Optimization of pricing policy of electric vehicle charging station based on big data

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Abstract

The guideless charging behaviour of electric vehicles(EVs) will lead to load fluctuation and increase the difficulty of power system control. By formulating a reasonable pricing strategy, the orderly charging behaviour of EVs can be fully encouraged, which is conducive to improving the stability of the system and the economic benefits of charging stations. Compared with the current pricing strategy optimization method, the pricing strategy based on big data will provide a research methodology to capture the relationship between charging load and pricing strategy. Firstly, by analysing EV user's behaviour with big data, a charging load predicting model is proposed. Secondly, a causality model is built to study the relationship between pricing strategy and EV load. Thirdly, the optimization model about pricing strategy of charging station is established under three angles of minimum loss in power system, highest user satisfaction and maximum benefit of charging station. Then, the optimization problem solved by using particle swarm optimization(PSO). Finally, by taking the IEEE9 as an example, the validity of the EV charging load predicting model and the feasibility of the charging station pricing strategy optimization model are analysed and verified.

Keywords: Electric vehicle, load forecasting, big data, charging station pricing policy

1. Introduction

Electric Vehicle (EV) has incomparable advantages over traditional vehicle in energy-saving and emission-reduction. Therefore, the popularity of EVs is an inevitable trend. The disorderly charging behaviour of EVs might have negative impacts to power grid such as overload and power quality degradation. Thanks to the energy storage characteristic, a proper charging strategy of EVs can not only depress or even eliminate the negative effects to power grid, but also improve the economic benefits of charging stations. As the most important controllable factor, pricing policy is the key to guide the orderly charging behaviour of EVs. To reduce the negative impacts and take full advantage of positive effects, it is essential to study the relationship between time-space distribution of EV load and charging station pricing policy.

In the study of pricing policy of charging station, Reference [1] considers the secure operation of power grid and the individualized demand of EV users, a multi-objective charging optimization model based on Time-of-Use(TOU) pricing policy is proposed, which considering the maximization economic benefits of power grid and charging stations. Reference [2] based on the charging/discharging characteristics of EV and demand theory, On the basis of analysing charging/discharging cost and benefit of EVs, a peak-valley TOU pricing policy model is established, which aims at minimizing load fluctuation. On the basis of considering both the benefit of power grid and the satisfaction of EV's user, a response model of EV's charging power to electricity price changes is established in Reference [3], and the optimal peak-valley TOU pricing policy is designed.

In previous studies, the optimization model of charging station pricing policy is based on optimizing the system load, model not only ignores the individual differences of pricing policy in different charging station but also neglects the individual differences of corresponding degree for each EV user. In this study, the accurate extend of the impact of pricing policy can be determined by data-mining techniques which based on massive dataset. Based on the results, the EV load might be regulated by devising different TOU pricing policy for each charging station.

The remainder of the paper is organized as follows: Section 2 analyses the sources and characteristics of big data of EV, then proposes a data mining-based model to generate the big data of EVs. Section 3 uses support vector regression(SVR) to model the relationship between the EV load and pricing policy, which is the instant when the price of electricity changes. Section 4 establishes optimization model of charging station pricing policy, the pricing policy of charging station is optimized by using particle swarm optimization (PSO) algorithm. Section 5 presents our conclusions.

2 Data Mining-Based Model

Data Mining (DM) techniques are adopted to study the relationship between the EV load and various factors. DM techniques always need a great quantity of input dataset. Since the big data in this case are unavailable in the real world, the first step in modeling is to analyse the factors related to EV charging load. The second step is to generate great quantity of simulation data. With this model, a massive simulation dataset can be obtained.

2.1. Factors of EV load

Factors of EV load are divided into three aspects as following:

2.1.1. Factors of EV

In terms of a single EV, its charging load is mainly determined by the nature characteristics of battery, the user's habits and the travel demand. Mainly depends on the following factors:
1) Battery characteristics: Including the battery size, charge/discharge rate, self-discharge rate and battery type, which determine the charging/discharging power and charging load curve.
2) User's habits: Including preferences in charging location, expected state of charge(SOC) and charging mode. The difference in charging habits will disperse EV load in time and space.
3) Travel demand: Including travel time, distance, frequency and destination. These factors will affect the charging time, charging power, charging location and so on.
4) Penetration of EV: It is mainly related to the price of EV and the subsidy policy. It determines the proportion of EV charging load to system load.

