Application of support vector machine in driving ranges prediction of pure electric vehicle with dual – energy storage system based on particle swarm algorithm

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Received 1 July 2014, www.cmnt.lv

Abstract

Driving ranges was a key factor that may affect the popularization and development of pure electric vehicle (PEV) with dual-energy storage system (DESS). It relied on neural network for its prediction. However, the prediction effect was not satisfactory due to local minimization, slow convergence rate, overfitting phenomenon and so on. In order to be more accurate in prediction, this paper introduced the Support Vector Regress (SVR) to the vehicle with parameters optimized by particle swarm optimization (PSO). Compare to BP neural network algorithm, PSO-SVR algorithm is more accurate and practical.

Keywords: pure electric vehicle with dual-energy storage system, particle swarm optimization algorithm, support vector machine, driving ranges

1 Introduction

Electric vehicles (EV) are more environmental-friendly with less noise and save more energy compared with fuel vehicles. But their driving ranges are a big problem, with the battery of EV as the primary obstacle. Therefore, it is significant to study the relationship between SOC (state of charge) of batteries and driving ranges.

In recent years, many experts and scholars propose the prediction methods based on non-linear theory. Li Dinggen, Deng Jie, et al study the relationship curves between SOC of batteries and driving ranges according to the energy equivalent principle between EV energy consumption and output energy of batteries [1]. Xu Wenle uses RBF neural network to predict driving ranges according to EV speed, temperature, current and voltage. It is proved to be feasible after the comparison between predicted data and actual data [2]. Zhang Wanxing establishes a SOC model of lithium iron phosphate battery through BP neural network and simulates driving ranges of the model in cruise software [3].

At present, the prediction of EV driving ranges by neural network is widely accepted. Neural network can map the complex nonlinear relationship and has strong nonlinear fitting ability. However, its learning speed is slow and samples should be of high quality. If there are a large amount of samples, the system may be in the state of local minimization and the generalization ability will be far from satisfactory [4-7]. Vanpik proposes a new machine learning method: support vector machine (SVM) [8]. It can address the nonlinear problem, cope with small samples, high dimension and local minimal phenomenon [9]. So it points a direction for EV driving ranges prediction. The paper uses SVM to predict PEV with DESS driving ranges. As the prediction accuracy of SVM is closely related to training parameters, particle swarm is introduced to optimize the parameters. The results show that the accuracy rate of prediction based on PSO SVM is higher, therefore, it can apply in the prediction of EV driving ranges.

2 The principle of PSO algorithm to optimize parameters of SVM

2.1 SVM REGRESSION MODEL

The method of SVM is based on VC dimension theory of statistical learning and minimal principle of structural risk, in which the main idea of classification is to find the optimal classification plane and improve the accuracy rate of classification [10,11]. The regression is based on classification. It estimates the function through sample learning [12].

Suppose regression training sample set is: $A=\{(x_1, y_1), \ldots(x_l, y_l)\}$, where, $x_i \in X=R^n$, $y_i \in Y=R$, i=1, 2, …, l. x_i refers to input variables, y_i refers to expected values corresponding x_i and l refers to the number of training samples. Regression function is described as:

$$f(x)=< w\, x > + b, \quad (1)$$

where $w \in R^n$, it refers to weight vector. $b \in R$, it refers to s bias threshold. < > refers to inner product operation. In order to ensure the generalization ability of SVM model,

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$\frac{1}{2}\|w\|^2$ should be minimized. Regression diagram of two-dimensional plane is shown in Figure 1, where dots refer to the training samples and the solid line refers to the ultra plane $f(x)$. The dotted lines H_1 and H_2 refer to the planes which are parallel to $f(x)$ and the distance between the dotted lines and $f(x)$ is ε. Regression aims at finding optimal solution of Equation (2).

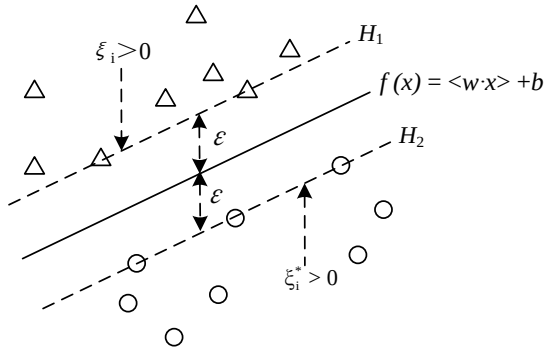

FIGURE 1 Diagram of SVR

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*), \tag{2}$$

s.t. $f(x_i) - <w\, x_i> - b \le \varepsilon + \xi_i$,

$<w\, x_i> + b - f(x_i) \le \varepsilon + \xi_i^*$,

$\xi_i, \xi_i^* \ge 0$,

i=1,2, …, N,

where C refers to penalty factor. ξ_i and ξ_i^* refer to slack variables. ε refers to insensitive loss coefficient. If there is the nonlinear relationship between the input variables and expected values, the kernel function will be introduced in SVM operation. Map input variables into high dimension space so the nonlinear problem in low dimensional space is shifted to a linear problem in high dimensional space [13,14]. In this paper, RBF is selected as the kernel function:

