Impact of Electric Vehicles and Solar PV on Future Thailand's Electricity Daily Demand

Sukita Kaewpasuk[1], Boonyarit Intiyot[2], and Chawalit Jeenanunta[3]

[1,2] Department of Mathematics and Computer Science, Faculty of Science,
Chulalongkorn University, Bangkok, Thailand
[3]School of Management Technology, Sirindhorn international Institute of Technology (SIIT),
Thammasat University, Pathumthani, Thailand
E-mail: s.kaewpasuk@gmail.com, boonyarit.i@chula.ac.th, chawalit@siit.tu.ac.th

Received: August 14, 2019/ Revised: September 18, 2019/ Accepted: September 18, 2019

***Abstract*—In the next few decades, solar PV and electric vehicles (EVs) will become a major potion in Thailand's power system. In this paper, we aim to study the impact of future solar PV installation and EV charging on Thailand's power system and to provide the efficient load demand management policy. Firstly, the future power load demand, solar PV installation, and the number of EVs are forecasted by ARIMA models. Next, various scenarios of EV charging demand are generated by varying the charging schedule which is controlled by a smart grid system and charging policy. Future load demand curve in each EV charging scenario is analyzed based on demand response and the effect to electricity power producer is discussed.**

***Index Terms*—Demand Response, Electricity Demand, Electric Vehicles (EVs), Solar PV, Thailand's Power System**

I. Introduction

Renewable energy is the key point in a current electric power system. Plug-in renewable energy such as solar PV and wind power are encouraged over the past decade. Each country employs different renewable energy types depending on their location and technology. Moreover, each renewable type has different power output behavior which leads to the changing of production and demand curve. The most prevalent renewable energy type in Thailand is solar power since it has been supported by the government. The power output from solar energy make the load demand in midday decrease.

Another factor that will significantly affect the demand curve in the near future is the consumption from the electric vehicle (EV), which starts to break into the global automobile market. Although the increasing number of EV cars implies the decreasing of oil fuel consumption, EV car charging will cause the considerably increase in the electricity consumption.

If the renewable energy and EV charging enter the power system without control, the demand may be extremely high or extremely low in some periods. This leads to the high spinning reserve power. Therefore, the peaks of total load demand should be maintained or reduced to satisfy the demand management based on demand response. This can be accomplished by scheduling the EV charging to avoid the peak load periods and provide the most equally distributed load demand.

In this paper, the objective is to analyze the future effect of solar power and EV charging on Thailand's daily electricity demand and to provide policy recommendation on EV charging schedule. First, the future value of load demand and solar PV installation are forecasted by ARIMA model using historical data. Next, scenarios of charging are determined under the concept of a smart charging system. Then, the effect of EV charging schedules on Thailand's load demand with solar power are plugged into the system is analyzed. The scenario where the load demand is the most equally distributed throughout the day will be recommended. The benefit of the smart EV charging system will be discussed by comparing with other net load demand scenarios.

The remaining paper is organized as follows. The literature review about the power system, solar penetration, and electric vehicles is in the next section. Next, the research methodology which consists of the forecasting technique for the daily demand and the scenarios generation of EV charging is presented. Lastly, the research results and conclusion are discussed.

II. Literature Review

The solar PV power has penetrated Thailand's power system since 2002 and has significantly increased since 2011 [1]. References [2] and [3] shows that the solar PV installed in Thailand's industry sector would reach 3,131 MW and the solar PV installed in Thailand's household sector would reach 2,656 MW in 2037. Consequently, the projected power production from the installed solar PV would be large enough to affect the production planning of power system. The uncertainty of solar PV output made the power system management more complex. Good forecasted solar PV output data can help ease the production planning of the power system.

There are many research studies trying to forecast the power output from solar PV with various methods. Mellit, Benghanem, and Kalogirou proposed a combined method to forecast the solar radiation that includes wavelet theory and neural networks method [4]. In another study by Chen, Duan, Cai, and Liu, the daily solar PV output was forecasted by artificial neural network based on type of the weather [5]. According to Perez et al. in [6], they evaluated the solar irradiance that directly related to solar PV power output. Their result showed that as the number of solar PV plants increased, the fluctuate of solar PV output decreased.

In addition to the forecasting methods that were proposed to increase the accuracy, many production models were also proposed to handle the uncertainty from solar PV output. Osório, Lujano-Rojas, Matias, and Catalão, proposed the unit commitment problem with the penetration of renewable energy. A new scenario-based method was applied to generate scenarios of wind and solar. Then, they solve the unit commitment problem with these scenarios by priority list method [7]. Kaewpasuk, Intiyot, and Jeenanunta introduced the stochastic recourse model for unit commitment problem that integrated with renewable energy and analyzed the relation between the amount of renewable penetrated and the spinning reserve [8]. Moreover, Liu, Botterud, Zhou, and Du proposed the unit commitment model with a fuzzy variable in renewable output energy and reserve power, and then solved it with the fuzzy max-min method [9].

Electric vehicles (EVs) were recently introduced to automobile market and got a lot of attention. According to IEA report in [10], EVs would be promoted to reach 220 million cars in 2030. Having EVs in the system seems to affect the pattern of load demand. Since the demand response of the power system management must be preserved [11], the load demand when EV car charging is included should be equally distributed throughout the day. Qian et al. in [12] simulated EV charging effects on load demand by simulating daily load demand of power system where EV charging was assumed to be normally distributed. According to [13], the impact of EVs and solar PV on the electricity industry was studied where the overall productivity of the electricity industry was determined by a Monte-Carlo-based portfolio model. The solar PV output was simulated by the system advisor model. Their scenarios of EV charging were separated into unmanaged and managed charging. In [14], Yang, Li, Niu, and Xue studied the unit commitment problem of power systems with renewable generations and EV plug-in. Scenarios of renewable generating and EV charging were generated by Latin hypercube sampling and solved by a meta-heuristic method. The management of load demand for demand response is also studied in smart grid. In [15], Nguvauva and Kittipiyakul proposed an algorithm to schedule EV charging to reduce the peak demand in the evening. The limitation of this research was that the charging station must be smart charging, meaning the power charging must be fully controlled by the smart grid.

III. Research Methodology

A. *Forecasting electricity demand data*

The study began with preprocessing the data which were then used for forecasting the future yearly and daily demand by ARIMA model. The data of load demand power were obtained from the Electricity Generating Authority of Thailand (EGAT) that is the major electricity production sector in Thailand. The obtained data consisted of yearly load demands and daily load demands. The future yearly load demands were forecasted using historical data directly whereas the future daily load demands were forecasted using preprocessed data. In the preprocessing of the daily data, the daily load demands were classified into 7 groups based on the pattern of daily load demand which were summer-weekday group, summer-weekend group, rainy-weekday group, rainy-weekend group, winter-weekday group, winter-weekend group, and long-vocation group. The pattern of daily load demands in the same group had similar peak and off-peak periods. Therefore, a day in each group can represent other days in the same group. In this study, the daily demand from 2006 to 2017 was collected as the data for the forecasting. Then, the ARIMA model with 48-time-period cycles was used to forecast the future demands.