2.1.2. Factors of EV charging station

EV charging load is also affected by the charging mode, location and pricing policy of EV charging stations. Mainly depends on the following factors:
1) Charging characteristics: Including charging power and efficiency of charging station, which affect charging duration and queuing waiting time;
2) Location of charging station: Influenced by the traffic flow in the area where the charging station is located, which affect the spatial distribution of EV load.
3) Pricing policy of charging station: A controllable factor that will encourages EV owners to change their charging behaviour, which affect the temporal distribution of EV load.

2.1.3. Factors of distribution network

Distribution network provides information such as structure of distribution network and real-time electricity price for EV users and charging station operators.

Considering the value, timeliness and reliability of the above factors, the following factors closely related to EV charging load are selected. The usage of factors are shown in Table 1.

Table 1. Factors used to simulation the charging schedules

Side	Factors	Symbol	Data usage
Electric Vehicle	Battery size	E_0	Calculate benchmark data
	State of charge at time t	SOC_t	Calculate the charging demand
	Battery charging rate	R_p	Calculate the charging duration
	Current energy stored in the batter	E_t	Analyze charging location
	Distance of trip j for EV_i	$l_{i,j}$	Analyze whether to charge
	The upper limit value of SOC	SOC_m	Calculate the charging duration
	The lower limit value of SOC	SOC_a	Calculate the charging duration
Charging Station	Instant when the price increase	t_{up}	Analyze whether to charge
	Instant when the price decrease	t_{down}	Analyze whether to charge
	Efficiency of charging station	η	Calculate the charging efficiency
Distribution Network	Electricity price of power grid	P_g	Device the pricing policy
Other	EV number	i	EV number
	Trip number	j	Trip number
	Line number	k	Power line number

2.2. Simulation of the charging schedules

In order to predict the EV charging load, the charging schedules should be known. It is reasonable to assume that traditional vehicles are just being replaced by EVs in the future. Consequently, charging schedule model is established based on the historical travel information of traditional vehicles. The information can be obtained from the National Household Travel Survey(NHTS), which has adopted real-world travel dataset of 150,147 households.

The following assumptions are made. First, the study considers a simple TOU pricing policy with only two price gradients in one day. t_{up} and t_{down} are the instants when the prices increases and decreases. Second, the charging power and efficiency are constant. Finally, the power consumption per kilometer is fixed. The process of charging schedules model is shown as Fig. 1.
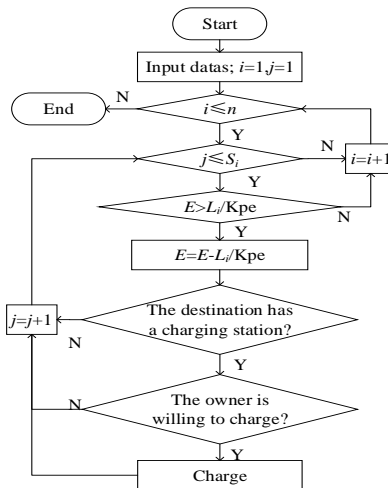

Fig. 1. Process of charging schedules model

First, the input data are the variables in Table 1, which include E_0, SOC_t, R_p, E_t, $l_{i,j}$, SOC_m, SOC_a, t_{up}, t_{down}, η for each EV. Second, the daily travel information for trip j of EV i is read. If the remaining energy will enable the distance of trip j, EV won't charge. Then, the model judges whether a charging infrastructure is available at the destination of trip j. The probability that charging infrastructure offers a service is denoted as ρ, and its value varies from 0 to 1. Third, when a charging service is available, the model judges whether the owner is willing to charge based on the owner's charging habits. Finally, the lowest cost is pursued under the condition that the energy will enable to continue the next trip $j+1$.

3. SVM Predicting Model

A large amount of valuable data is hidden in the big data related to EV load. Through the data-mining technology, the charging load of each EV can be analysed. Support Vector Machine (SVM) is a learning system using a linear function in high-dimensional feature space, by some nonlinear function mapping the input vector to a high-dimensional feature space. In this paper, support vector machine (SVM) is used to predict the influence degree of pricing policy on EV load.

