Bayesian Network based Real-time Charging Scheduling of Electric Vehicles

Hongtao Ren, Fushuan Wen, Chengwei Xu
College of Electrical Engineering
Zhejiang University
Hangzhou, China
hongtao.ren@zju.edu.cn; fushuan.wen@gmail.com;
chengwei.xu@outlook.com

Jinqiao Du, Jie Tian
Shenzhen Power Supply Bureau Co., Ltd.
Shenzhen, China
tianjie@sz.csg.cn ;
dujinqiao@sz.csg.cn

***Abstract*—The electricity purchase cost of an electric vehicle (EV) charging station (EVCS) with photovoltaic (PV) facilities can be reduced by matching the EV charging load and PV generation output. However, the uncertainties of the EV charging demand and photovoltaic generation output impose difficulties to real-time charging scheduling. In this paper, an EV charging scheduling model based on the spot pricing of electricity with an objective of minimizing the electricity purchase cost of an EVCS is proposed. The historical data of PV generation output and EV charging demands are employed in forming the daily charging optimization model, and the daily optimal charging scheduling is carried out and a training sample set is then attained. The Bayesian network (BN) based real-time EV charging scheduling, that is carried out in a recursive way with one time period ahead considered, is next addressed, and the BN structure is determined by the hill climbing algorithm with Bayes scoring employed. The EV charging schedule is subsequently determined by the Bayesian inference. A case study based on an EVCS in an industrial park is carried out to demonstrate the proposed method, and comparisons between the proposed method and the deterministic real-time scheduling method are also detailed.**

Keywords — electric vehicle, photovoltaic, real-time scheduling, charging scheduling, Bayesian network

I. Introduction

With continuous enhancement of battery and charging technology of electric vehicles (EVs), the EV industry is undergoing a period of rapid development. The market share of EVs has already exceeded 20% in some European countries, and many countries are planning to electrify their transportation sectors in the near future [1]. However, numerous and extensive access of EV charging loads to a distribution network (DN) concerned is likely to bring significant impacts on the DN [2]. Through real-time scheduling of EV charging and collaborative operation with distributed photovoltaic (PV) facilities, both the negative impacts of the EV access on the DN and the operation cost of electric vehicle charging stations (EVCSs) can be reduced [3].

In developing a real-time EV charging scheduling model, both current and future EV charging demands and PV generation outputs need to be employed. In existing publications, future EV charging loads and PV generation outputs are predicted first, and each EV is then scheduled based on these predictions. Considering that the future charging demand is not known a priori, a model predictive control (MPC) method is proposed in [4] to obtain an approximate optimal solution for online the EV charging scheduling problem. In [5], the information interaction among different charging stations on the basis of MPC is studied and a scheduling strategy is formulated to minimize regional energy consumption while respecting power flow and voltage constraints. In [6] a smart EV charging algorithm is developed and implemented for smart homes/buildings with a PV system, with two stages, i.e. prediction and scheduling included. An online predictive control paradigm is developed in [7], to adaptively estimate EV charging demands using kernel-based methods. Based on MPC, the real-time scheduling problem addressed in [8] aims to minimize the cost with load balance constraints respected, using an improved prediction of wind power outputs and EV parking events.

However, the charging behavior of each EV (arrival-departure time, charging power demand, and others) and the output of each renewable energy generation are uncertain, and cannot be accurately predicted. Stochastic optimization methods such as chance constraint programming and stochastic programming are used to solve the EV scheduling problem with uncertainties in some existing publications [9],[10]. In these methods, a decision is usually made by a specific event/scenario, such as the largest credible contingency. However, because the stochastic nature of the system and the probabilities of events under different operation scenarios are not systematically modelled, these approaches are not applicable for an actual scenario with many sources of uncertainty [11].

The multi-scenario probability approach is also employed to address uncertain problems [12]. Each candidate solution is evaluated with respect to different scenarios and the objective function is then obtained by weighting the evaluation results according to the probabilities of the considered scenarios. Because of the heavy calculation burden, this approach is not applicable for large-scale complex systems [13].

