Machine Learning based and Multi-Agent System based Control and Optimization Approaches for Electric Vehicles, Power Grids, and their Interactions

電気自動車，電力網およびそれらの相互作用のための機械学習とマルチエージェントシステムに基づく制御および最適化法

Nguyen Dinh HOA
グエン ディン ホア

Paradigm shifts on energy generation, consumption, storage, and trading, due to the deep penetration of renewable and distributed energy resources, e.g., solar, electric vehicles, etc., pose significant challenges to the operation and management of current and future energy systems. A solution proposed in this research is a unified framework based on multi-agent system and machine learning for the optimization, control, and prediction of energy networks at different levels to cope with uncertainties and random perturbations. Thus, the stability, robustness, and resiliency of energy systems are enhanced in addition to their autonomy.

太陽光，電動化車両といった再生可能で分散型のエネルギー資源への依存度が今後ますます高くなると考えられる。これによって，エネルギー生産／消費／蓄積／輸送においてパラダイムシフトが起こり，現在および未来のエネルギーシステムの操作と管理においては，今までにない大きな挑戦が求められる。本研究で提案する解決策は機械学習とマルチエージェントシステム[*1]に基づく統一した枠組みであり，さまざまなレベルで，不確かでランダムに受ける影響に対処するために，電力網を最適化し，制御し，そして予測する手法である。これによって，エネルギーシステムの自律性だけでなく，安定性，頑強性，そして復元力が強められる。

*1：マルチエージェントシステム：エージェントとは管理したい対象毎に設けられる機能単位。マルチエージェントシステムは，そのエージェントが他のエージェントと連動する分散処理システム。

Introduction

Most parts of current electric power grids around the globe were built decades ago using the top-down approach, i.e., power is generated at central generation units located far away from end-users, which is then transmitted through very long transmission and distribution lines, and hence, incurs much power losses and construction, maintenance, and expansion costs. Moreover, conventional power plants utilizing fossil-based resources are polluted causing severe problems to the environment and society. Fortunately, recent advances on harvesting renewable energy have opened up other clean ways of power generation, and the developed information and communication technology (ICT) have made the communication between different grid components possible. These lead to the concept of smart grid. However, the large integration of renewable energy to the grid creates crucial problems, e.g., frequency and voltage instability, because of the fluctuating and intermittent nature of renewable sources. Additionally, the central deployment of renewable generation, e.g., solar farms and wind farms, requires a large area, a high construction cost, and is not always accepted by the public. Therefore, simply integrating renewable and distributed energy resources into the current grids built based on a top-down approach is not an appealing solution.

Multi-agent system (MAS) provides a powerful framework for hierarchical, decentralized system operation and management where no centralized entity is needed and agents coordinate themselves to achieve their own local goals as well as the global targets for the whole multi-agent system.[1-3] Different parts of an energy grid or an electric vehicle (EV) at different system levels can be considered as agents. For example, each generation unit and each household in an electric power grid can be regarded as an agent. On the other hand, each cell in a battery bank or in a fuel cell stack can also be cast as an agent. Then one global target of the grid is to guarantee the supply-demand balance so that the grid frequency is stabilized, and a local aim of one household is to have enough energy at any time, while the local purpose of a battery pack or fuel cell stack is to achieve the equal state-of-charge (SoC) or energy level of all battery cells or all fuel cells.

Moreover, in the transforming energy grids where much more renewable energy resources and EVs will be integrated, reverse power flows from excess renewable energy or from EVs to the bulk grids cause severe problems on the grid voltage and frequency. Therefore, in parallel with the enhancement and expansion of the existing grid infrastructure and markets, new bottom-up forms of energy grids and markets should be developed. Particularly, localized and decentralized energy grids and markets are promising candidates, for instance peer-to-peer (P2P) microgrids (see Figure 1 for illustration) equipped with distributed ledger technologies such as blockchains. These P2P microgrids can be established within local communities in which energy is generated and consumed by prosumers with rooftop photovoltaic (PV) panels or small-scale wind turbines, EVs, fuel cell based combined heat and power (FC-CHP) units, etc. Then surplus energy is sold directly to consumers inside such P2P microgrids without going back to the main grid. In these scenarios, P2P micrgrids can also be cast as MASs.