In this paper, the SVM model constructs the loss function based on structural risk minimization and determines the prediction function by minimizing the objective function shown in Formula (1).

$$\begin{cases} \min\left[\frac{1}{2} w^T w + C \sum_{i=1}^{n} \left(\theta_i + \theta_i^* \right) \right] \\ s.t. f\left(x_i \right) - y_i \leq \varepsilon + \theta_i \\ y_i - f\left(x_i \right) \leq \varepsilon + \theta_i^* \\ \theta_i \geq 0, \theta_i^* \geq 0, i = 1, 2 \dots n \end{cases} \tag{1}$$

Where C is the punishment coefficient, θ_i and θ_i^* are the relaxation factor, and ε is the insensitive loss coefficient.

Formula (1) can be transformed into the dual problem of Formula (2) by Lagrange multiplier.

$$\begin{cases} \max \sum_{i=1}^{n} \left[y_i \left(\alpha_i^* - \alpha_i \right) - \varepsilon \left(\alpha_i^* + \alpha_i \right) \right] \\ -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\alpha_i^* - \alpha_i \right) - \varepsilon \left(\alpha_j^* - \alpha_j \right) K\left(x_i, x_j \right) \\ s.t. \sum_{i=1}^{n} \left(\alpha_i^* - \alpha_i \right) = 0 \\ 0 \leq \alpha_i, \alpha_i^* \leq C, i = 1, 2 \dots n \end{cases} \tag{2}$$

Where, α_i and α_i^* are the Lagrange multiplier; $K(x_i, x_j)$ is a kernel function that satisfies Mercer's condition. In this paper, Gaussian kernel function shown in equation (3) is selected as the kernel function.

$$K\left(x_i, x_j \right) = \exp\left(-\frac{\|x_i, x_j\|}{\sigma^2} \right) \tag{3}$$

Where, σ^2 is the broadband parameter of Gaussian kernel function.

The optimal predicting function can be obtained by solving equation (2), as shown in equation (4).

$$f(x) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^* \right) K\left(x_i, x_j \right) + b \tag{4}$$

Equation (5) can be obtained from KKT condition.

$$b = y_i + \varepsilon - \sum_{i=1}^{n} \left(a_i^* - a_i \right) K\left(x_i, x_j \right) \tag{5}$$

In our study, y_i is the load of EV i and x is (t_{up}, t_{down}, t). The function is shown as equation (6).

$$P(t_{up}, t_{down}, t) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) e^{-\gamma \left\| (t_{up}^i, t_{down}^i, t) - (t_{up}, t_{down}, t) \right\|^2} + b \tag{6}$$

By solving the SVM predicting model, the causality model is obtained, which can quantify the impact of TOU pricing policy on EV charging load.

4. Pricing Policy Model of Charging Station

The charging station's price signal or charging service plan can mobilize users' charging behaviour or exchange users' charging control right. Users' response to pricing policy can change the temporal and spatial distribution of load. Therefore, the pricing policy model is established under the following three angles of maximizing the benefit of charging station, improving user's satisfaction and reducing power system loss.

4.1. The optimization objective of pricing policy

The optimization objectives will be established from the following three perspectives:

Maximizing the benefit of charging station: In the economic market, charging stations maximize their economic benefits by formulating reasonable electricity prices based on the day-ahead load forecasting, as shown in Formula (7).

$$\max C = \sum_{i=1}^{N} \sum_{t=1}^{T} P_{ch,i}^t I_i^t \Delta t \left(\pi_t - \mu_t \right) \tag{7}$$

Where, C is the benefit of charging station, $P_{ch,i}^t$ is the charging power of EV i at time t, π_t and μ_t are the price of power grid and charging station at time t, respectively. I_i^t is the charging state of EV i at time t, among them, $I_i^t = 1$ means that the EV i is charging while $I_i^t = 0$ means the opposite.

Improving user's satisfaction: The charging station optimize the pricing policy according to the response degree of users to pricing policy. Users are encouraged to change their charging behaviour then their consumption capacity is fully tapped，as shown in Formula (8).

$$\max \theta_i = 1 - \frac{\sum_{t=1}^{T} \pi_t P_{ev,i} I_i^t - \cos t_i^{\min}}{\cos t_i^{\max} - \cos t_i^{\min}} \tag{8}$$

Where, θ_i is the satisfaction of EV i owner, $P_{ev,i}$ is the rated power of EV i, $\cos t_i^{\max}$ and $\cos t_i^{\min}$ represent the consumption of EV i when charging at the maximum and minimum electricity price, respectively.