B. *Forecasting solar PV daily production*

Installed solar PV in Thailand has been started in 2002. The cumulative installed capacity was only 3 MW in 2002 and increased to 2,667 MW in 2017 [1]. Installed capacity from 2002 to 2017 from GIZ was the data for an ARIMA model of the forecasting process. Not only installed solar PV but also solar PV production was forecasted. A solar PV production that directly affects the load demand can be calculated from the installed capacity, a function of external factors, and efficiency of solar PV technology. According to the report from [16], a value of the efficiency of solar PV was less than 10 percent in 2007 and increased to 46 percent in 2017. By this historical data, the value of efficiency was estimated by linear regression model and approximated to be 80 percent in the next 10 years. In this research, the external factors consist of irradiance and temperature, whose function values were calculated from historical installed solar PV and its production data. Finally, the solar power was computed from the product of solar PV installed, the efficiency value, and the value of the function of external factors in each time period.

C. Forecasting EV charging demands

Forecasting EV charging demand requires the estimation of the number of EVs and their battery capacities in the future as well as the future amount of each type of the charging systems. In this study, the forecasted amounts of EVs were obtained from the previous study of Electricity Generating Authority of Thailand, Metropolitan Electricity Authority, and Provincial Electricity Authority in [17]. However, the forecasted EV data did not specify their battery capacities. To approximate the proportion of EV battery capacities in the future market, the data from EVs plug-in U.S. data in [18] were used. This data contained the current number of EVs with more than 28 EV models e.g. Tesla model X, BMW Active E, Nissan LEAF, and BMW i8. Knowing the model of an EV implies knowing its battery capacity. Hence this can be used to serve our purpose. The amount of charging systems was assumed to be the same as the number of EVs. However, proportion of each type was estimated using the data from [10], which classified the types of charging system of U.S. into 3 types i.e. level-1 charging (AC current with 3.7 kW), level-2 charging (AC current with 22 kW), and fast charging (AC current or tri-phase with 43.5 kW).

D. Generating scenarios of load demand, solar PV power, and EV charging

The forecasted values of load demands, solar PV installed, and EV charging in the previous section were combined to generate the possible net load demand of the power system. Firstly, the simulation of load demand and solar PV were generated from a normal distribution with mean f and standard deviation $(u - l)/6$where f, u, l are the forecasted value, upper bounded forecasted value at the 80% confidence interval, and lower bounded forecasted value at the 80% confidence interval, respectively. The simulation was generated for 500 replications.

After scenarios of load demand with solar PV output were generated, scenarios of EVs charging were set up. EV models and charging systems were grouped by their battery capacity and type of charging station, respectively. This study separated EVs model into three groups based on the size of the battery regardless of their battery type. The first group was EVs with small battery whose capacity less than 10kWh. The second group was EVs with medium battery whose capacity was 10-30 kWh. The third group was EVs with large battery whose capacity was more than 30 kWh.

This study assumed that every EV was charged fully only 1 time a day and the number of charging stations equaled to the number of EVs. For simplicity, each EV was assigned to only one charging station and vice versa. In this study, it was assumed that the large size battery group was assigned to the fast charging stations for charging. If the number of large size battery EVs is larger than the number of fast charging stations, the remaining large size battery EVs will be assigned to the level-2 charging stations, and so on. On the other hand, if the number of large size battery EVs is less than the number of fast charging stations, the remaining fast charging stations will be assigned to the medium size battery EVs and so on. Given the forecasted values, the EV charging was classified into 5 groups as shown in **Error! Reference source not found.**. In order to generate scenarios of EVs charging, the period of charging in each group was varied and different distributions was applied, namely normal distribution and uniform distribution. Initially, scenarios of EVs charging were set up based on the current charging system power consumption and human behavior. After that, more scenarios were generated by changing the period of charging to generate the load demand corresponding to the demand response. The period of charging for every station was scheduled under a concept of smart EV charging in [15].

Lastly, all scenarios of EV charging schedules were applied to 500 simulated of load demands with solar PV output for each demand group that was assumed in section forecasting electricity demand data. To achieve the best demand response of demand management, the load demand curve should be flat as much as possible because it requires less ramp up/ramp down in the generator units.

E. Analyzing the future load demand following solar PV installation and EV charging schedule

To analyze the range of load demand in the future, the extreme case of them also observed. Scenarios of load demand and power output of solar PV were obtained from three values, namely the forecasted value, upper bounded forecasted value, and lower bounded forecasted value at the 0.8-confidence interval. Scenarios of load demand integrated with solar PV consisted of two extreme cases and a normal case. The first extreme case, denoted by D1, was a combination of the upper bounded forecasted value of load demand and lower bounded forecasted value of solar PV output. The second extreme case, denoted by D3, was a combination of the lower bounded forecasted value of load demand and upper bounded forecasted value of solar PV output. The normal case, denoted by D2, was obtained from a combination of the forecasted value of load demand and solar PV output. For example, assumed that the forecasted value, lower bounded forecasted value, and upper bounded forecasted value in midday period of load demand were 26.7GWh, 25.4 GWh, and 28.1 GWh, respectively and the forecasted value, lower bounded forecasted value, and upper bounded forecasted value in midday period solar PV output were 3.5 GWh, 3.2 GWh, and 3.8 GWh, respectively. Then, a total demand in a midday of scenario D1 was 24.9 GWh, which was calculated by subtracting 3.2 GWh of lower bounded forecasted value of solar PV output from 28.1 Ghof upper bounded forecasted value of load demand. Similarly, total demand in a midday of scenario D2 and D3 were 23.2 GWh and 21.6 GWh, respectively.

All EV charging schedules were applied to scenarios D1–D3. The scenario with the smallest fluctuation in load demand throughout the 48-time period provided the best charging policy. The range of the future net load under the best policy was also recommended.

IV. Research Results

A. *Forecasting electricity demand results*

The load demand forecasting process started with yearly demand forecasting. The result of yearly demand forecasting is shown in Fig. 2. For example, in 2028, yearly consumption was approximately 260 GWh. In 2038, yearly consumption was more than 310 GWh. The trend of yearly consumption was almost linearly increasing.

Examples of the forecasted daily load demands from summer-weekday group are shown in Fig. 3. The patterns of peak and off-peak periods were similar in every year e.g. the evening peak period occurs between 8-11 pm. Meanwhile, the mean of load demand increased every year corresponding to the trend of the yearly consumption.