The mentioned concept and description of MAS above is exhibited in Figure 1. Here, an energy system at a specific scale is represented by a cyber-physical system in which the energy exchange is conducted at the physical layer, whilst the information exchange between agents is

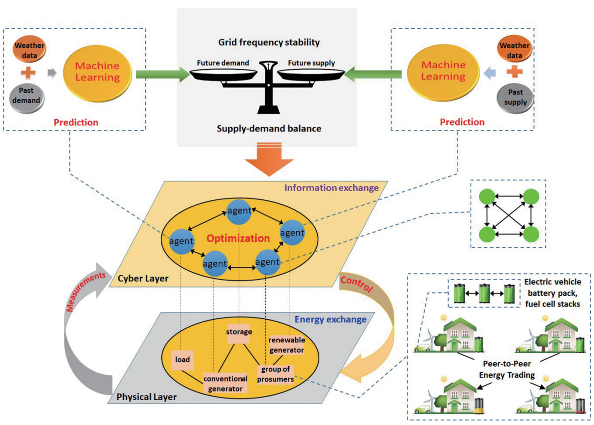


Figure 1 Illustration for the proposed machine learning based and multi-agent system based control and optimization approaches for energy grids

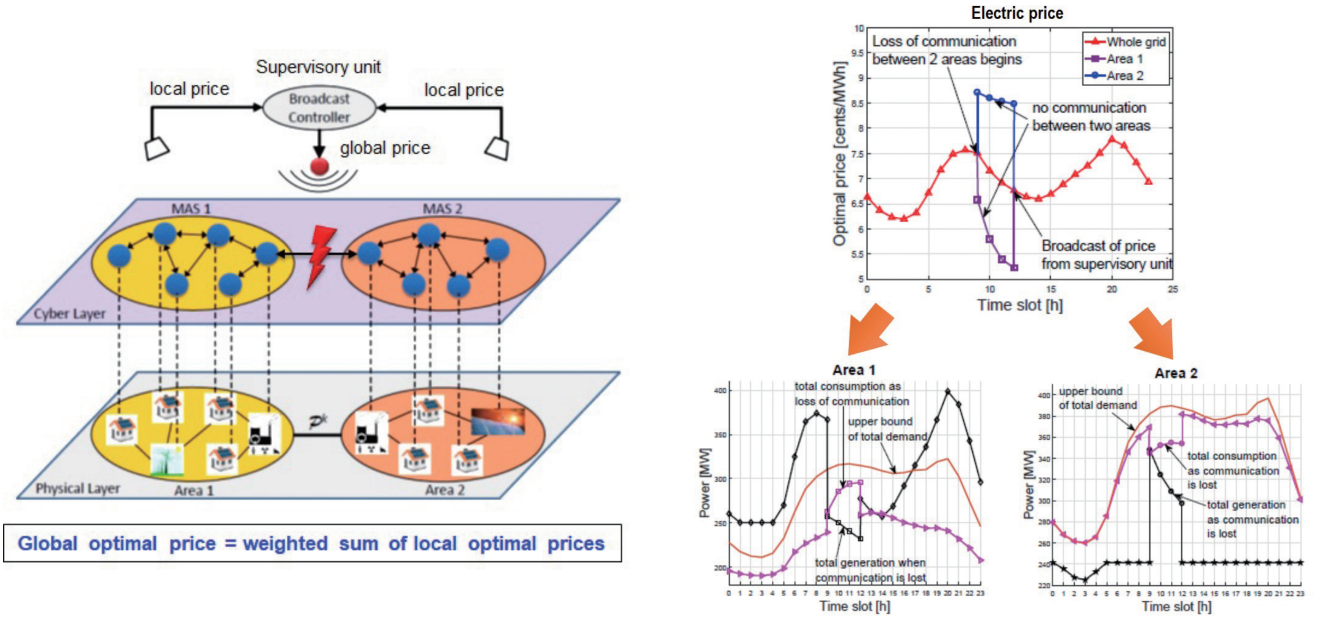
made at the cyber layer. The physical measurements will be utilized at the cyber layer for the prediction and optimization of energy demand and supply executed by embedded algorithms in each agent. Consequently, control commands will be sent back to the physical layer to adjust the outputs of demand and supply units accordingly.