Reducing power system loss: In the case of incentive compensation for the charging station by the power grid, the charging station actively guides the EV to play a role in reducing the loss of power system and equipment. Loss refers to the active power loss of lines, transformers and reactive power compensation equipment, as shown in Formula (9).

$$\min P_d = \sum_{k=1}^{m} \left(P_k^2 + Q_k^2 \right) \frac{R_k}{U_k^2} \tag{9}$$

Where, P_d is the loss of power system, P_k and Q_k are the active power and reactive power of line k respectively, and U_k is the voltage of line k.

Establishment of the pricing policy model considering the above three directions, the expression is shown in Formula (10).

$$\max f = \omega_1 C + \omega_2 \sum_{i=1}^{N} \theta_i - \omega_3 P_d \tag{10}$$

Where, ω_1, ω_2 and ω_3 are the weight coefficients that the sum is equal to 1, N is the number of EVs.

4.2. Constraints

In terms of constraints, the constraints related to the unit are consistent with the traditional problems and are no longer listed. For a single vehicle, the following constraints should be considered:

1) Constraint on the use of EVs:

$$SOC_a \le SOC_t \le SOC_m \tag{11}$$

Where, SOC_t is the state of charge at time t, SOC_a and SOC_m are the minimum and maximum state of charge by users, respectively. That is to say, the charging state of electric vehicles in the travel process always within the user's expectation range.

2) Technical constraints of EVs:

$$0 \le P_{c,i} \le P_{c,\max} \tag{12}$$

Where, $P_{c,i}$ is the charging power of EV at time t, and $P_{c,\max}$ is the maximum allowable charging power of EV.

3) Energy Balance Constraints of EVs:

$$SOC_{t+1} = SOC_t + \eta_{c,h} P_{ch}^t I^t \Delta t - \frac{\Delta t}{\eta_{dch}} P_{dch}^t \left(1 - I^t\right) \tag{13}$$

Where, SOC_{t+1} is the state of charge at time $t+1$; SOC_t is the state of charge at time t; η_{ch} is the charging efficiency of EV; η_{dch} is the discharge efficiency of EV; P_{dch}^t is the discharge power of electric vehicle at time t.

For the charging station, the following constraints should be considered:

1) Charging power constraint of charging station:

$$0 \le P_{sta.t} \le P_{sta.\max} \tag{14}$$

Where, $P_{sta.t}$ is the charging power of charging station at time t, and $P_{sta.\max}$ is the maximum allowable charging power of charging station.

2) Number constraint of charging EVs in charging stations:

$$0 \le N_{sta.t} \le N_{\max} \tag{15}$$

Where, $N_{sta.t}$ is the number of charging EVs in charging station at time t, and $N_{sta.\max}$ is the maximum allowable number of EV charged in charging station at time t.

For the distribution network, the following constraints should be considered:

1) Constraints of power flow balance:

$$g_{i,t}\left[V_i\left(t\right), P_i\left(t\right), Q_i\left(t\right), P_{ch,i}\left(t\right)\right] = 0 \tag{16}$$

Where, $V_i(t), P_i(t), Q_i(t), P_{ch,i}(t)$ respectively represents the voltage at node i at time t, the active power injection excluding the EV charging load, the reactive power injection excluding the EV charging load, and the charging power of EVs.

2) Constraints of voltage:

$$V_{min} \leq V_i(t) \leq V_{max} \tag{17}$$

That is, the voltage of node i at time t is always within the allowable range.

Through the above load predicting model of EV, the charging load of charging stations under different real-time electricity pricing policies can be predicted. Based on the predicted results, pricing policies are formulated for each charging station. In this paper, particle swarm optimization (PSO) algorithm is used to optimize the pricing policy model of charging stations.

1)Obtain charging demands of EVs. According to section 2, the EV charging load is predicted.

2)The optimization objective of pricing policy is optimized by particle swarm optimization algorithm under the constraint of section 3.4.

3)Users independently respond to the pricing policy of charging station. After the charging station has issued the pricing policy, users can choose the charging mode and time independently.

5. Case Analysis

In the future development, user's travel process is only to replace traditional vehicles with EVs, so it is reasonable to assume that the travel process of EV is consistent with that of the traditional vehicle.