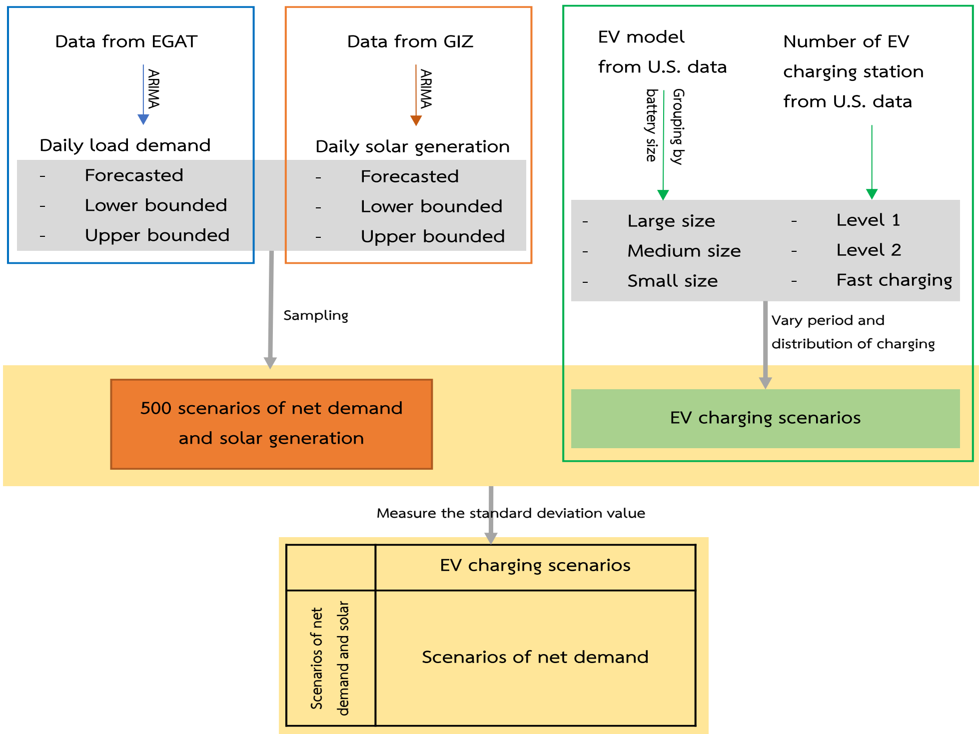

Fig. 1. Over all of research methodology

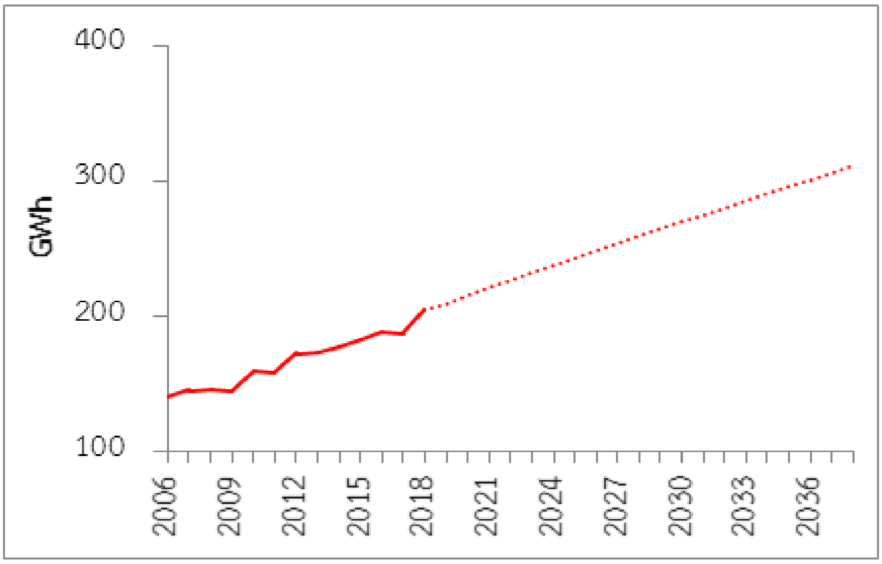

Fig. 2. Yearly power consumption

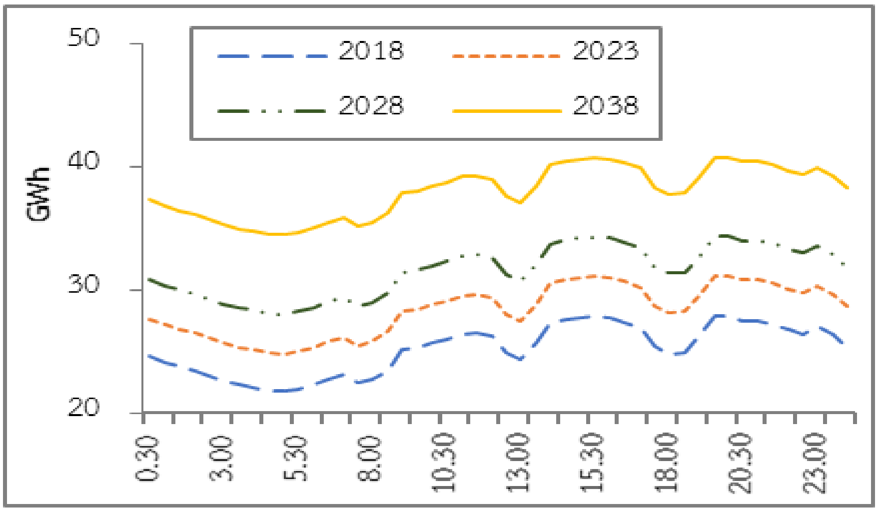

Fig. 3. Forecasted daily load demand of summer-weekday.

B. Forecasting solar PV daily production results

Solar PV daily productions in Thailand were approximated in the second process at the efficiency of solar production equal to 80%. The examples of solar daily production are shown in Fig. 4. This figure illustrates similar production pattern each year i.e. the solar power has high power output at midday and has zero power output in the evening until sunrise.

C. Forecasting EV charging demand results

For EV data, the proportions of EV cars based on battery size were investigated and are shown in Fig. 5. In the early stages, the medium group was a majority but as time went by, its size stayed approximately the same and no longer the dominant one. On the contrary, the small and the large groups which came later but grew faster than the medium group. For example, the number of EV cars in large group increased approximately 65% from 2014 to 2015. The data from Fig. 5 was used to forecast the proportion of each group in future based on linear regression and approximation. In our forecast, we assume the proportion of each group stayed the same for 2018-2038 although the number of EV cars increased. As the result, the forecasted proportions were 60%, 30%, and 10% for large, medium, and small size battery groups, respectively.