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

where g refers to the parameter of RBF kernel function. With Lagrangian function, the optimization of Equation (2) will be shifted to solving quadratic programming.

$$\max W(\alpha_i, \alpha_i^*) = -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) - \varepsilon\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) + \sum_{i,j=1}^{n} f(x_i)(\alpha_i - \alpha_i^*), \tag{4}$$

s.t. $\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0$, $0 \le \alpha_i \le C$ i=1,2, … , N,

$0 \le \alpha_i^* \le C$,

where α_i and α_i^* refer to Lagrangian multiplier.

$$w = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x). \tag{5}$$

So the Equation (1) can be expressed as:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x) + b. \tag{6}$$

2.3 THE BASIC PRINCIPLE OF PSO

PSO [15-17] is a new algorithm of swarm intelligence which is proposed by Kennedy and Eberhart. Its basic idea originates from the research on artificial life and birds preying behavior. The difference between PSO and the genetic algorithm is that PSO has not selection, crossover and mutation. It finds the optimal solution through searching the optimal solution of particles in the solution space. Suppose there are D particles in the swarm, the position vector of the *i-th* particle is $X_i = \{X_{i1}, X_{i2}, \dots, X_{id}\}^T$. The velocity vector of the *i-th* particle is $V_i = \{V_{i1}, V_{i2}, \dots, V_{id}\}^T$. The position vector of each particle corresponds to a fitness function value. In the iterative process, the particle updates own speed and position through tracking the optimal position of individual best position and global best position.

$$V_{id}^{k+1} = wV_{id}^k + c_1 r_1(P_{id}^k - X_{id}^k) + c_2 r_2(P_{gd}^k - X_{gd}^k), \tag{7}$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1}, \tag{8}$$

where P_{id}^k refers to the individual extremum of the *k-th* iteration. P_{gd}^k refers to the global extremum of the *k-th* iteration. c_1 and c_2 refer to acceleration constant. r_1 and r_2 are random numbers from zero to one. w refers to inertia weight.

2.3 PSO ALGORITHM FOR PARAMETERS OF SVM

In real situation, the choice of SVM parameters affects its performance to a great. The penalty factor *C* can define a Lagrange multiplier [18] and it also reflects the degree of punishment in the given feature space when the training model distributes erroneous sample data. The smaller the *C* value is, the smaller the punishment of sample data will be, but the bigger the training errors are. If the *C* value is greater, there will be more learning accuracy. But the generation ability of the model decreases. The appropriate *C* value can anti-interfere to a certain extent and enhance the stability of the model. *g* is the width coefficient of RBF kernel function which reflects the radial range of RBF core. If *g* value is smaller, the connection among SVM is loose and the generalization ability of model increases. If the *g* value is bigger, the number of support vectors will increase. But mode complexity also increases and is prone to produce under fitting [19]. Optimal methods for parameters of SVM are commonly used the grid search method [20,21], genetic algorithm and PSO. The paper uses PSO to optimize the parameters of SVM.

The steps of particle swarm algorithm to optimize the parameters of SVM are as follows:

1) Initialize the parameters *C* and *g* of PSO and determine the population size, then initialize the speed and position of the particle and set the number of iterations.

2) Regard individual optimal solution P_{ibest} of each particle as the current position and the current particle is substituted into the SVM model, and then calculate the fitness value of each particle. Regard the particle with maximum fitness value corresponding to individual optimal solution as the current global optimal solution P_{gbest}.

3) Update the position and speed of the particle according to the equation (7) and the equation (8).

4) Compare the fitness value of each particle with P_{ibest}. If the fitness value is better, P_{ibest} will be updated. Otherwise, the original value is retained.

5) Compare the fitness value of each particle with P_{gbest}. If the fitness value is better, P_{gbest} will be updated. Otherwise, the original value is retained.

6) Judge whether the system meets the exit conditions. If it does, the optimal fitness value will be returned. Otherwise, skip to step 2).

Flow chart of the algorithm is shown in Figure 2.