Take the IEEE9 system shown in Fig.2 as an example, and the appendix for system parameters are shown in the appendix. According to the National Household Travel Survey (NHTS), the factors related to EV charging load are selected as shown in Table 2. The travel behaviour of EVs is analysed to obtain the charging load of each electric vehicle, and the charging load at each moment is calculated as shown in Fig.3. Based on the model proposed in this paper, the calculation example designs nine price policies as shown in Table 3. It is assumed that the price policies of charging stations connected to the same node are the same, and the price of the power grid and charging stations is shown in Table 4.
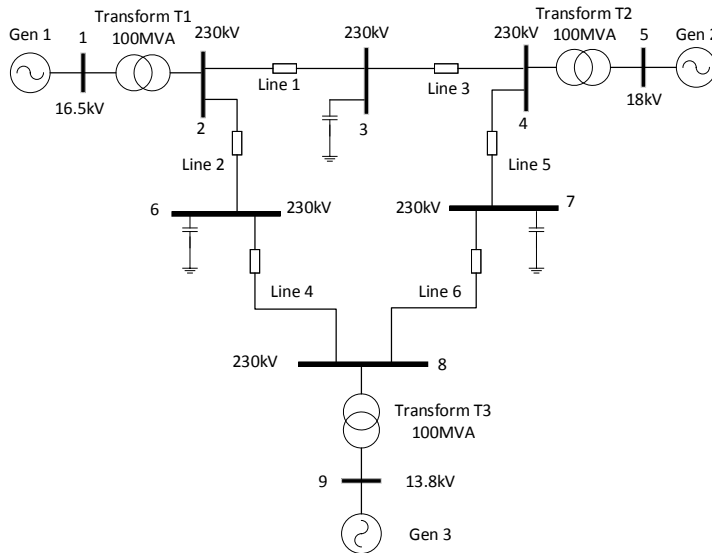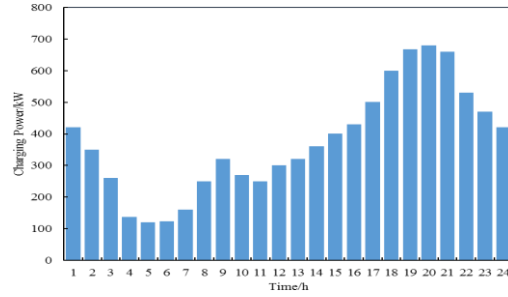

Fig.2. IEEE9 system

Fig.3 EV's charging load in one day

Table 2. The definition and range of variables

Variables	Definition	Value
$E_0(kwh)$	Rated Capacity of EV Battery	14~38
$R_p(kw)$	Charging Rate of Charging Station	1.4~7.7
$R_h(kw)$	Charging Rate in Residential Areas	1.4~7.7
$SOC_m(\%)$	Maximum state of charge	50~100
$SOC_a(\%)$	Minimum state of charge	0~50
$\rho(\%)$	Permeability of Charging Station	0~100
E_f	Charging Efficiency of Electric Vehicles	0.8~0.95
t_{up}	Instant when the price of electricity increases	4~6 h
t_{down}	Instant when the price of electricity decreases	22~24 h
t_{ch}	Charging time of electric vehicles	1~24 h
SOC_0	Initial state of charge of electric vehicles	0~100
N	Number of electric vehicles	10000
ρ_{ev}	Penetration of electric vehicles	10%

Table 3. Electricity pricing policy

Time	1	2	3
Peak-periods	4:00-22:00	4:00-23:00	4:00-24:00
Off-Peak-periods	22:00-4:00	23:00-4:00	24:00-4:00
Time	4	5	6
Peak-periods	5:00-22:00	5:00-23:00	5:00-24:00
Off-Peak-periods	22:00-5:00	23:00-5:00	24:00-5:00
Time	7	8	9
Peak-periods	6:00-22:00	6:00-23:00	6:00-24:00
Off-Peak-periods	22:00-6:00	23:00-6:00	24:00-6:00

Table 4. Electricity price

Electricity price of grid/($/kWh)		Electricity price of charging station/($/kWh)	
Peak-periods	0.071	Peak-periods	0.077
Off-Peak-periods	0.053	Off-Peak-periods	0.057

5.1. EV charging load predicting

The support vector machine(SVM) predicting model was established for the pricing policy of charging stations, and the charging load of 10,000 EVs was analyzed. According to the statistics, the predicted
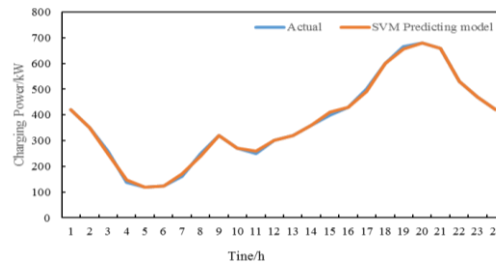
charging load of EV in a day is shown in Fig 4.