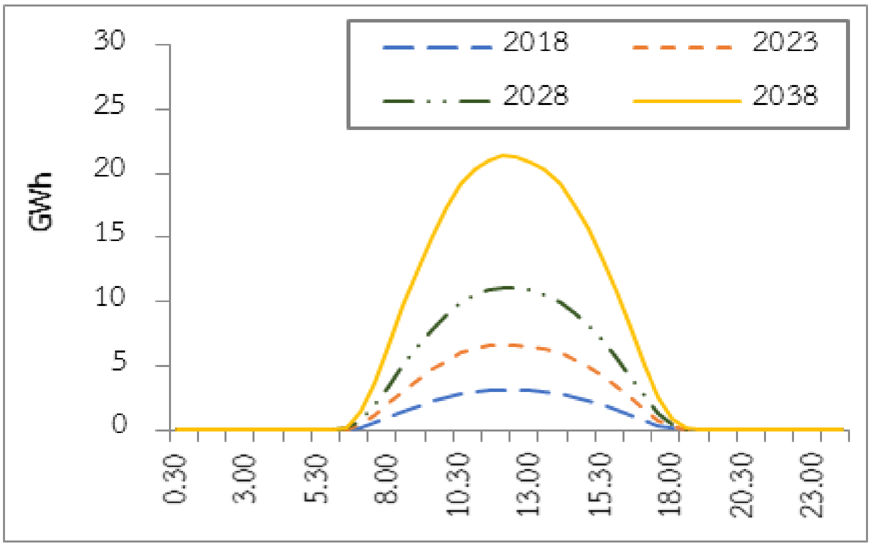

Fig. 4. Forecasted solar PV daily production

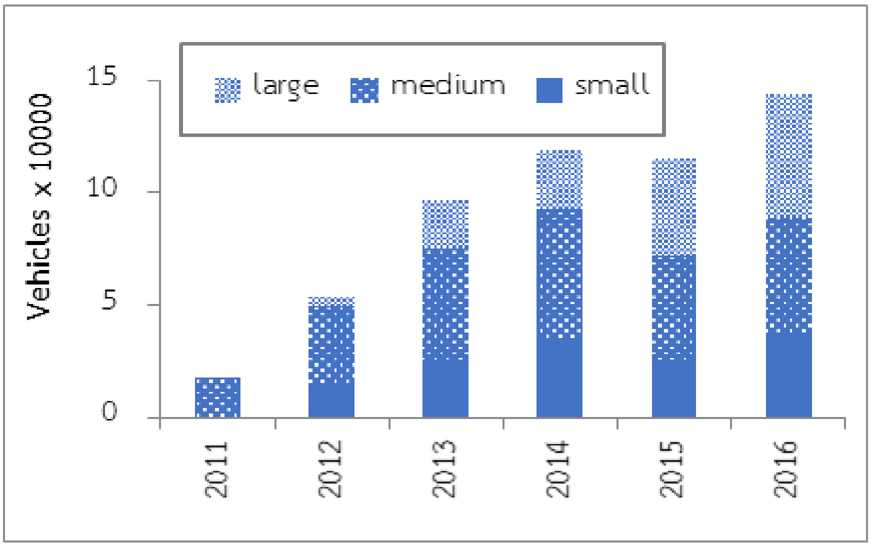

Fig. 5. U.S. EV sales in each battery size.

The proportions of EV charging stations were obtained from U.S. charging station in [10]. Their proportions of level-1, level-2, and fast charging were 6%, 80.7%, and 13.3%, respectively. Groups of EV charging were established by applying the assumption shown in section 3.4 to the proportion of EV cars and charging stations which were obtained in the previous step. The proportion of each charging group are shown in **Error! Reference source not found.**. Moreover, the power consumption and charging time were also calculated and are shown in this table.

D. EV charging schedules

In this section, we discuss how to generate the EV charging scenarios. The scenarios were set up under the smart charging system where the power of charging was controllable by the policy maker. These scenarios were generated by varying the starting and ending charging time period of each group that depends on 1) their power consumption of EV charging, 2) the pattern of load demand, and 3) solar power output. In this paper, we assumed the starting charging time of EV was classified into 6 types that were 6 p.m. –12 a.m. called Nighttime, 6 a.m. –7 p.m. called Solar operation time, 12 a.m. – 6 a.m. called After midnight time, 7 p.m. – 6 a.m. in next day called Non-solar operation time, 4 a.m. – 9 p.m. called Extended solar operation time, and All day. The distribution of the starting and ending charging time was either normally distributed [N] or uniformly distributed [U]. For example, the first scenario (S1) assumes that the starting charging times of all groups occur in 6 p.m. – 12 a.m. and are distributed normally during that period with mean at 9 p.m. and S.D. equals 1 hour represented by [N] Night. This scenario did not involve smart charging and therefore was the most possible situation in current technology of EV charging station.

TABLE I
THE CHARGING PERIOD OF EACH EV CHARGING GROUP

EV charging Group		1	2	3	4	5
Detail of charging		Small size battery by level1	Small size battery by level2	Medium size battery by level2	Large size battery by level2	Large size battery charging by fast charging
Percentage respect whole EV car		6%	4%	30%	46.70%	13.30%
Charging time(hour)		3	0.5	1	4	2
Total power consumption of EV charging (MWh)	2028	541.24	357.58	5363.66	33397.73	9403.47
	2038	5097.53	3367.74	50516.1	314546.89	88563.9
	S1	[N] Night (6 p.m. – 12 a.m.)	[N] Night	[N] Night	[N] Night	[N] Night
	S2	[N] After midnight (12 a.m. – 6 a.m.)	[N] After midnight	[N] After midnight	[N] Solar operation time	[N] After midnight
	S3	[N] Solar operation time	[N] Solar operation time	[N] Solar operation time	[N] Solar operation time	[N] Solar operation time
	S4	[U] All day	[U] All day	[U] All day	[N] Solar operation time: 40% [U] All day: 60%	[U] All day
	S5	[U] Non-solar operation time	[U] Non-solar operation time	[U] Non-solar operation time	[N] Extended solar operation time (4 a.m. - 9 p.m.)	[N] Extended solar operation time

The motivation of these smart charging scenarios is as follows. If the solar power output is high, the pattern of the total load demand in the midday will be a concave curve. Therefore, the starting charging times should be moved to the solar operation time in order to keep the load demand most equally distributed throughout the day. Since the total charging power consumption was dominated by the 3rd, the 4th, and the 5th groups, these groups had high priority when the moving of starting charging times was required. The distribution of the staring charging times was chosen so that the total load demand curve was flat as much as possible. For example, in case that the period of the starting charging time was the same as the solar operation time, the distribution of the staring charging times should be normal since the solar power output curve throughout the day is similar to the curve of a normal distribution function. The resulting scenarios (S2 – S5) are shown in **Error! Reference source not found.**.