Given the background described above, the following studies are carried out in this paper: 1) A collaborative scheduling mechanism between the EV charging demand and PV generation output is proposed to minimize the operation cost of an EVCS; 2) The BN is adopted to address the real-time EV charging scheduling problem with uncertainties and time constraint; 3) The proposed method is demonstrated by actual parking data and PV generation outputs in an industrial zone.

The remainder of this paper is organized as follows. In Section II, a cooperative daily scheduling strategy between an EVCS and a PV generation facility is presented, to produce samples for training a BN. The BN of an EV scheduling problem is established in Section III. Numerical

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simulations are carried out in Section IV, and the paper is concluded in Section V.

II. Daily Charging Scheduling Model of EVs

According to generation costs and power demands in different time periods, the electricity price in the spot electricity market is set at different levels for each time period (such as 30min, 15min, 5min) to guide electricity consumption of consumers. The electricity price in the spot electricity market is usually higher at the peak period and lower at the off-peak period. The system load variance, as well as the operation cost of the concerned distribution system, can be reduced by improving the load profile through variable price of electricity. At the same time, the electricity purchase cost of an EVCS can be reduced by properly scheduling the charging load of EVs.

In the spot electricity market environment, the following linear integer programming model can be used to minimize the purchase cost of an EVCS:

$$\min \sum_{t=1}^{24} P_t^{evcs} c_t \tag{1}$$

$$P_t^{evcs} = \sum_{n \in \Omega_t^{ev}} z_{n,t}^{ev} P^{ev} - P_t^{pv} \tag{2}$$

Where, P_t^{evcs} is the charging power of the EVCS at time t. c_t is the electricity purchase price of the EVCS at time t. P^{ev} is the charging power of EVs. Ω_t^{ev} is the set of EVs parked in the EVCS at time t. $z_{n,t}^{ev}$ is a decision variable of charging and discharging for EV n, with 1, -1 and 0 respectively denoting charging, discharging and parking only or not in the EVCS. P_t^{pv} is the generation output from the PV facilities in the EVCS at time t.

Charging control of an EV needs to accommodate several constraints, such as the EV battery capacity, EV user charging demand, PV generation output. These constraints are formulated as follows.

A. Battery capacity constraint

The state of charge (SOC) is used to formulate the operation requirement of the battery of an EV:

$$0.2 \le SOC_{n,t} \le 0.8 \quad \forall n \in \Omega^{ev} \tag{3}$$

Where, $SOC_{n,t}$ is the SOC of EV n at time t. Ω^{ev} is the set of EVs parked in the EVCS.

During the charging process of an EV, the relationship between the SOC and the charging state could be expressed as

$$SOC_{n,t+1} = SOC_{n,t} + P^{ev} z_{n,t}^{ev} \tag{4}$$

B. Charging demand constraint

An EV can only be charged or discharged during the time period it is parked in an EVCS, as formulated by:

$$\begin{cases} z_{n,t}^{ev} = 0 \text{ or} \pm 1, & T_n^{park,s} \le t \le T_n^{park,e} \\ z_{n,t}^{ev} = 0, & \text{otherwise} \end{cases} \tag{5}$$

Where, $T_n^{park,s}$ and $T_n^{park,e}$ are the starting and end time points of the parking of EV n respectively.

The SOC of each EV at the beginning of parking is taken as its initial SOC, and the SOC of the EV at the end of parking should not be less than the user's expected SOC.

$$SOC_{n,t} = SOC_n^{ei}, \quad t = T_n^{park,s} \tag{6}$$

$$SOC_{n,t} \ge SOC_n^{ep}, \quad t = T_n^{park,e} \tag{7}$$

Where, SOC_n^{ei} and SOC_n^{ep} are the initial SOC at the beginning of parking and the expected SOC at the end of parking, respectively.