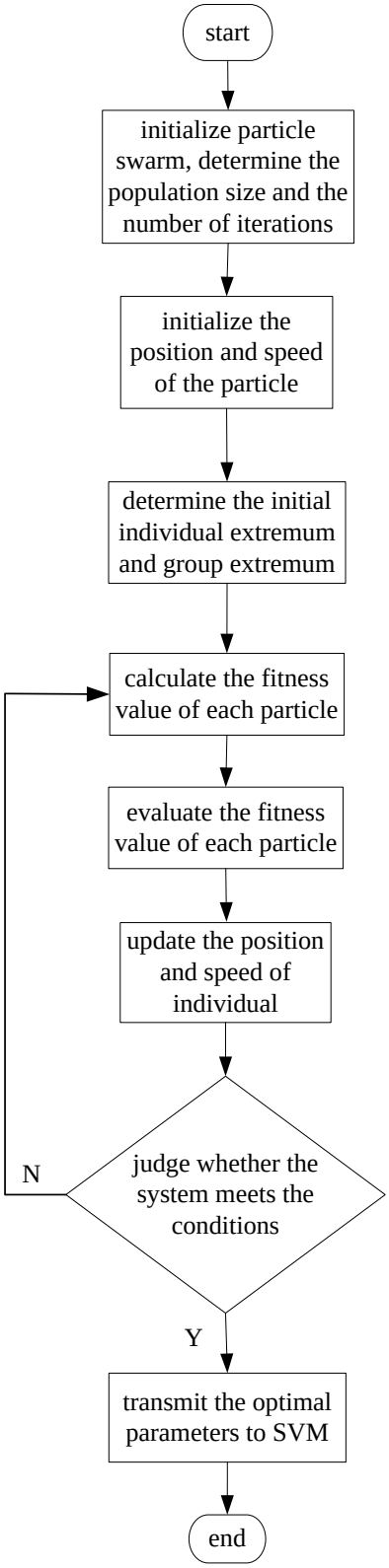

FIGURE 2 Flow chart of PSO-SVR

3 Driving Ranges prediction of PEV with DESS

3.1 CALCULATING DRIVING RANGES

The driving ranges are one of the economic performances of EV. It refers to the distances from the completion of charge to the required standard. At present, EV driving ranges is calculated in the way that the output energy of batteries is equal to consumption energy of EV [22]. The driving force of EV:

$$F_t = mgf + \frac{C_D A v^2}{21.15} + \delta m j, \tag{9}$$

where m refers to EV mass; f refers to the coefficient of rolling resistance; C_D refers to the coefficient of aero dynamic drag; A refers to frontal area; v refers to the driving speed of EV; δ refers to the coefficient of increased mass; j refers to the acceleration of EV. The expression of EV in the acceleration and deceleration is:

$$S = \frac{v^2}{2j}. \tag{10}$$

The battery consumption energy is expressed as:

$$E_B = \frac{F_t S}{\eta \eta_M \eta_C \eta_B \times 3600}, \tag{11}$$

where F_t refers to the driving force of EV;S refers to the driving ranges of EV; η refers to mechanical transmission efficiency; η_M refers to the efficiency of motor driving; η_C refers to the efficiency of motor controller; η_B refers to the efficiency of discharged batteries[23]. The parameters of PEV with DESS in the paper are shown in Table 1.

TABLE 1 The parameters of PEV with DESS

Parameter	Value	Parameter	Value
Vehicle Weight/kg	520	Mechanical transmission efficiency	0.92
Frontal Area/m^2	1.05	Motor driving efficiency	0.93
Coefficient of Aero Dynamic Drag	0.35	Motor controller efficiency	0.96
Coefficient of Rolling Resistance	0.015	Discharged batteries efficiency	0.85

The driving conditions of EV include starting, acceleration, uniform speed, deceleration and stop. The driving distances of a complete driving condition is called driving section. The driving ranges are acquired by accumulated driving sections.

$$S = \sum_{i=1}^{k} S_i, \tag{12}$$

where S_i refers to the driving distances of EV in each section; k refers to the number of driving condition [24]. The driving condition of EV in the paper is shown in Figure 3.

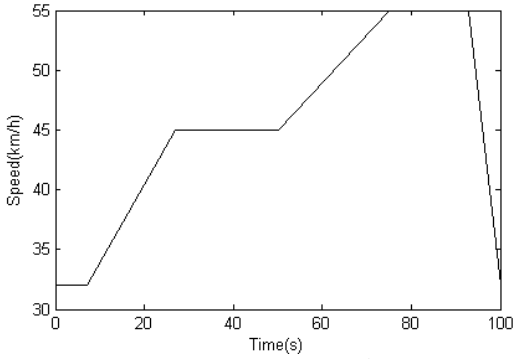

FIGURE 3 The cycle curve of EV

As we can see from Figure 3:

1) Electric vehicles drive at uniform speed from 0 to 7 seconds. Driving distances $S_1=v_1t$=62.23m; driving force $F_{t1} = mgf + C_D Av/21.15$ = 77.81N; Energy consumption of batteries $E_{B1} = F_{t1} \times (S_1/1000)/\eta\eta_M\eta_C\eta_B\times3600$= 0.0019kw·h.