Multi-Agent System for Energy Grid Optimization and Control

As the future energy grids will become more and more decentralized, and simultaneously energy markets will be liberated where consumers have right to choose which sources of energy to buy and generators can select where to sell energy to, current centralized control and management approaches will no longer be valid. Instead, distributed control and optimization methods need to be utilized. As such, MAS-based optimization and control approaches will be suitable for decentralized operation and management of energy grids, where portions of grids will act as agents, at different scales.[4-9]

In [4] and [7], the so-called dynamic social welfare maximization (DSWM) problem was investigated in which the benefit of not only energy generators but also energy consumers are maximized. Moreover, optimal real-time energy prices were derived by all generators and consumers, based on which they adjust their energy outputs correspondingly. In those researches, each generator or consumer is treated as an agent, and decentralized alternating direction method of multipliers (ADMM) approaches were proposed to solve the DSWM problem in parallel by each agent. Thanks to those ADMM approaches, agents can simultaneously attain their own objectives of benefit maximization and local constraints satisfaction, while sharing privacy-protected information with some other agents to achieve the global target of supply-demand balance. Further, a novel control structure was proposed in [4] to handle the disconnected communication between agents in presence of cyber-attacks, where a supervisory unit measures different energy prices in different areas due to cyber-attacks and then calculate the global optimal price to broadcast back to all agents in all areas. Hence, the grid resiliency is guaranteed. The proposed structure and the simulation results for the MAS-based ADMM optimization approach applied to a modified IEEE 39-bus system in [4] are depicted in Figure 2.

A similar ADMM approach to that in [4] was also employed in [9] for the optimal energy management in microgrids with rooftop PV prosumers and EVs. Consequently, the optimal energy price inside the



(a) (b)

Figure 2 (a) Price regulation mechanism for grid recovery under cyber-attacks proposed in [4], and (b) The optimal electric price, power generation and consumption in two areas in the grid

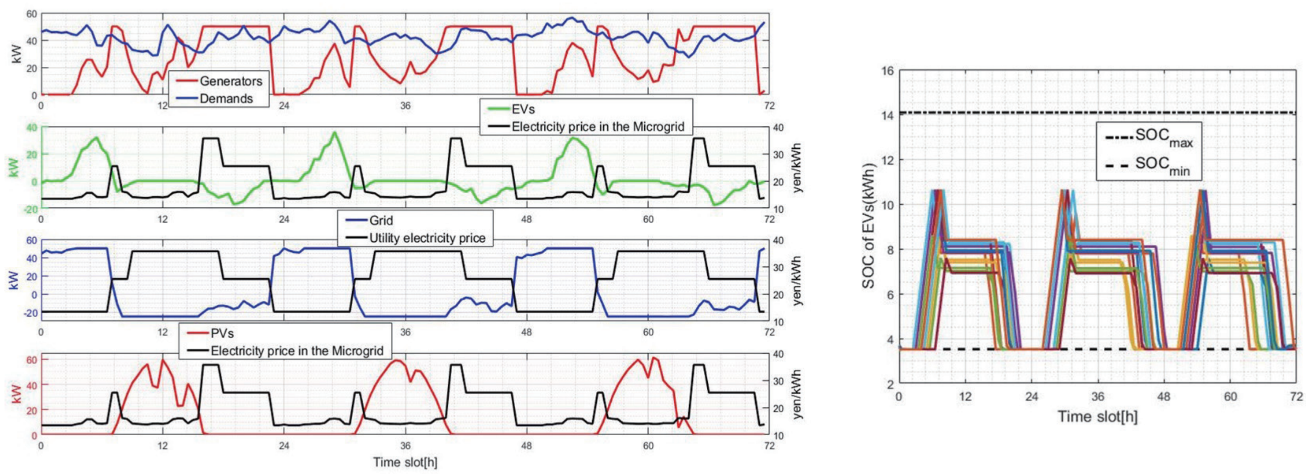
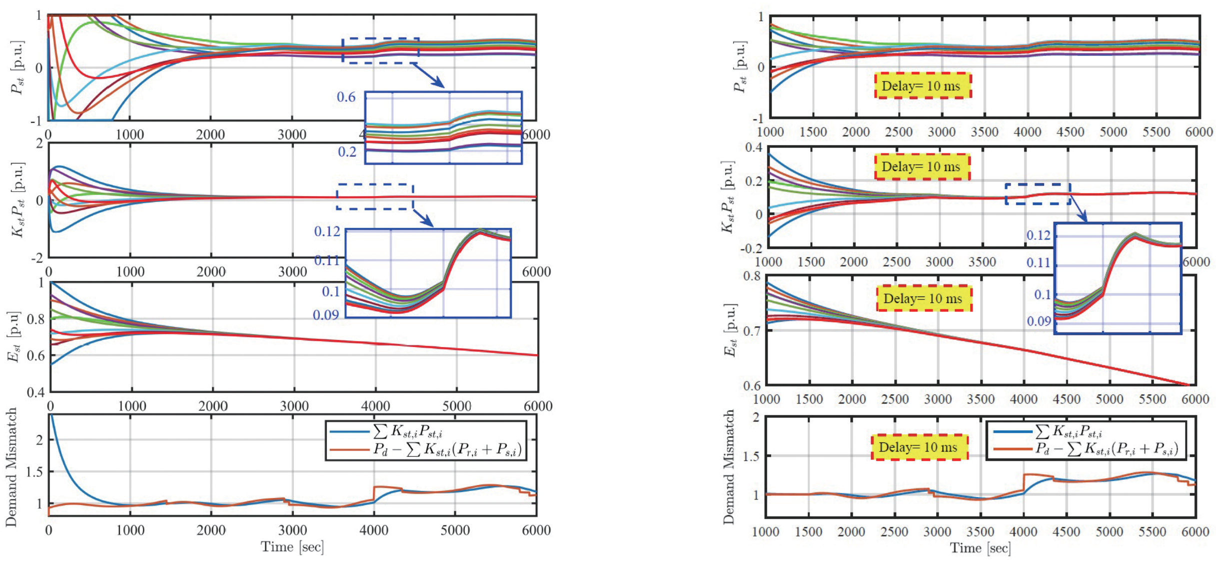