C. PV generation output constraint

PV facilities provide power only for the charging of EVs, as formulated by

$$P_t^{pv} \le z_{n,t}^{ev} P^{ev} \tag{8}$$

By solving the developed optimization model, the daily charging schedule of each EV in an EVCS can be obtained. In carrying out daily charging scheduling, both charging demands of EVs and PV generation outputs during the scheduling period are employed. However, in making the charging decision at time t, the charging demand and PV output power after time t are unknown. Therefore, the developed optimization model cannot be directly applied to real-time scheduling of EV charging.

The historical charging demand and PV generation output data are employed in forming the proposed optimization model for attaining the optimal EV charging plan, which are used to provide samples for parameter learning and structure learning of the BN.

III. BN for Real-time Charging Scheduling of EVs

A. BN structure for EV charging scheduling

BN is a directed acyclic graph model representing the set of random variables and their conditional dependencies. Such a network consists of a structure and a variety of parameters. The structure refers to the directed acyclic graph, each node depicts a random variable, and each directed arc connecting a pair of nodes represents the cause-and-effect relationship between two variables.

The real-time charging scheduling of EVs here refers to a recursive one with one time period ahead considered.

Based on the daily charging scheduling model, the main factors having impacts on real-time charging scheduling of EVs include the starting time of charging, the number of parked EVs in the industrial park, EV charging demand, PV generation output, and electricity price in the spot electricity market. These factors are pre-known before a decision is made, but the nodes after the decision are no longer observable. Generally, there are causal relationships between these nodes. However, if those nodes with causal relationship are connected directly, it will be hard to solve the BN for large-scale problems because of dimension explosion in parameter learning. By comparing different connection structures of BN, the most suitable BN structure can be selected.

The Bayesian structure learning mainly involves two problems: the selection of scoring function, and the selection of the search method. The Bayes scoring metric measuring the coincidence of a structure with given sample data is presented first. The posterior probability obtained from the sample data is used as a scale to measure the quality of a network structure. To compare two network structures G_1 and G_2 with sample data D, the likelihood ratio can be employed, as defined in (9).

$$\frac{P(G_1|D)}{P(G_2|D)}=\frac{P(G_1,D)}{P(G_2,D)} \tag{9}$$

$$\begin{aligned} P(G,D)&=P(G)P(D|G)=P(G)\prod_{i=1}^{N}p(x_i|G)\\ &=P(G)\prod_{i=1}^{N}\prod_{j=1}^{q_i}\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\prod_{k=1}^{r_i}N_{ijk}! \end{aligned} \tag{10}$$

Where, N is the number of nodes; x_i is the value of node i; r_i is the number of possible values of node i; q_i is the number of possible combinations values of parent nodes of node i; N_{ij} is the number of combination value of the parent node of node i is j in sample set D; N_{ijk} is the number of samples in D in which the value of x_i is k and the parent node of node i is j.

Based on the scoring function, the hill climbing algorithm is employed to search the network structure. The scoring and search algorithm starts from a graph without edges and generates a series of models by adding, deleting, or reversing an edge to modify the current model locally. The model with the minimal score will be adopted as the basis for the next round of search, and this procedure will be carried out iteratively until the score no longer decreases. The algorithm is summarized in Algorithm I.

After the optimal BN structure is obtained, the parameters are trained by Bayesian estimation.

Once the uncertainties in the concerned problem are modeled by BN, the results of the reasoning can be obtained by applying new evidence into the BN. The probability of a variable can be calculated by giving a value to each of the other variables. For example, the marginal distribution $P(D = d_1)$ of node D with one parent node can be calculated as

$$\begin{aligned} P(D=d_1)&=P(D=d_1|C=c_1)P(C=c_1)\\ &+P(D=d_1|C=c_2)P(C=c_2)+\cdots \end{aligned} \tag{11}$$

ALGORITHM I. BN STRUCTURE LEARNING BASED ON HILL CLIMBING ALGORITHM

Algorithm: Structure learning of BN

Input:

F: the scoring function

Output:

G: the optimal structure of BN

Steps:

```
G←G0; oldScore←F(G0);
WHILE true DO
  G*←null; newScore←+∞
  FOR each G' obtained by adding,
  deleting or reversing an edge on G DO
    tempScore←F(G')
    IF tempScore< newScore THEN
      G*←G'; newScore←tempScore
    END IF
  END FOR
  IF newScore<oldScore THEN
    G←G*; oldScore←newScore
  ELSE
    RETURN G
  END IF
END WHILE
```

B. Real-time charging scheduling based on BN

Real-time charging scheduling is carried out in a recursive way with one time period ahead considered. The probability distribution of the optimal charging number can be determined by introducing pre-known variables into the BN. Directly choosing the charging scheduling with the highest probability may cause huge losses in other possible situations, which will lead to a drop in overall profits of the EVCS. The probability weighted average of the inference results of the charging number of EVs is adopted to determine the optimal number of EVs for charging in this work, so as to comprehensively consider various possible situations.

$$N_t^{ev}=\sum_{P\geq\alpha}P\left(N_t^{infer}\right)*N_t^{infer} \tag{12}$$

Where, α is the confidence interval; $P\left(N_t^{infer}\right)$ is the probability that the optimal charging number is N_t^{infer}; N_t^{ev} is the optimal charging number of EVs at time t, attained by the Bayesian inference.

In order to develop the real-time charging schedules for EVs, an urgency index of charging is defined in (13) for determining the charging order of EVs.

$$U_{n,t}=\frac{\left(SOC_n^{ep}-SOC_{n,t}\right)/P^{ev}}{T_n^{park,e}-t} \tag{13}$$

The larger the urgency index of an EV is, the more urgent this EV will be scheduled for charging. Giving the priority to an EV with a high urgency index for charging has a positive impact on the charging scheduling of the EVCS in later time. After that, in order to accommodate the charging demand constraints, an EV with the urgency index more than 1 must also be charged, so that the actual number of charging EVs may be larger than the planned number of charging EVs.

IV. Case Study

In order to demonstrate the effectiveness of the proposed model, an actual case of an industrial park is employed.

A. *Case Settings*

The location of the industrial park and the surrounding fast EVCSs are shown in Fig.1.

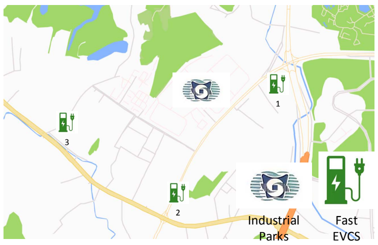

Fig. 1. Geographic sketch map of an industrial park

Based on the traffic flow at the entrance of the industrial park and the statistics of daily driving mileage of EV users, the charging demand of EVs can be obtained. The EVCS is equipped with a rooftop PV facility with the maximum output power of 200kW, and the historical power generation and meteorological data of surrounding PV facilities are collected as the historical data of this PV facility. The daily charging scheduling model in Section II is used to determine the optimal charging scheduling. Both the collected data and calculated results are used for training the BN.

B. *BN for real-time scheduling of EVs*

According to the data collection, the pre-known nodes in the BN include: the charging start time, weather, temperature, PV output, the number of parked EVs in the industrial park, the number of EVs charging at a fast EVCS nearby, the number of EVs charging at the studied EVCS.

The hill climbing algorithm based on the Bayes scoring metric is used to determine the structure of the BN, and the attained structure of the BN is shown in Fig. 2.