E. The effect of solar PV and EV charging schedule on future load demand

To study the effect of solar PV and EV charging schedule on future load demand, the scenario of no EV charging (S0), the scenario of current charging without any control policy(S1), and four scenarios of charging schedule controlled by smart charging system (S2 – S5) were applied to the 500 simulated of load demands integrated with solar power for each load demand group and compared. The results of net load demand in 2028 and 2038 are shown. To investigate the effect of EV and solar PV on load demand, the average of the standard deviation value for each load demand group and each EV charging scenario were observed. The standard deviation value of each case in 2028 and 2038 are shown in **Error! Reference source not found.** and **Error! Reference source not found.**, respectively. The values in boldface indicate the best scenarios for each demand group.

TABLE II
AVERAGE OF STANDARD DEVIATION VALUE IN 2028

Demand groups	Scenarios of EV charging					
	S0	S1	S2	S3	S4	S5
summer weekday	3,628.00	5,039.05	2,838.77	**2,611.79**	3,300.65	2,870.95
summer weekend	3,820.78	8,521.57	3,472.60	**2,686.42**	2,984.56	5,239.27
rainy weekday	3,575.83	4,996.99	2,861.31	**2,698.25**	3,274.01	2,894.44
rainy weekend	3,739.01	5,189.15	3,015.17	**2,765.65**	3,424.20	3,000.87
winter weekday	3,476.63	4,831.05	2,673.62	**2,493.29**	3,154.76	2,727.99
winter weekend	3,701.55	5,044.42	2,914.64	**2,597.10**	3,356.40	2,873.51
vocation	4,744.24	5,974.84	3,964.34	**3,421.17**	4,358.47	3,788.03

TABLE III
AVERAGE OF STANDARD DEVIATION VALUE IN 2038

Demand groups	Scenarios of EV charging					
	S0	S1	S2	S3	S4	S5
summer weekday	5,789.12	21,650.39	7,620.14	11,126.93	**3,311.22**	6,178.50
summer weekend	6,017.89	26,031.04	**3,332.72**	10,824.41	5,822.83	2,1843.14
rainy weekday	5,729.38	21,646.66	7,881.65	11,447.79	**3,531.11**	6,519.59
rainy weekend	5,888.68	21,816.48	7,835.64	11,187.51	**3,492.68**	6,234.09
winter weekday	5,569.14	21,372.64	7,580.27	11,232.94	**3,128.48**	6,211.04
winter weekend	5,865.24	21,560.52	7,639.80	10,924.04	**3,221.46**	5,869.64
vocation	7,034.31	22,230.16	7,657.91	9,930.80	**3,958.57**	4,935.71

The result from **Error! Reference source not found.** and **Error! Reference source not found.** shows that the scenario S1, in which all groups were charged with the starting times normally distributed from 6 p.m. to 12 a.m. has the highest standard deviation value in every case. In 2028, the lowest average value of the standard deviation value of each demand group comes from applying EV charging scenario S3 to the load demand. Since solar power plug-in makes the net load demand dropped during midday, charging EVs during that time as in S3 can fill up the drop demand. In 2038, EV charging scenario S4 gives the smallest standard deviation value. Due to the amount of solar penetration, appropriate amount of charging with the starting times normally distributed in the solar PV operation time of the biggest group can fill in the drop of the net load demand. Others are charged with starting times uniformly distributed all day and therefore did not affect the standard deviation value much. Examples of the comparison among the netload demand without EV charging, the demand without controlled EV charging schedule, and the demand with controlled EV charging schedule for 2028 and 2038 for each demand group are shown in Fig. 6 to Fig. 11. The results illustrate that the charging of EV with appropriate timing leads to a more effective load demand management of the power system which will provide efficient generator units operations.

