A real-time smart grid system via artificial intelligence - Innovation for Taiwan’s smart grid system

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1. Introduction

According to Ministry of Economic Affairs of Taiwan (2020), Taiwan government plans to convert 25% of the conventional fuel generation to renewable energy by 2025. In addition, the government discusses the potential challenges of 100% renewable target, especially the challenges of the outdated grid system. The grid system needs to be improved immediately due to the following issues.

1. Renewable generation is intermittent and unpredictable (Dusparic et al. 2015). Unlike fuel generation, renewable energy mostly depends on weather.
2. Unpredictable energy consumption pattern of the customers is also a serious issue for the grid stability. Each customer has their own consumption pattern due to the different degrees of discomfort while decreasing energy consumption (Yu et al. 2016; Lu and Hong 2019). In this case, it will be difficult to match the energy consumption with adequate supply.
3. Energy price (including demand response mechanism) cannot respond quickly to the unstable energy generation and energy demand (Lu et al. 2018). The major stakeholders will all lose profit due to untimely response of energy price.
4. Customers lack knowledge to response the energy supply and price fluctuation. The feedback will be required to enable customers to understand the potential benefits and how to engage into the system.
5. The information sharing and computation ability in the current grid system are still limited. Due to unpredictable energy supply and demand, the information sharing quality and velocity need to be improved to better the performance of the whole system.

Therefore, the report proposes a smart grid system to improve the reliability of the grid system(matching unpredictable renewable generation and demand) and reduce energy cost for all the stakeholders (grid operators and customers). The expected outcome of the smart grid system is shown in Table. 1.

Table. 1 expected outcome of the smart grid system

Desired outcome	Measured output and/or target
Future energy generation and energy demand prediction	• Predict the future hourly energy generation and energy demand with 90% R-Squared accuracy.

Dynamic demand response mechanism	• With consideration of discomfort cost and incentive income, the mechanism should provide the most profitable hourly energy price and incentive rate for all the stakeholders.
Optimized operating schedule for appliances	• The schedule should strive for at least 20% saving for all the stakeholders. • Control the energy consumption curve close to the availability curve
Smart sensors	• Collect the real-time energy consumption data (including consumption pattern, priority and quantity) of the customers. • Collect the environment data in each customer's house.
Recommender system for electricity usage	• Send the energy consumption feedback to the customers. • Customers can set the preference of the schedule in the system, enhancing the engagement of the customers.
Communication network	• At least 90% of appliances can share the data with the other appliances and the grid operators.

2. Scope

The influenced scope of the smart grid system includes systems and stakeholders. Systems for the smart grid system include energy management system (EMS) in grid station and smart agent (SA) for appliances in each customer's house. EMS predicts the future energy generation and energy demand, and estimates the energy price and incentive rate based on the predicted generation and demand. SA collects more than 90% of appliances' energy consumption information and optimizes the operating schedule of the appliances. Stakeholders include grid operators and customers. Grid operators are energy supplier, determining energy price and incentive rate. Customers are home or business owners consuming energy.

3. Overview

The report presents a flowchart to show the processes, system and stakeholders involved in the innovation, as shown in Fig. 2. The system starts to run as the day begin (i.e., h = 0 am). At each hour, the system first receives the historical energy information from previous hours, including energy demand, energy consumption, energy price and incentive rate. Based on historical data and weather data, EMS predicts hourly energy generation and demand for the following 24-h hours. Next, EMS calculates the optimal hourly energy price and incentive rate for the following 24-h hours to bridge the gap between the energy generation with energy demand. In the next step, the system will operate in the customer's side to optimize the energy consumption. Different with the energy demand, the energy consumption is the adjusted energy demand (i.e. energy demand reduction and increase) based on the proposed energy price and incentive rate to minimize the cost of electricity and discomfort, as shown in Fig. 3. For this purpose, SA optimizes the schedule of each appliance to estimate the most cost-effective consumption curve. In addition, SA collects the hourly energy consumption data (including energy consumption pattern, priority and quantity) of the customers for the future prediction and optimization. At the end of the day (i.e., h = 24 pm), SA sends the feedback and recommendation of the future electricity usage to the customers, and the customers are able to set the preference of the future schedule.