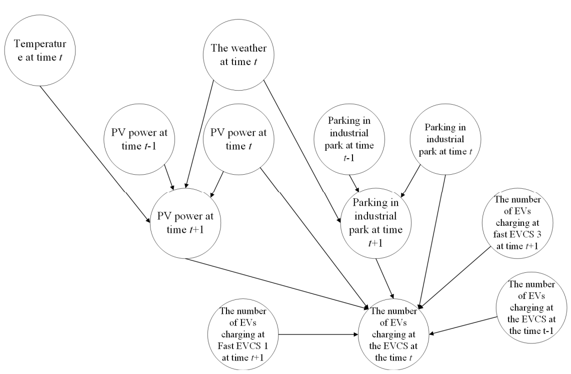

Fig. 2. BN structure for real-time charging scheduling of EVs

By importing test samples into the BN, the real-time charging schedule of EVs can be formulated. The real-time charging schedule of EVs in a given day is shown in Fig. 3.

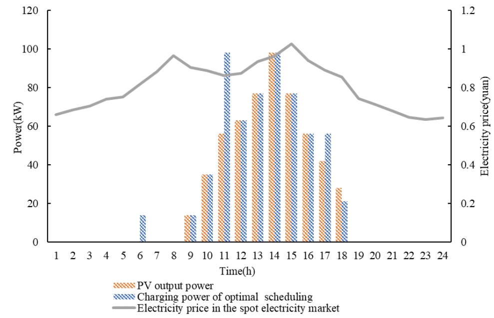

Fig. 3. Optimal charging scheduling of EVs

As shown in Fig. 3, the daily charging schedule tends to match the charging power of EVs and PV output, and the electricity purchase cost could then be reduced. Meanwhile, the unmatched charging power of EVs is scheduled at time periods with low electricity price. However, due to the parking time constraint of EVs, curtailment of PV power output still happens in some time periods.

Comparisons between the results attained by real-time charging schedule and daily charging schedule of EVs are shown in Fig. 4.

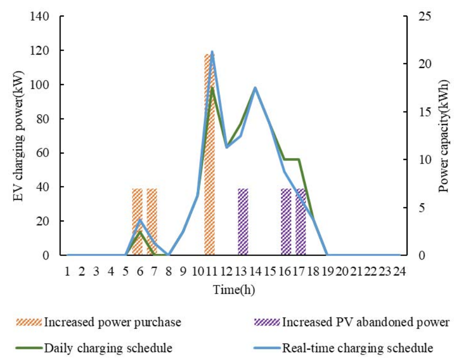

Fig. 4. Comparisons between the results attained by real-time charging schedule and daily charging schedule of EVs

Due to the uncertain PV generation output and charging demands of EVs, more EVs are scheduled to be charged in the early morning when the electricity price is low. However, when the actual PV generation output is higher than the predicted, or the number of charging EVs is less than the predicted, the PV generation output cannot be fully employed. Compared with the optimal charging schedule, the electricity purchase cost is higher by 29.96 *CNY*, and the PV curtailment power is 21kW more.

C. *Performances comparison of different algorithms*

In order to compare the performance of different algorithms, an evaluation index based on the electricity purchase cost of the EVCS is defined in (14).

$$I^{al} = \frac{\sum_{i \in I} \left[\left(c_i^{al} - c_i^{op} \right) \Big/ c_i^{op} \right]}{N^I} \tag{14}$$

Where, I^{al} is the evaluation index of an algorithm; I is the set of the test samples; c_i^{al} is the actual electricity purchase cost of the EVCS for sample i of the proposed algorithm; c_i^{op} is the electricity purchase cost of the EVCS in sample i of the optimal charging scheduling; N^I is the number of test samples.

The deterministic real-time charging scheduling method makes the charging schedule by employing forecasted data. The attained outcomes by the deterministic real-time scheduling method and the proposed BN based method are listed in Table I for comparisons.

TABLE I. COMPARISONS BETWEEN THE BN BASED AND DETERMINISTIC METHODS

	BN based method	Deterministic method
Index	10.45%	16.21%
PV curtailment power	11.5kW	17.4kW
Computation time per day	0.41s	16.64s

From Table I, it is clear that compared with the deterministic method, the proposed BN based method leads to lower electricity purchase cost of the EVCS and less PV power curtailment. In addition, the proposed method is more computationally efficient, and can be applied on a shorter time scale.