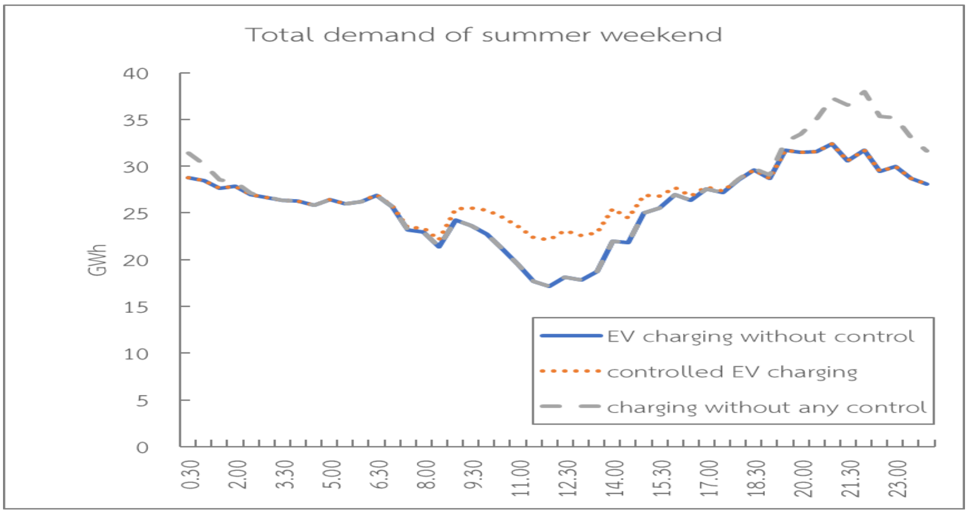

Fig. 6. Total demand of summer weekend in 2028

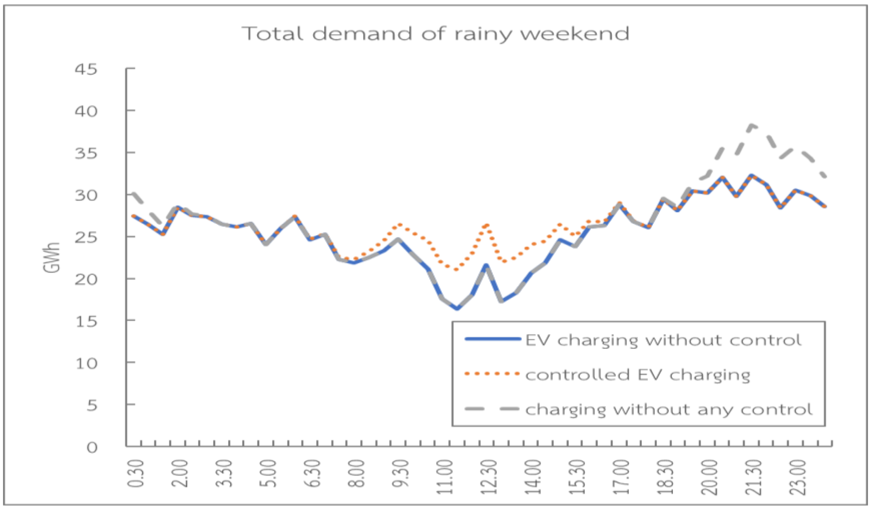

Fig. 7. Total demand of rainy weekend in 2028

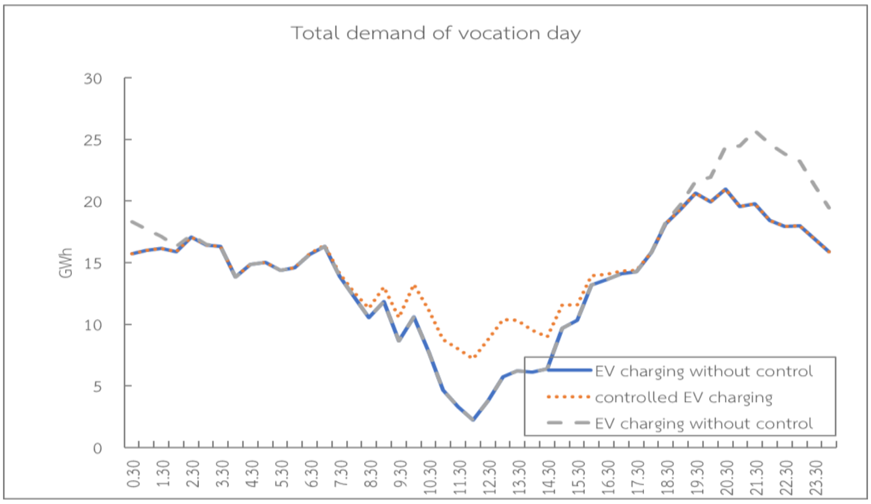

Fig. 8. Total demand of vocation day in 2028

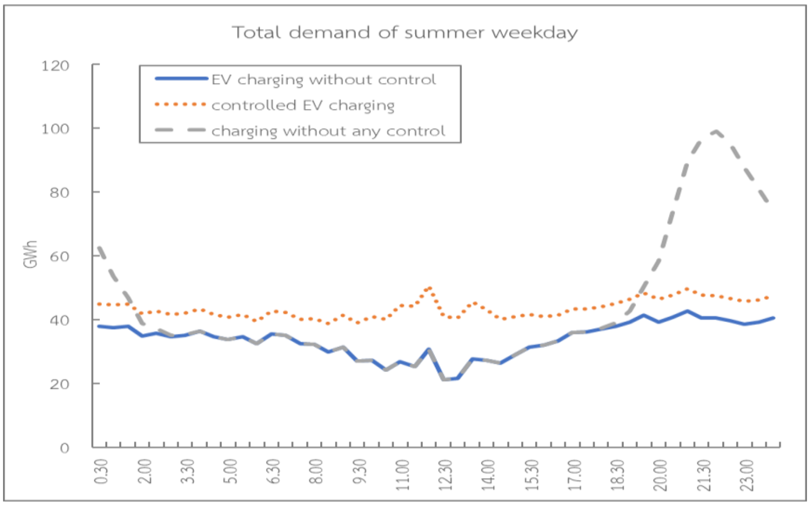

Fig. 9. Total demand of summer weekday in 2038

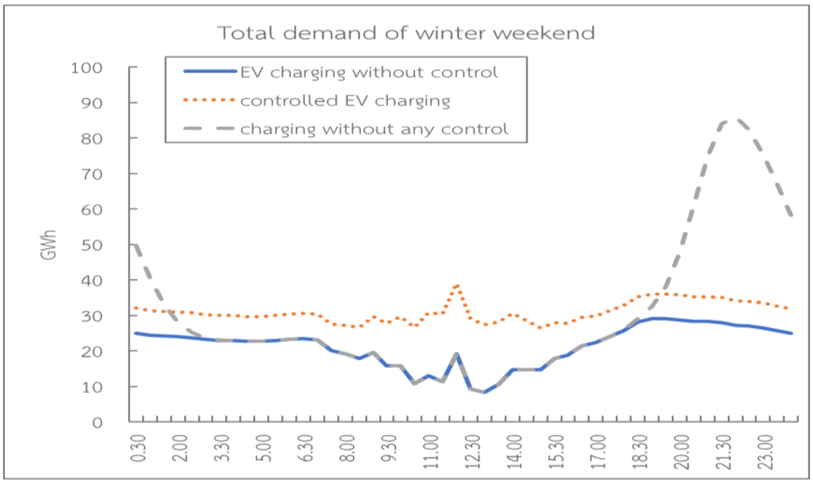

Fig. 10. Total demand of winter weekend in 2038

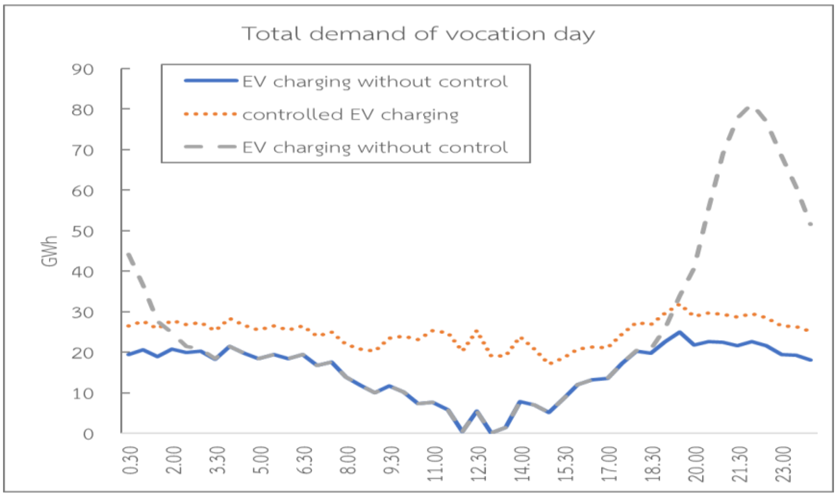

Fig. 11. Total demand of vocation day in 2038

TABLE IV
THE STANDARD DEVIATION VALUE OF LOAD DEMAND FOR EACH EV CHARGING SCHEDULE SCENARIO (MWH)

Year	2028			2038		
Load demand with solar power cases / EV charging scenario	D1	D2	D3	D1	D2	D3
without EV charging	2178.587	3422.03	5116.309	2007.732	5335.304	9884.803
S1	**3730.570**	**4890.604**	**6435.925**	**19192.840**	**21532.410**	**24570.980**
S2	**1649.608**	2566.629	4237.480	10010.450	7270.744	7094.198
S3	2094.521	**2312.019**	**3715.659**	15245.340	10885.570	7027.118
S4	2028.445	3071.839	4718.059	**4374.174**	**2393.391**	6093.654
S5	1986.199	2602.342	4135.414	10186.260	5736.129	**2618.362**