Figure 3 Behaviors of agents in a microgrid under the proposed decentralized ADMM approach [9]



(a) (b)

Figure 4 Distributed BESSs responses under: (a) variant wind speed and no time delays, (b) invariant wind speed and time delays

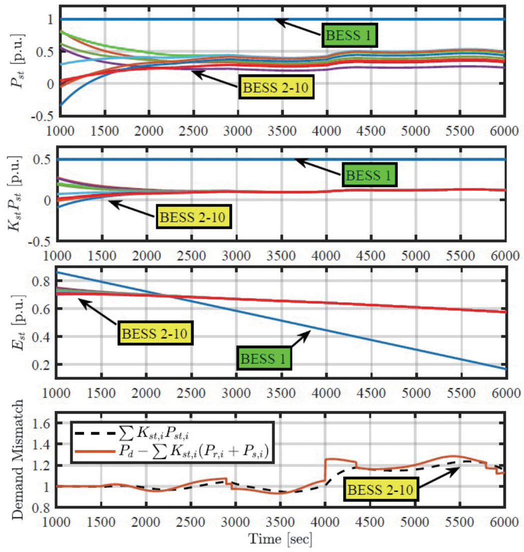


Figure 5 Distributed BESSs responses under communication failure

considering microgrid as well as the optimal scheduling of diesel generators, household consumption, and EV charging/discharging for a 3-day period are displayed in Figure 3.

On the other hand, the consensus theory for MASs were employed in the control designs in [5], [6], [8] for distributed battery energy storage systems (BESSs) taking into account the heterogeneity of BESSs rated capacities and inter-BESS communication delays. The advantages of distributed or on-site BESSs are to enhance the storage functionality and flexibility, since the storage function of a centralized BESS could be lost if a single battery pack is broken. Additionally, distributed BESSs can support the active and reactive power control through which the frequency and voltage regulations are obtained. The key idea here is to control distributed BESS such that they equally share their active and reactive powers depending on their rated capacities and charging/discharging rates, using consensus theory for MASs. The simulation results for a wind farm with 10 wind turbines equipped with 10 on-site BESSs in [8] are exhibited in Figure 4 and Figure 5.