V. CONCLUDING REMARKS

Facing with new challenges brought by uncertain factors of EV charging demand and PV generation output to the real-time charging scheduling of EVs, a BN based real-time scheduling model is proposed in this paper. In the developed model, the causal relationships between different factors are described by a directed acyclic graph. The final charging schedule is determined by the Bayesian inference. Numerical results show that the uncertain factors in the real-time scheduling problem of EV charging can be properly taken into consideration by the BN model. Compared with the deterministic method, the charging cost of the EVCS is reduced by around 6% by the proposed method.

In our future research effort, daily charging demands of EVs and daily generation outputs from PV facilities will be modeled in a more systematic way.

REFERENCES

[1] Z. Wei, Y. Li, Y. Zhang and L. Cai, “Intelligent parking garage EV charging scheduling considering battery charging characteristic,” IEEE Trans. Ind. Electron, vol. 65, no. 3, pp. 2806-2816, March 2018.

[2] W. Jiang and Y. Zhen, “A real-time EV charging scheduling for parking lots with PV system and energy store system,” IEEE Access, vol. 7, pp. 86184-86193, 2019.

[3] Y. Song, Y. Zheng and D. J. Hill, “Optimal scheduling for EV charging stations in distribution networks: a convexified model,” IEEE Trans. Power Syst., vol. 32, no. 2, pp. 1574-1575, March 2017.

[4] W. Tang and Y. J. Zhang, “A model predictive control approach for low-complexity electric vehicle charging scheduling: optimality and scalability,” IEEE Trans. Power Syst., vol. 32, no. 2, pp. 1050-1063, March 2017.

[5] Y. Zheng, Y. Song, D. J. Hill and K. Meng, “Online distributed MPC-based optimal scheduling for EV charging stations in distribution systems,” IEEE Trans. Ind. Inform., vol. 15, no. 2, pp. 638-649, Feb. 2019.

[6] Y. Wi, J. Lee and S. Joo, “Electric vehicle charging method for smart homes/buildings with a photovoltaic system,” IEEE Trans. Consum. Electron., vol. 59, no. 2, pp. 323-328, May 2013.

[7] B. Wang, Y. Wang, H. Nazaripouya, C. Qiu, C. Chu and R. Gadh, “Predictive scheduling framework for electric vehicles with uncertainties of user behaviors,” IEEE Internet Things J., vol. 4, no. 1, pp. 52-63, Feb. 2017.

[8] Q. Huang, Q. Jia and X. Guan, “Multi-timescale optimization between distributed wind generators and electric vehicles in microgrid,” IEEE International Conference on Automation Science and Engineering (CASE), Gothenburg, 2015, pp. 671-676.

[9] D. Chen, S. Hou, N. Gong, W. Zhang and H. Li, “A chance-constrained two-stage stochastic UC considering uncertain renewable energy output And demand response,” IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), Singapore, 2018, pp. 419-424.

[10] J. Donadee and M. Ilić, “Stochastic co-optimization of charging and frequency regulation by electric vehicles,” North American Power Symposium (NAPS), Champaign, 2012, pp. 1-6.

[11] H. Holttinen, M. Milligan, E. Ela, N. Menemenlis, J. Dobschinski and B. Rawn, "Methodologies to determine operating reserves due to increased wind power,” IEEE Trans. Sustain. Energy, vol. 3, no. 4, pp. 713-723, Oct. 2012.

[12] C. Cai, H. Liu, H. Zheng, F. Chen, L. Deng and Q. Xu, “Microgrid multi-source coordination optimal control based on multi-scenarios analysis,” The Journal of Engineering, vol. 2017, no. 13, pp. 1457-1461, 2017.

[13] D. Jost, M. Speckmann, F. Sandau and R. Schwinn, “A new method for day-ahead sizing of control reserve in Germany under a 100% renewable energy sources scenario,” Electr. Power Syst. Res., vol. 119, pp. 485-491, 2015.