F. The resulting future load demand following solar PV installation and EV charging schedule

To construct the future load demand range, the most equally distributed of the load demand with solar power and EV charging in the three cases D1 – D3 was analyzed. The result from Table IV shows that the scenario S1, in which all groups were charged with the starting times normally distributed from 6 p.m. to 12 a.m., has the highest standard deviation value in every case. For D1 case in 2028, the lowest standard deviation value comes from applying EV charging scenario S2 to the load demand. Since the D1 case comes from the upper bound of load demand and the lower bound of solar power, the peak of the resulting load demand appears from 8 p.m. to 11 p.m. The scenario S5 makes the net load demand for this case fluctuated the least because the starting times are not in the peak period i.e. the most power consumption group starts charging during solar operation time while the starting times of other groups are normally distributed after midnight until 6 a.m. For the cases with more solar PV penetration (D2 and D3), the lowest standard deviation value comes from applying EV charging scenario S3. Since solar power plug-in makes the net load demand dropped during midday, charging EVs during that time as in S3 can fill up the drop demand. In 2038, the projected net load demand curve of D1 is almost flat. Thus, EV charging scenario S4, where all groups were charged with the starting times uniformly distributed all day, cause the curve fluctuated the least. The standard deviation value of the load with EV charging has the lowest value, which is the same as the load without EV charging. For load demand D2 in 2038, EV charging scenario S4 gives the smallest standard deviation value. Due to the amount of solar penetration, appropriate amount of charging with the starting times normally distributed in the solar PV operation time of the biggest group can fill in the drop of the net load demand. Others are charged with starting times uniformly distributed all day and therefore did not affect the standard deviation value much. In the case D3, the solar power penetration is very high. Therefore, EV charging scenario S5 which mainly charging in extended solar operation time give the smallest value of standard deviation. Scenario D2 that includes the forecasted value of load demand and solar power was the most possible load demand whereas scenarios D1 and D3 that were the extreme cases were the possible largest and smallest load demand in the future, respectively. Therefore, the estimated power load demand in 2028 and 2038 come from the demand which is the most equally distributed in case D2 whereas the possible largest and smallest value come from the most equally distributed cases D1 and D3, respectively. The estimated power load demand range of 2028 is shown in Fig. 12. In this figure, the estimated load demand was generated from the load demand case D2 integrated with the scenario of EV charging S3.The possible largest was generated the from load demand case D1 with the scenario of EV charging S2 and the possible smallest was generated from the load demand case D3 with the scenario of EV charging S3. The estimated power load demand range of 2038 is shown in Fig. 13. In 2038, the estimated power load demand was generated from the load demand case D2 with the scenario of EV charging S4. The possible largest and smallest were generated from the load demand case D1 with the scenario of EV charging S4 and the load demand case D3 with the scenario of EV charging S5, respectively.

The peak of the estimated load demand is also considered. The most possible load demand when solar PV and EV integrated to the system in 2028 has peak 34,312 MW whereas the peak of possible largest load demand is 38,646 MW and the peak of possible smallest load demand is 29,978 MW. In 2038, the most possible load demand when solar PV and EV integrated to the system has peaked at 47,732 MW. The peak of possible largest load demand is 56,265 MW and the peak of possible smallest load demand is 38,457 MW.

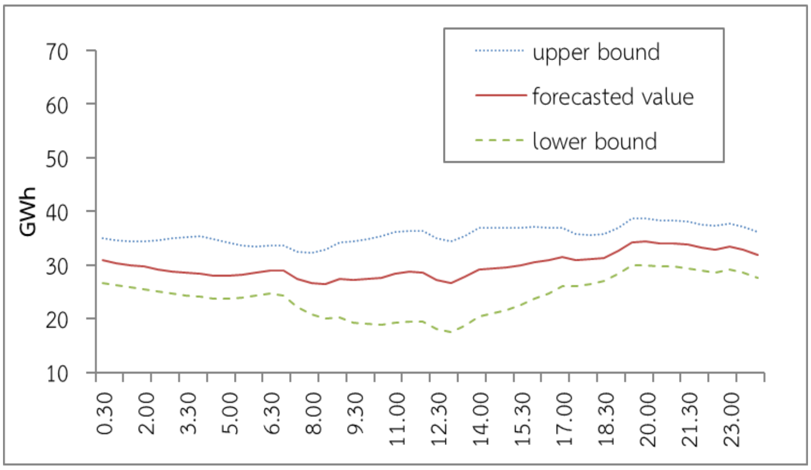

Fig. 12. Estimated power consumption when controlled EV charging is scheduled in 2028.

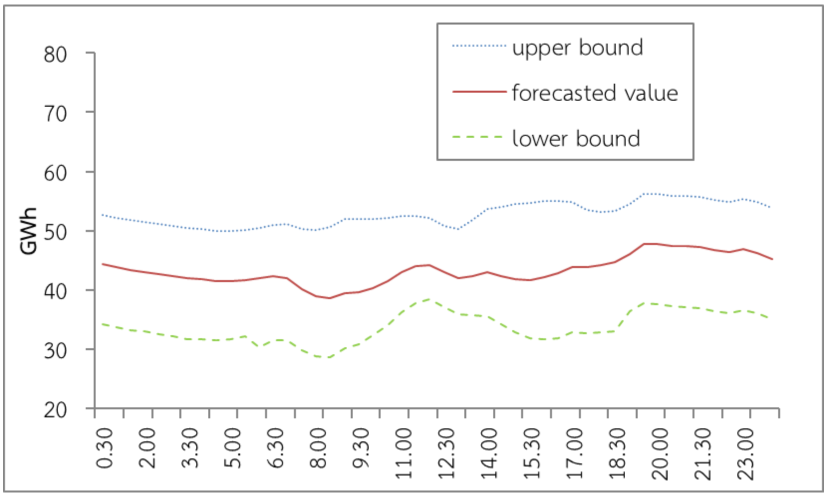

Fig. 13. Estimated power consumption when controlled EV charging is scheduled in 2038.

V. Conclusion and Discussion

In this paper, the effect of solar PV and EV charging on daily load demand was studied. The possible load demand in the future was analyzed by varying the periods and distribution of EV charging. The future load demand and solar PV installation were forecasted by ARIMA model. Scenarios of EV charging were generated under the concept of a smart charging system and integrated into the load demand with solar power and then the most equally distributed scenario of load demand was observed and applied to construct the estimated load demand range in the future.