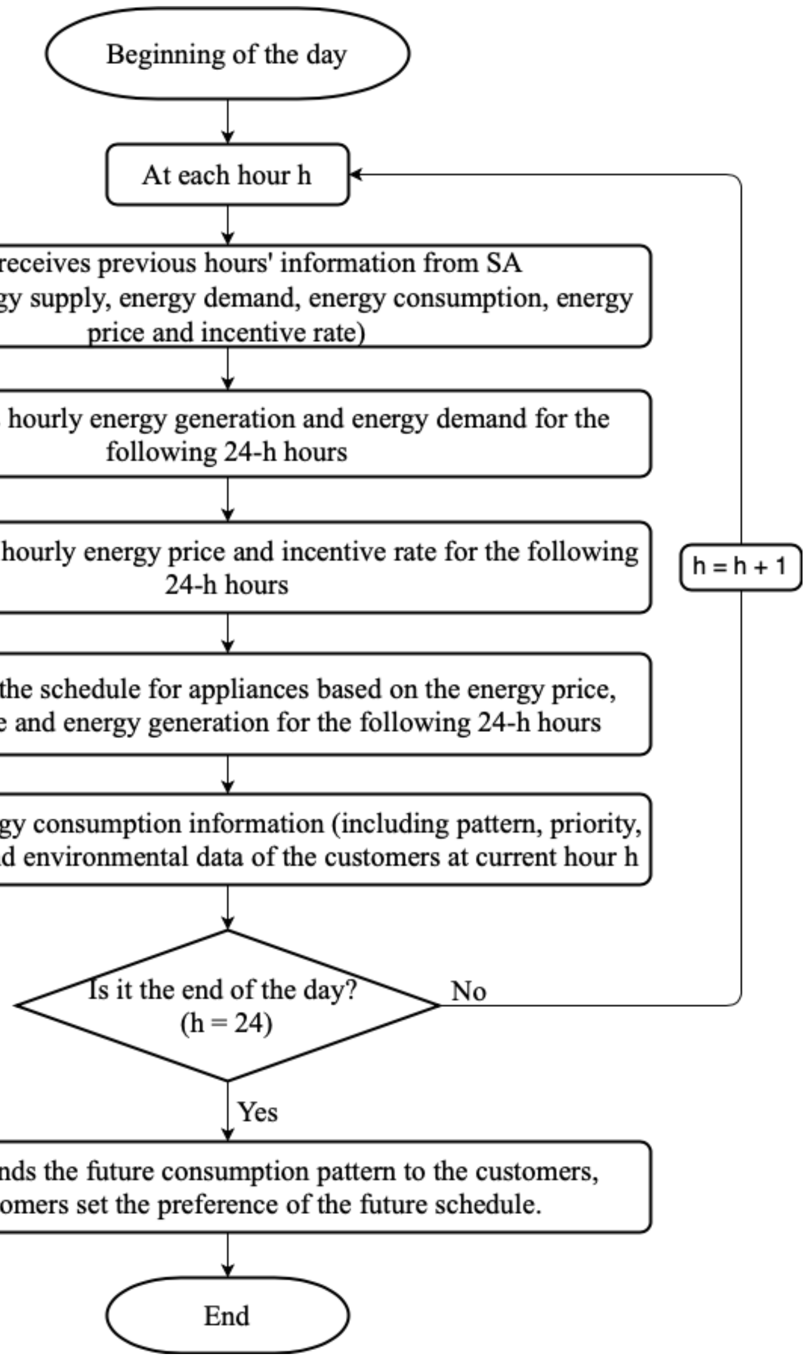

Fig. 2 Flowchart for the proposed smart grid system

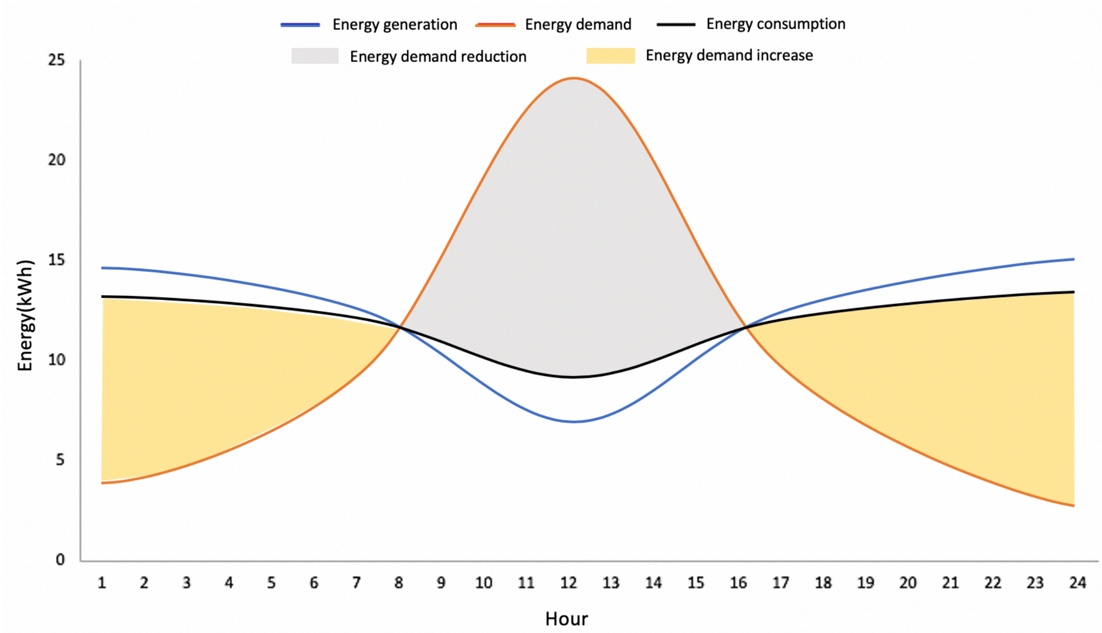

Fig. 3 energy simulation chart at h = 0 am

Unlike the existing smart grid system, the system doesn't just consider the future energy availability and utilize demand response mechanism to decrease the peak-demand. The report intends to match the consumption with generation (i.e. maximizing the demand of the customers while the renewable availability is the highest). Therefore, the report incorporates the customers' side as a part of the smart grid system. The system optimizes the schedule of each appliance to make the best use of energy availability. In addition, the system generates a sequence of hourly predictions for the following 24-h hours. In this way, the system is able to explore the better long-term result, whereas the existing smart grid system usually exploits the best short-term result without the consideration of the long-term benefits.

We divide deeper into the proposed process (Fig. 2). The report illustrates enabling technology and relevant data of each step. The critical success factors are also discussed.

- ## Energy Management System (EMS)

EMS is operated in the generation and distribution side by grid operators. The system predicts the energy generation and demand, and calculates the optimal demand response strategy to match the demand with the generation. It contains three main capabilities, including future energy generation prediction, future energy demand prediction and dynamic demand response mechanism.

1. Future energy generation prediction

Deep Neural Network (DNN) is widely used for the energy generation forecast. It is good at handling the non-linear relationship problems accurately (Panapakidis and Dagoumas, 2016; Ryu, Noh and Kim, 2016). Therefore, EMS implements DNN to predict the future hourly energy availability, as shown in Fig. 3. To capture the risk of the weather for the better accuracy, the input features include historical weather data, such as cloud cover ratio, wind direction, wind speed...etc.

2. Future energy demand prediction

The report implements DNN to predict future hourly energy demand of the customers, as shown in Fig. 3. The input features include historical energy consumption pattern, consumption amount, consumption priority…etc. In addition, the model incorporates the customers' feedback into account, enabling customers to learn from customers' habits.

