DECISION-MAKING FOR MULTI-MICROGRID MANAGEMENT SYSTEM USING ALTERNATING DIRECTION METHOD OF MULTIPLIERS

Dongho Han and Jay H. Lee*
Department of Chemical and Biomolecular Engineering, Korea Advanced Institute of Science and Technology (KAIST)
291 Daehak-Ro, Yuseong-Gu, Daejeon 34141, Republic of Korea

Abstract Overview

Smart grid technology represents a new way to build and operate energy networks using more and better information while including various renewable energy sources. A localized and distributed version of smart grids covering relatively small areas is known as microgrid. To achieve more efficient and reliable energy supply in a microgrid network, a more flexible and robust management system is needed. This study presents a decision-making strategy for a cooperative multi-microgrid system comprised of multiple microgrids, which can share energy with each other. The targeted system is formulated as a multi-agent system where each microgrid is regarded as a decision-maker, and the decision-making for the entire system is developed based on distributed optimization to reduce the computational cost. As an algorithm for distributed optimization, the alternating direction method of multipliers (ADMM) is used which has been applied to problems in statistics and machine learning. To predict the amounts of renewable energy generation and make the optimization problem more realistic, stochastic models of the wind speed and solar intensity are developed and incorporated into the decision-making.

Keywords

Multi-microgrid system, Alternating Direction Method of Multipliers, Uncertainty modeling.

Introduction

Smart grid represents the next generation energy network where information and communication technologies (ICT) are used to enable more efficient and informed decision-making in energy generation, storage, and distribution. Besides the traditional energy sources, it is expected to include various renewable energy sources, such as wind and solar power, which are intermittent and stochastic. A microgrid is a localized and distributed version of smart grid that focuses on relatively small areas. Generally, a microgrid comprises local generation units for renewable energy or conventional energy generator, energy storage system such as batteries to store the renewable energy, demand response to consumers, and connections to the main grid for energy sale/purchase (Olivares et al., 2014).

The multi-agent system (MAS) framework has recently been popular in various fields (e.g., microgrid operation, systems engineering, robotics, and game theory) to describe and mathematically formulate a system where there are more than one decision makers, i.e., agents (Olivares et al., 2014 and Vlassis, 2007). In MAS, multiple agents coexist in an environment and make decisions simultaneously while having particular interactions with each other. A system of multiple coexisting microgrids is called a multi-microgrid system (MMGS) and can be formulated as MAS where each microgrid represents a decision maker.

* To whom all correspondence should be addressed

In this work, a management system of MMGS is formulated as MAS, and a decision-making strategy is developed based on the alternating direction method of multipliers (ADMM), which is a widely applied distributed optimization algorithm (Boyd et al., 2011 and Tang and Daoutidis, 2018). The performance of distributed optimization is assessed by comparing with the centralized optimization in terms of the computational cost as well as the achieved result. In addition, stochastic models are developed and incorporated into the optimization problem to handle the intermittent and uncertain characteristics of renewable energy generation. Finally, results of the decision-making strategy incorporating the stochastic models are presented and analyzed.

System and Problem Description

Two-Agent Multi-Microgrid System

The MMGS in this study consists of two microgrids: MG1 and MG2. Each of MG1 and MG2 has its own renewable energy generation unit, energy storage, conventional energy generator, and consumer (see Figure 1). For renewable energy generation, MG1 produces wind energy using wind turbines, and MG2 produces solar energy using solar panels. Both microgrids can purchase energy from a common main grid. The most relevant aspect of the system is that MG1 and MG2 can exchange energy with each other as needed.

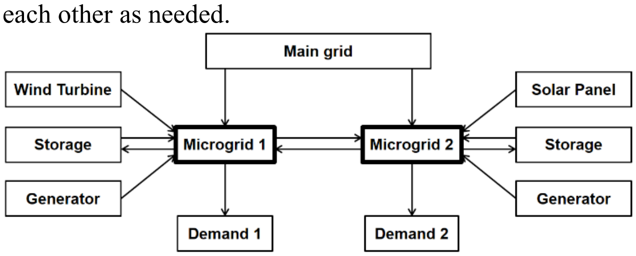

Figure 1. The studied MMGS consists of two microgrids

Decision-Making Problem

To develop a decision-making strategy of the system, an optimization problem has been formulated. Objective function is to minimize the summation of overall costs for all energy dispatches and turning on/off the conventional energy generator.

MG1 and MG2 make a set of hourly decisions for one-day operation. Decision variables of each microgrid include: (1) a binary variable for turning on/off the conventional energy generator, (2) amount of conventional energy to generate, (3) amount of generated renewable energy to provide to consumers, (4) amount of generated renewable energy charged to the energy storage, (5) amount of discharged energy from the storage, (6) amount of energy to purchase from the main grid, and (7) amount of energy, positive or negative, to exchange with the other microgrid.

Required input variables for each daily operation are: (1) hourly profiles of the renewable energy generation from wind turbines and solar panels, (2) hourly profiles of the energy demand from consumers in MG1 and MG2, (3) an upper bound of the total sharing amount between MG1 and MG2, and (4) the initial charged level of each energy storage.

Equality constraints include: (1) total energy balance in each microgrid including the demand, (2) renewable energy balance in each microgrid, and (3) energy sharing (i.e., exchange) balance. Inequality constraints include: (4) capacity of each storage, (5) limits on energy purchase from the main grid, and (6) upper bound on the total sharing amount between MG1 and MG2 over a whole day. Note that constraints (3) and (5) represents connecting constraints that make the decisions of MG1 and MG2 interconnected.