The result shows that when the solar power is integrated to the power system, the net load demand in solar operation time is dropping. The more increase in solar PV installation in 2028 and 2038 implies the more decrease of the net load demand in solar operation time period. The consumption from the EV charging integrated to the power system increases the total consumption of load demand. If the EV charging plugs into the power system without any control, the power consumption from EV charging will increase the peak of load demand at night that affects the stability of the power system. More effective demand management provides a more stable system. Therefore, the appropriate net load demand could only be obtained from the controlled scheduling of EV charging by the smart charging technology. This is the key future technology to provide better EV charging policy. It can be suggested that the EV should be promoted with the controlled charging period. From the most equally distributed load demand in results, the suitable charging period is during the solar operation period (6 a.m. – 7 p.m.) and after midnight period (12 a.m. – 6 a.m.). Alternatively, if the smart charging technology is not a viable option, the government may use the pricing policy to provide incentive for EV charging during the certain period.

From the point of view of the production sector, the most equally distributed load implied the stability of power production and reservation. Therefore, the best scenario that is suggested in this research can be applied to be the EV charging policy in the future. Moreover, the estimated load demand range can be the support information for power system management. For example, the peak of forecasted total load demand in 2028 is 35,000 MW approximately, then EGAT which has current capacity of only 25,000 MW should have a plan for the increase of total consumption in 2028.

References

[1] P. Sundarajumpaka. (2018). Thailand Solar PV Policy Paper 1/2018, Deutsche Gesellschaft für Internationale Zusammenarbeit, Germany. [Online]. Available: http://www.thai-german cooperation.info/admin/uploads/publication/55b1dd373 23b0e40b63b2853f260a831en

[2] W. Pannakkong, P. Saophan, R. Chaysiri, J. Tang, J. Buddhakulsomsiri, P. Parthanadee, C. Jeenanunta, and H. Vitharana. "Forecasting solar power for self-consumption of households in Thailand using system dynamics model," in *Proceedings of the 23rd Asia-Pacific Decision Science Institute International Conference-APDSI,* 2018, pp. 264-271.

[3] C. Maitreesorasunte, J. Tang, R. Chaysiri, C. Jeenanunta, W. Pannakkong, H. Vitharana, and P. Parthanadee. "Forecasting self-consumption solar power capacity of industry and business sector in Thailand: a system dynamic model," in *Proceedings of the 2nd International Conference on Engineering Innovation*, 2018, pp. 111-116.

[4] A. Mellit, M. Benghanem, and S. A. Kalogirou. "An adaptive wavelet-network model for forecasting daily total solar-radiation," *Applied Energy*, vol. 83, no. 7, pp. 705-722, July. 2006.

[5] C. Chen, S. Duan, T. Cai, and B. Liu. "Online 24-h solar power forecasting based on weather type classification using artificial neural network," *Solar energy*, vol. 85, no. 11, pp. 2856-2870, 2011.

[6] R. Perez, M. Taylor, T. Hoff, and J. Ross. "Reaching Consensus in the Definition of Photovoltaics Capacity Credit in the USA: A Practical Application of Satellite-Derived Solar Resource Data,"*IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 1, no. 1, pp. 28-33, 2008.

[7] G. J. Osório, J. M. Lujano-Rojas, J. C. O. Matias, and J. P. S. Catalão. "A new scenario generation-based method to solve the unit commitment problem with high penetration of renewable energies,"*International Journal of Electrical Power & Energy* Systems, vol. 64, pp. 1063-1072, 2015.

[8] S. Kaewpasuk, B. Intiyot, and C. Jeenanunta. "Stochastic unit commitment model for power system with renewable energy," in *Proceeding of 2017 International Electrical Engineering Congress (iEECON)*, 2017, pp. 257-260.

[9] C. Liu, A. Botterud, Z. Zhou, and P. Du. "Fuzzy energy and reserve co-optimization with high penetration of renewable energy," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 2, pp. 782-791, 2017.

[10] IEA. (2018). Global EV Outlook 2018: Towards cross electrification. IEA. France. [Online]. Available: https://webstore.iea.org/download/direct/1045?fileName=Global_EV_Outlook_2018

[11] D. Hurley, P. Peterson, and M. Whited. (2013). Synapse energy economics. USA. [Online]. Available: https://www.synapse-energy.com/project/demand-response-power-system-resource

[12] K. Qian, C. Zhou, M. Allan, and Y. Yuan. "Load model for prediction of electric vehicle charging demand," in *Proc. International Conference on Power System Technology*, 2010, pp. 1-6.

[13] P. Vithayasrichareon, G. Mills,andI. MacGill. "Impact of Electric Vehicles and Solar PV on Future Generation Portfolio Investment,"*IEEE Transactions on Sustainable Energy,* vol. 6, no. 3, pp. 899–908, 2015.

[14] Z. Yang, K. Li, Q. Niu, and Y. Xue. "A comprehensive study of economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles," *Energy Conversion and Management*, vol. 132, pp. 460–481, 2017.

[15] T. Nguvauva, and S. Kittipiyakul. "Maximum Utilization of Allocated Power for Scheduling of Smart Home Appliances," in *Proc. ECTI-CON*. 2018.

[16] Fraunhofer Institute for Solar Energy Systems. (2018). "Photovoltaics Report," Fraunhofer Institute, Germany.[Online].Available: https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/Photovoltaics-Report.pdf

[17] Electricity Generating Authority of Thailand, Metropolitan Electricity Authority, and Provincial Electricity Authority. (2016). "Summary report: Thailand's electrical power system development plan for supporting electric vehicles," Thailand. [Online]. Available: http://www.mea.or.th/profile/3253

[18] Alternative Fuels Data Center. (2016). "U.S. Plug-in Electric Vehicle Sales by Model," USA. [Online]. Available: https://www.afdc.energy.gov/data/

Sukita Kaewpasuk is a Ph.D. student in Department of Mathematics and computer science, Chulalongkorn University. She was born in Prachinburi, Thailand, in 1993. She received the bachelor's degree of sciences in Applied mathematics from Thammasat university, 2015 and Master of Sciences in Applied Mathematics and computational Science from Chulalongkorn university, 2017. Her research interests are in area of operations research and optimization.

Boonyarit Intiyot is an assistant professor of Department of Mathematics and Computer Science, Faculty of Science, Chulalongkorn University. He received a B.S. degree in Mathematics from University of Delaware, a M.S. degree in Mathematics from University of Arizona, and a Ph.D. in Industrial and Systems Engineering from Virginia Polytechnic Institute and State University. His research interests are in area of linear optimization models and applications of operations research.

Chawalit Jeenanunta is an associate professor of School of Management Technology (MT), Sirindhorn International Institute of Technology, Thammasat University, Thailand. He received a B.S. degree in Mathematics and Computer Science, and M.Sc. in Management Science from University of Maryland and he received his Ph.D. in Industrial and Systems Engineering from Virginia Polytechnic Institute and State University. His Research interests are in area of applications of operations research, simulation, large-scaled optimization and supply chain management.