3. Dynamic demand response mechanism

Demand response (DR) is an efficient way to strengthen the grid's stability (Lu, Hong, and Zhang, 2018). DR is divided into two categories, price-based and incentive-based. Price-based DR provides varying energy price to the customers (Luo, Hong, and Kim, 2016), whereas incentive-based DR provides incentives to the customers to sell the electricity back to the grid (Shen et al, 2014). Both programs intend to match the energy demand with energy generation by encouraging the customers to reduce their peak load and increase their off-peak load.

Reinforcement learning (RL) is good at solving DR problems with its sequential actions and states environment (Lu, Hong, and Zhang, 2018). Therefore, EMS estimates both energy price and incentive rate via RL for the following 24-h hours based on the prediction of hourly energy generation and demand. The objective function of the RL aims to minimize the cost of both customers and grid operators. In this way, the DR mechanism of EMS can not only improve grid system's reliability but also reduce energy cost for both the stakeholders.

• Smart Agent (SA)

SA is operated in the customers' side. Each house has one SA to connect all the appliances. It has four main capabilities, including optimized operating schedule for appliances, smart sensors to collect the consumption data, recommender system for electricity usage and communicating network.

1. Optimized operating schedule for appliances

As Fig. 3 shows, the energy consumption is the combination of energy demand increase and reduction, which bridges the gap between the energy generation and energy demand. SA utilizes RL to optimize the operating schedule of the appliances with the aim of minimizing user dissatisfaction costs and energy bills and stabilizing grid system. The on/off status of the appliances are controlled by SA. For example, electric vehicles can interact with grid to support charging demands and help customers to sell the electricity to the grid operators at the most profitable and reasonable time.

2. Smart sensors

Smart sensors (Fig. 4) enable SA to acquire energy consumption information, including consumption pattern, priority, and quantity. The consumption pattern of customers enables SA to understand the priority of the appliances' usage. The amount of energy consumption provides the relative importance of the dissatisfaction cost under given energy cost and incentive rate. In addition, the smart sensors also acquire environmental data in each house, such as temperature and humidity.

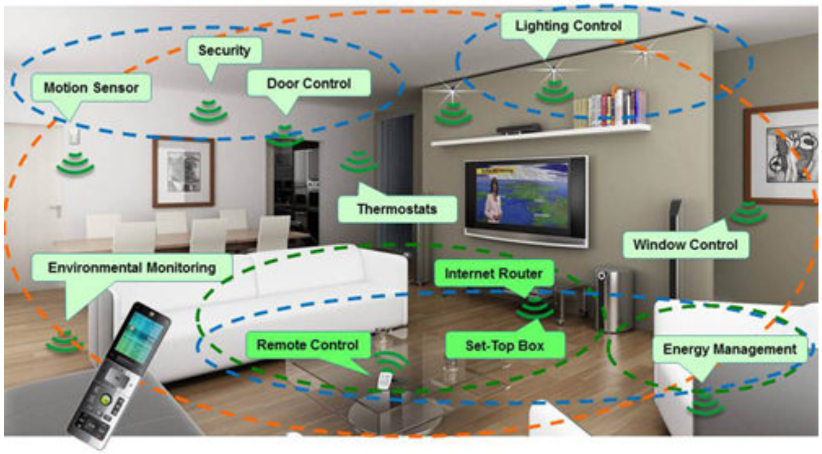

Fig. 4 smart sensor system, Ref: (IoT, 2020)

3. Recommender system for electricity usage

According to Department of Energy in USA, 170 Kwh is wasted due to insufficient knowledge on energy usage by the customers. Therefore, to enable active participation of customers, the recommender system in SA sends feedback and suggestion back to the customers. The customers can realize the potential saving and health benefits (such as decreased CO2 emission) on the daily summary report. The customers can also engage in the system by setting the preference of the schedule. All the interactions are carried out on a simple mobile app, as shown in Fig. 5.