Optimization Methods

There are two approaches to solving a decision-making problem of MAS: centralized optimization and distributed optimization. This study applies the two approaches and compares the results in terms of computational cost and achieved objective value to verify the benefits and shortcomings of distributed optimization. At this point of the comparison, uncertainty in the renewable energy sources (i.e., wind and solar) is not considered.

Centralized Optimization Using Method of Multipliers

In this approach, all decision variables of MG1 and MG2 are combined into one variable vector x (i.e., agent), and made together as a single combined system. Therefore, it becomes a centralized optimization, which is computed by a single agent. The decision-making problem is formulated as Eq. (1a) and solved in a centralized manner by using the method of multipliers (Boyd et al., 2011). It solves a dual problem by iterative gradient ascent using the augmented Lagrangian (Eq. (1b)). Each iteration to find the optimal value comprises a Lagrangian minimization step with respect to the primal variable (x) and a dual variable (y) update step as shown in Eq. (1c) and Eq. (1d).

$$\begin{aligned}&\text{minimize } f(x)\\&\text{subject to } Ax = b\end{aligned} \tag{1a}$$

$$L_\rho(x, y) = f(x) + y^T(Ax - b) + (\rho/2)\|Ax - b\|_2^2 \tag{1b}$$

$$x^{k+1} = \underset{x}{\operatorname{argmin}}\, L_\rho(x, y^k) \tag{1c}$$

$$y^{k+1} = y^k + \rho(Ax^{k+1} - b) \tag{1d}$$

where ρ is the penalty parameter working as a step size.

Distributed Optimization Using Alternating Direction Method of Multipliers (ADMM)

In contrast to the centralized optimization, this approach based on ADMM uses two distinct decision variable vectors, and uses a distributed optimization computed by multiple agents (Boyd et al., 2011). All the decision variables for MG1 and MG2 are represented in vectors x and z, respectively. The decision-making problem is formulated in a distributed manner as Eq. (2a) where two variables x and z are split in the objective function but connected by the constraints. As in method of multipliers, it solves the dual problem by iterative gradient ascent using the augmented Lagrangian (Eq. (2b)). However, the main difference is that the decision variables are split into two parts and solved with the respective part of the separable objective function. Therefore, the two variables are updated based on each minimization step in a sequential (i.e., alternating) manner, unlike the combined step in the centralized optimization. In other words, each iteration in ADMM to find the optimal value comprises two Lagrangian minimization steps, each with respect to each primal variable (of x and z) and a dual variable (y) update step as shown in Eq. (2c), Eq. (2d), and Eq. (2e).

$$\begin{aligned}&\text{minimize } f(x) + g(z)\\&\text{subject to } Ax + Bz = c\end{aligned} \tag{2a}$$

$$\begin{aligned}&L_\rho(x,z,y) = f(x) + g(z) + y^T(Ax + Bz - c)\\&+(\rho/2)\|Ax + Bz - c\|_2^2\end{aligned} \tag{2b}$$

$$x^{k+1} = \underset{x}{\operatorname{argmin}}\, L_\rho(x, z^k, y^k) \tag{2c}$$

$$z^{k+1} = \underset{z}{\operatorname{argmin}}\, L_\rho(x^{k+1}, z, y^k) \tag{2d}$$

$$y^{k+1} = y^k + \rho(Ax^{k+1} + Bz^{k+1} - c) \tag{2e}$$

Uncertainty Modeling

In developing decision-making strategies for a smart grid system, prediction of the amount of renewable energy generation is crucial and difficult because of its intermittent and uncertain nature (Powell et al., 2012 and Shin et al., 2017). Since wind and solar power have been considered in this study, wind speed and solar intensity over a year are considered for the uncertainty modeling. Hourly average data for the wind speed and solar radiation are gathered from the National Wind Technology Center (NWTC) and the Solar Radiation Research Laboratory (SRRL) located in Colorado, USA (Andreas and Stoffel, 1981 and Jager and Andreas, 1996). Using the collected data for the wind speed and solar intensity for 10 years from 2008 to 2017, multi-scale nonstationary stochastic models are developed based on several techniques of time-series modeling, regression and Markov Chain Monte Carlo (MCMC). The models for every month are separately developed by considering the variation divided into two types: inter-day and intra-day variation as in Shin et al. (2017). Subsequently, the decision-making strategy based on ADMM is developed considering the uncertainty on wind and solar power generation.

Conclusions

Microgrid is a localized and distributed version of a smart grid focusing on small areas. This study develops a decision-making strategy of a cooperative MMGS where multiple microgrids coexist. First, the MMGS was formulated as MAS. Then the problem was solved by both the centralized and distributed optimizations, and the distributed optimization showed a lower computational cost while achieving the same objective function value. For this result, the decision-making algorithm was developed based on ADMM. In addition, uncertainty modeling for wind speed and solar intensity was implemented to predict the amounts of renewable energy generation in order to make the decision-making more practical and realistic. However, if the decision-making is done independently for each daily operation, some day-to-day inconsistencies known as end-effect can occur, which is undesirable. For the future work, to relieve the end-effects and improve the robustness of the strategy, value function approximation solved by a reinforcement learning technique will be considered.

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