of Monte Carlo simulations increases, the computational cost increases proportionally. Furthermore, the computational cost will drastically increase as the number of the constituent MGs increases. To alleviate the growth in the computational cost, several MGs within a close distance can be pre-clustered before the 2SSP is solved so that only the MGs within a same cluster can trade energy with each other. This approach is left for a future study.

Nomenclature

Abbreviations

- MG: microgrid
- DER: distributed energy resource
- ESS: energy storage system

Table 2
Sensitivity analysis of the daily total cost with respect to the UIC (for the case 2).

Multiplying factor of UIC	Electric cables	Capital cost	Expected operating cost	Total cost
0	28	$ 0	$ 13.245	$ 13.245
0.2	10	$ 3.751	$ 13.250	$ 17.001
0.4	9	$ 6.468	$ 13.916	$ 20.384
0.6	9	$ 9.702	$ 13.916	$ 23.618
0.8	8	$ 11.221	$ 15.702	$ 26.923
1.0 ($ 285,000 /mile)	8	$ 14.027	$ 15.702	$ 29.728
1.2	6	$ 9.923	$ 22.166	$ 32.089
1.4	6	$ 11.577	$ 22.166	$ 33.743
1.6	6	$ 13.231	$ 22.166	$ 35.396
1.8	6	$ 14.885	$ 22.166	$ 37.050
2.0	6	$ 16.539	$ 22.166	$ 38.704
2.2	5	$ 12.814	$ 27.340	$ 40.154

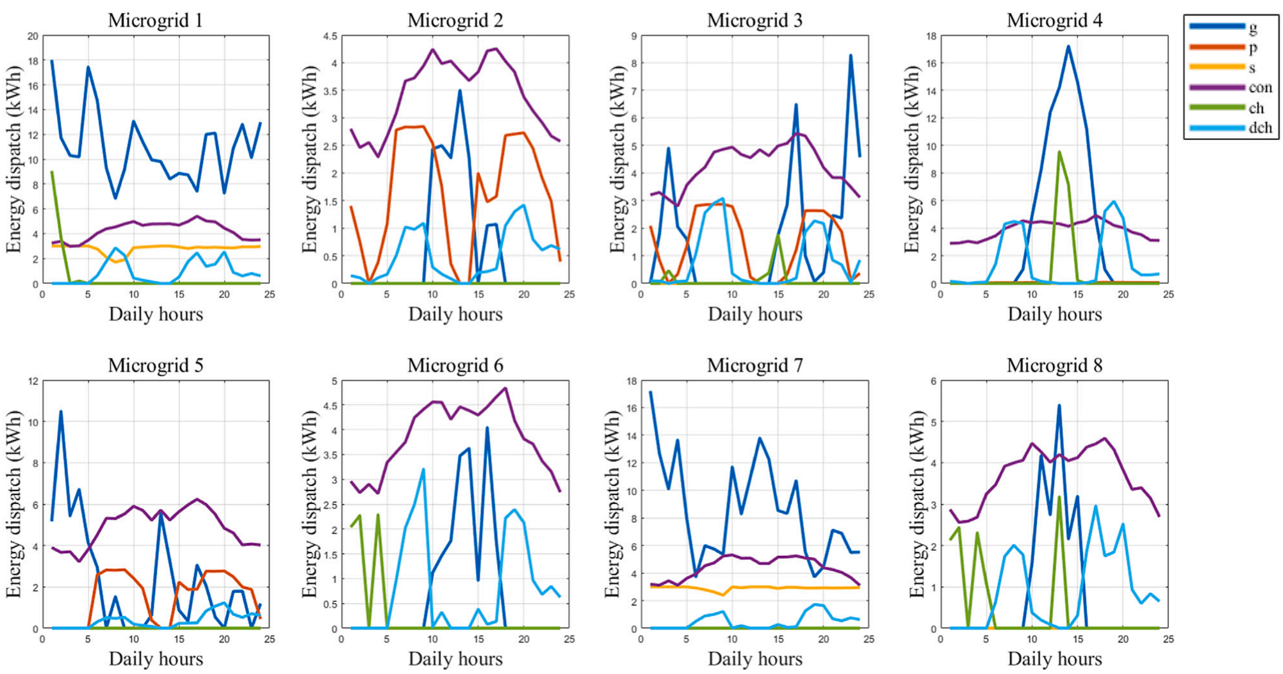

Fig. A.1. Energy dispatch planning in each of the 8 MGs in the studied MMG for the case 2.

- MMG: multi-microgrid
- MCMC: Markov Chain Monte Carlo
- 2SSP: two-stage stochastic programming
- UIC: unit installation cost
- GA: genetic algorithm

Indices/Sets

- i: Index for microgrids
- j: Index for microgrids (especially used to represent microgrids participating in energy trading)
- h: Index for hours in a day
- MG: Set of microgrids (={1,…,n})
- H: Set of hours in a day (={1,…,24})

Input Parameters

- G_i^h: Renewable energy generation in i at h
- P_i^{max}: Upper bound on the purchase from the main grid in i
- S_i^{max}: Upper bound on the sale to the main grid in i
- $pcon_i^h$: Preferred energy consumption of consumers in i at h
- $con_i^{h,min}$: Lower bound on the energy consumption in i at h
- $con_i^{h,max}$: Upper bound on the energy consumption in i at h
- η_{ch}^i: Conversion efficiency for charging the ESS in i
- η_{dch}^i: Conversion efficiency for discharging the ESS in i
- DoD_i: Depth of discharge that affects the lifetime of the ESS in i
- CH_i^{max}: Upper bound on charging the ESS in i
- DCH_i^{max}: Upper bound on discharging the ESS in i
- ESS_i^{max}: Given capacity of the ESS in i
- c_p^h: Cost of purchasing from the main grid at h
- c_s^h: Cost of selling to the main grid at h
- α_i: Sensitivity coefficient to the discomfort for consumers in i
- $c_{ESS,i}$: Cost of charging/discharging the ESS in i
- $c_{tr,ij}$: Cost of energy trading between i and j
- tr_{ij}^{max}: Upper bound on energy trading between i and j
- C_i^{IO}: Minimum operating cost under the independent operation of i
- C_{EL}: Capital cost for building an electric cable of a unit length
- $Dist$: Distance information between all pairs of microgrids

Decision Variables

- g_i^h: Renewable energy supplied to consumers in i at h
- p_i^h: Energy purchased from the main grid in i at h
- s_i^h: Energy sold to the main grid in i at h
- con_i^h: Energy consumption of consumers in i at h
- ch_i^h: Energy charged to the ESS in i at h
- dch_i^h: Energy discharged from the ESS in i at h
- tr_{ij}^h: Energy traded between i and j

CRediT authorship contribution statement

Dongho Han: Conceptualization, Methodology, Software, Investigation, Writing - original draft. **Jay H. Lee:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Energy dispatches in each of the 8 MGs for the case 2 are shown in each of the following graphs (see Fig. A.1).

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