Fig. 4. Charging load forecast of SVM predicting model

The error of SVM predicting model is within 10%, indicating the accuracy of the prediction.

5.2. Electricity price model of charging station

Matlab was used to solve the optimization of pricing policy model by particle swarm optimization(PSO) algorithm. In the case, it was assumed that the population number was 30 and the maximum iteration number was 600. Charging/discharging power and time of EVs are obtained under different electricity pricing policies. The corresponding optimal solution is obtained according to different optimization objectives. Since the penetration of EV is 10%, the loss of power system can be ignored. The model 1 represent the maximizing benefit of charging station model, the model 2 represent the maximizing user's satisfaction model, model 3 represent the integrated model by $\omega_1 = 0.5$, $\omega_2 = 0.3$ and $\omega_3 = 0.1$. The results are shown in Table 5 to Table 7.

Table 5. The pricing policy of the charging station

Nodes	1	2	3	4	5	6	7	8	9
Model 1	4	8	6	5	3	2	9	7	1
Model 2	2	7	9	3	8	5	6	1	4
Model 3	2	7	4	6	1	9	5	3	8

Table 6. The charging load of charging station

Unit: KW

Nodes	1	2	3	4	5	6	7	8	9
Model 1	253.4	400.8	317.9	404.2	572.3	405.0	322.1	412.8	259.7
Model 2	263.2	301.8	403.0	315.2	303.4	401.2	425.6	400.8	500.7
Model 3	485.8	412.5	428.4	409.5	286.7	308.4	408.7	318.9	260.8

Table 7. Other conclusions of the model

Items	Benefit of the charging station($)	user satisfaction	Reducing power system loss(KW)
Model 1	245.55	79%	68.688
Model 2	242.71	89%	68.688
Model 3	243.10	84%	68.688

When considering the maximum benefit of charging station, the satisfaction of users decreases slightly. In this case, it assumes that the penetration of EV is 10%, and the change of charging load has little effect on the system. With the development of EVs, when the penetration of EVs is large, the application of reducing power system loss model can effectively improve the security and economy of the power grid. By synthesizing various indicators, we can see that the comprehensive model balances the interests of all parties and achieves a win-win situation among the three parties.

6. Conclusion

The formulation of pricing strategy of EV charging stations is of great significance to the operation and management of charging stations and power grid dispatch. This study based on the big data related to EV load, a data mining-based model is proposed for modeling the charging schedules of EV, then a massive simulation dataset about EV load can be obtained. A SVM model is developed to analyze the relationship between pricing policy and EV load, with which the model can be used to evaluate the impacts of the pricing policy on the EV load quantitatively. Based on it, an optimization model is established to devise a TOU pricing policy for charging station. Finally, the IEEE9 is used as an example. The results show that the electricity pricing policy will affect the user's consumption behavior, and through the rational formulation of the pricing policy, the optimization objective can be effectively achieved.

Appendix A: An example appendix

A.1. IEEE9 system bus parameters

Table A1. IEEE9 system bus parameters

Bus number	Rated voltage /kV	Upper limited voltage /kV	Lower limited voltage /kV
1	16.5	18.15	14.85
2	18	19.8	16.2
3	13.8	15.18	12.42
4	230	253	207
5	230	253	207
6	230	253	207
7	230	253	207
8	230	253	207
9	230	253	207

A.2. IEEE9 system AC-line parameters

Table A2. IEEE9 system AC-line parameters

Bus I	Bus J	R	X	B
1	4	0	0.0576	0
4	5	0.017	0.092	0.158
5	6	0.039	0.17	0.358
3	6	0	0.0586	0
6	7	0.0119	0.1008	0.209
7	8	0.0085	0.072	0.149
8	2	0	0.0625	0
8	9	0.032	0.161	0.306
9	4	0.01	0.085	0.176

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Xu Tian, Yuan Xu concuted the research; Xiangcheng Zhang, Xue Ma analyzed the data; Yuan Xu, Su Zhang wrote the paper; all authors had approved the final version.

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