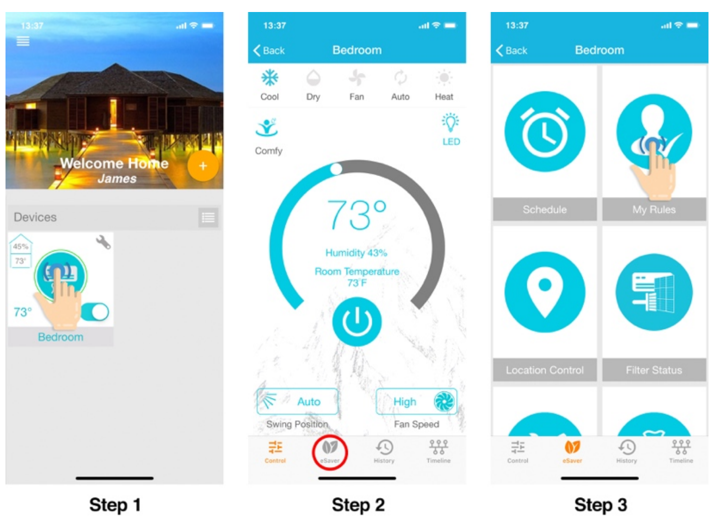

Fig. 5 setting the customer's own rule, Ref: (Cielo, 2020)

4. Communicating network

The interoperability of the network is the most important part of the system. The information needs to be transferred timely and accurately from the grid operator to customers. Communicating network enables all the SA to communicate with each other. SA can learn from each other to better the future optimized scheduling ability. In addition, the communicating network incorporates EMS as the hub of the system. The network not only sends the historical data to EMS but also notifies EMS about the damage of the system, such as malfunction of the sensors.

4. Findings

In incentive-based demand response for smart grid with reinforcement learning and deep neural network, Lu and Hong utilize reinforcement learning and deep neural network to obtain the optimal hourly incentive rate for all the stakeholders. Simulation results show that the framework is able to improve the profitability of all the stakeholders (Fig. 6).

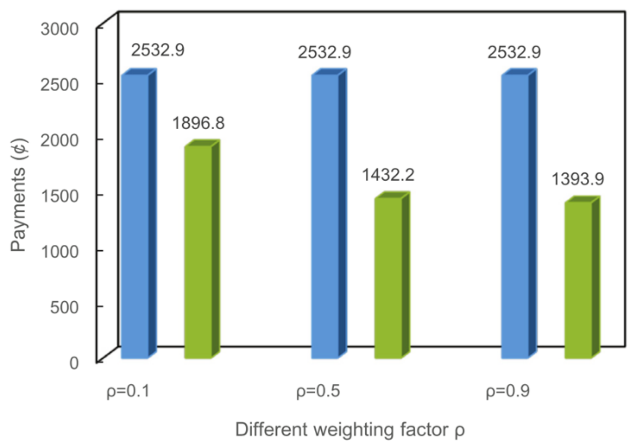

Fig. 6 cost comparison under different weighting factor for the service provider, Ref: (Lu and Hong, 2019)

Note: Blue bar represents the grid system without demand-response. Green bar represents the grid system with optimal demand response. Weighting factors represent the relative importance between the customer's incentive income and discomfort. The larger the value is, the more likely the customers will sell the electricity back to the grid operator for the incentive income.

According to Forbes magazine, the Boston consulting group (BCG) found that the energy retailer is able to increase their gross margin by more than 20% by combining the grid system with the customers. The system creates a detailed customer's information database to understand the preference of the customers. In this way, the system is able to response the pricing increases timely by customers' data.

Based on these two findings, both statistics shows that a smart grid system with the consideration of the customers can not only improve the stability of the grid system but also increase the profitability of all the stakeholders, supporting the applicability and benefits of the proposed system.