Machine Learning for Prediction of Energy Demand and Generation

To build up the so-called super smart society or society 5.0, the guarantee of enough energy at any time is a critical requirement, because any lack of energy will lead to severe problems to the society and economy. Hence, the prediction of energy demand including electricity demand is an essential problem for almost all parts in energy grids, e.g., power utility companies, smart homes, EVs, etc., for suitably scheduling and balancing their energy generation and consumption. It then turns out that machine learning (ML) based methods could provide good solutions for improving the accuracy of supply-demand balance.[10] Particularly, ML techniques can be used for predicting both renewable output power generation and load power demand, and can be run at different time scales, from real-time, hours to days, weeks, months, and seasons ahead. As a result, the power scheduling for conventional generation units such as thermal or hydroelectric ones can be appropriately planned in both short-term and long-term periods.

In order to do run ML methods, measurement data of historical weather conditions and historical data of renewable output power as well as power demand are needed for training parameters of ML models. Afterward, the obtained parameters will be employed for the prediction of future renewable output power and future power demand based on weather forecast data. The advantage of ML methods is on their ability to achieve reasonably accurate predictions in spite of inexact input data, hence the better supply-demand balance can be obtained.

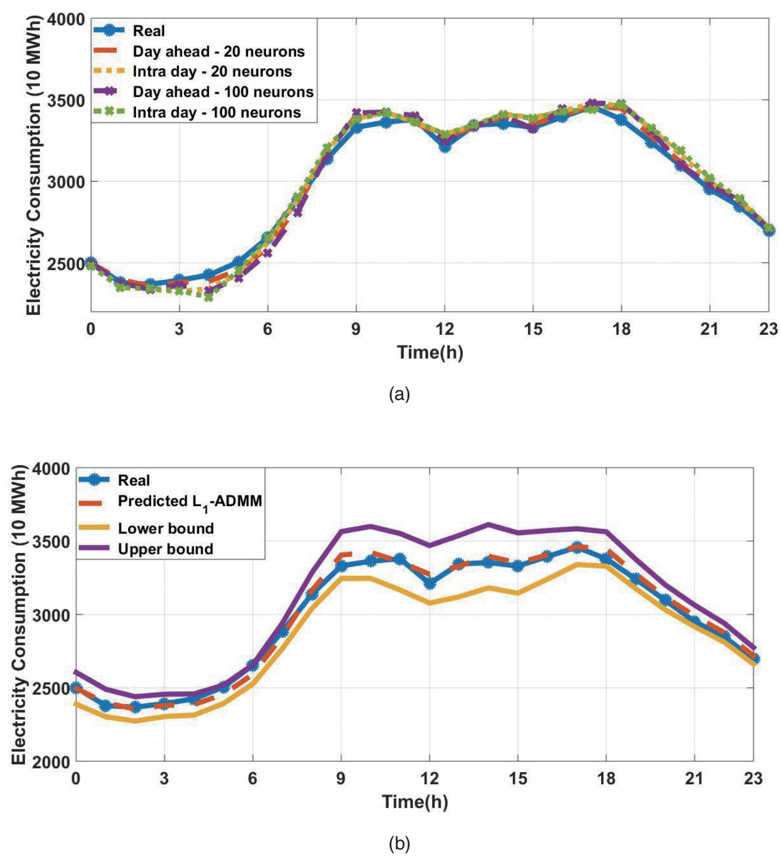


Figure 6 (a) Prediction curve, and (b) Prediction interval using standard deviation method for Tokyo electricity demand [10]

Further, the implementation of ML algorithms can be made at not only power utility companies but also end-users such as smart homes, which makes ML being a distributed intelligence for energy grids.

As an example, Figure 6 shows the demand prediction for Tokyo using a machine learning approach on 26 October 2018 based on data of weather and demand one month before. The ADMM method is employed for solving the least-absolute optimization problem to obtain the model parameters.[10]

Conclusion

This research has proposed a unified methodology based on multi-agent system for distributed implementation of the solutions to the problems of energy supply-demand balance, optimization of performance and efficiency of storage systems, robustness of energy grids to sudden changes. By means of multi-agent system, a wide range of power management and prediction functions required from in-vehicle battery to home, region, and even inter-region energy supply and demand will be executed by one or multiple agents, at different scales. Its way of system design and operation is consistent, which is well advanced and unique in this domain. Thus, the proposed research shows practical paths to solve the problems of upcoming energy network systems such as renewable energy integration and emergency power management.

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Nguyen Dinh HOA
グエン ディン ホア
Assistant Professor
International Institute for Carbon-Neutral Energy Research (WPI-I2CNER), Institute of Mathematics for Industry (IMI), Kyushu University
Ph.D.