5. Objections

Privacy is always a major issue in smart city. As the information of various source increases, the privacy issue will become more serious. In the example of ERP (electronic road pricing) system in Singapore, the government monitors the location of each vehicle at any given time. The system captures all the data of the users. A potential risk will arise if the system is hacked. For example, all the data is stolen or sold to the other companies. To solve this issue, the report builds the communicating network as a block chain system. Each SA and EMS is an individual block in the system. In this way, the privacy information can be stored in each block, preventing the leakage of privacy information.

6. Conclusion

The report proposes a smart grid system via artificial intelligence. The system implements DNN to predict energy generation and energy demand, and utilized RL to obtain the optimal sequential actions on a daily basis. In addition, the system optimized the energy consumption by incorporating the appliances' operating schedule into the system. By doing so, the system considers the supply and demand side as a whole to maximize the utilization of the renewable energy and enhance the profitability for all the stakeholders in the long-term perspective. And based on the two findings, it further supports the rationale of the report. For the concern of privacy in the smart system, the report also proposed corresponding solutions to enhance the systems' reliability.

Reference

Dusparic, I., Taylor, A., Marinescu, A., Cahill, V. and Clarke, S. (2015). Maximizing renewable energy use with decentralized residential demand response. *2015 IEEE First International Smart Cities Conference (ISC2)*, 1-6.

Yu, M., Lu, R. and Hong, S. (2016). A real-time decision model for industrial load management in a smart grid. *Applied Energy*, 183.

Lu, R. and Hong, S. (2019). Incentive-based demand response for smart grid with reinforcement learning and deep neural network. *Applied Energy*, 236, 937-949.

Lu, R., Hong, S. and Zhang, X. F. (2018). A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach. *Applied Energy*, 220, 220-230.

Ministry of Economic Affairs, R.O.C.(Taiwan) (2020). Energy conversion plan to renewable energy. https://www.moea.gov.tw/MNS/populace/Policy/Policy.aspx?menu_id=32800&policy_id=9, in Chinese (accessed July 20, 2020).

Department of Energy, USA (2020). The smart grid: an introduction. https://www.energy.gov/oe/downloads/smart-grid-introduction (accessed July 20, 2020).

Panapakidis, I.P. and Dagoumas, A.S. (2016). Day-ahead electricity price forecasting via the application of artificial neural network-based models. *Applied Energy*, 172, 132–51.

Ryu, S., Noh, J. and Kim, H. (2016). Deep neural network-based demand side short term load forecasting. *Energies*, 10(1):3.

Luo, Z., Hong, S.H. and Kim, J.B. (2016). A price-based demand response scheme for discrete manufacturing in smart grids. *Energies*, 9(8):650.

Shen, B., Ghatikar, G., Lei, Z., Li, J., Wikler, G., Martin, P., et al. (2014). The role of regulatory reforms, market changes, and technology development to make demand response a viable resource in meeting energy challenges. *Applied Energy*, 130:814–23.

Yu, M.,Hong, S.H. and Kim, J.B. (2016). Incentive-baseddemandresponseapproachforaggregated demand side participation. Smart grid communications (SmartGridComm). *2016 IEEE international conference on. IEEE*, 51–56.

IoT (2020). Smart sensors: is it the way to go? http://iotmaniac.com/smart-sensors-is-it-the-way-to-go/ (accessed July 23, 2020).

Cielo. (2020). How can I link Comfy mode when setting up schedule using Breez Eco. https://cielosupport.zendesk.com/hc/en-us/articles/360039486333-How-can-I-link-Comfy-mode-when-setting-up-a-Schedule-using-Breez-Eco- (accessed July 23, 2020).

IEEE. (2019). 3 Real-Life Examples of the Positive Impact of Smart Grid Data Analysis. https://innovationatwork.ieee.org/3-real-life-examples-of-the-positive-impact-of-smart-grid-data-analysis/ (accessed July 23, 2020).

Asiaone. (2016). New ERP system to be rolled out from 2020, https://www.asiaone.com/singapore/new-erp-system-be-rolled-out-2020 (accessed July 23, 2020).

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