2) Electric vehicles accelerate from 7 to 27 seconds. Driving distances $S_2 = v_2/2j_1$ = 432.78m; driving force F_{t2}= $mgf + C_D Av / 21.15 + m\times j$ = 173.28N; Energy consumption of batteries $E_{B2} = F_{t2} \times$ (S2 / 1000) / $\eta\eta_M\eta_C\eta_B\times3600$=0.0298kw·h.

3) Electric vehicles drive at uniform speed from 27 to 50 seconds. The method is the same as 1). Driving distances S_3= 287.5m; driving force F_{t3}= 79.16N; Energy consumption of batteries E_{B3}= 0.0091kw·h.

4) Electric vehicles accelerate from 50 to 75 seconds. The method is the same as 2). Driving distances S_4=1051.57m; driving force F_{t4}=134.57N; energy consumption of batteries E_{B4}= 0.0563kw·h.

5) Electric vehicles drive at uniform speed from 75 to 93 seconds. Driving distances S_5= 275.02m; Driving force F_{t5}= 80.5N; energy consumption of batteries E_{B5}= 0.0088kw·h.

6) Electric vehicles decelerate from 93 to 100 seconds. The driving distances $S_6=v/2j_3$=43.42m.

The total energy consumption of batteries is 0.106 kw·h and driving ranges is 2152.52m. The driving time of EV is 9500 seconds. The driving ranges of EV in the driving condition is S_{total}=2152.52×9500/100=204.49km.

3.2 SAMPLE DATA AND PROCESSING

The energy storage devices of PEV with DESS include batteries and ultra-capacitor. There is a close connection between SOC changes of batteries and ultra-capacitor and driving ranges. Establish the model of PEV with DESS under Matlab/simulink. When the pure electric vehicles run in the normal state, the SOC change curves of batteries and ultra-capacitor are shown in Figure 4. The curve of driving ranges and time is shown in Figure 5. In general, the safe working ranges of batteries SOC are from 0.4 to 1 and the safe working ranges of ultra-capacitor SOC are from 0.2 to 1 [25]. As can be seen in Figure 4, 9500 seconds are needed when the SOC of batteries decreases to 0.4 and the SOC of ultra-capacitor decreases to 0.2.

Import the data of Figure 4 and Figure 5 into Matlab. The mutation data are removed according to the denoising experience then the smoothness of the signal is improved. According to the above, the prediction sample data are available. They are shown in Table 2.

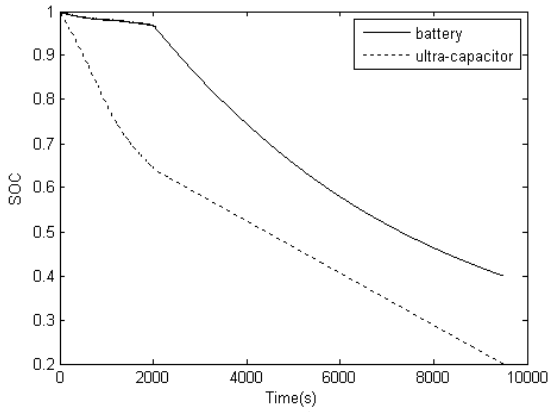

FIGURE 4 The SOC-time curve of battery and ultra-capacitor

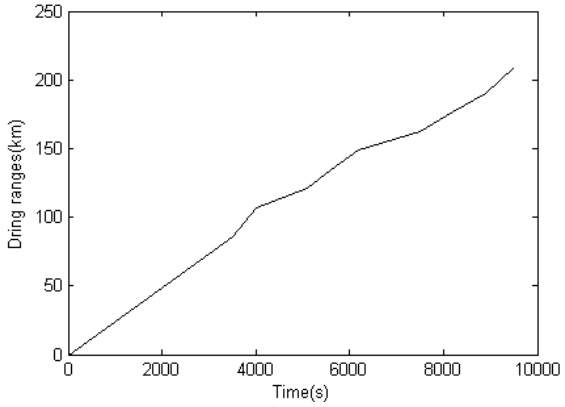

FIGURE 5 The curve of driving ranges and time

TABLE 2 The prediction sample data

NO.	Batteries SOC	Ultra-capacitor SOC	Driving ranges (km)
1	1	1	0
2	0.8212	0.5615	85.5521
3	0.7391	0.5117	106.9241
4	0.6656	0.4618	120.8139
5	0.6016	0.4115	134.7040
6	0.5464	0.3617	148.5938
7	0.4986	0.3113	162.4842
8	0.4572	0.2612	176.3737
9	0.4213	0.2116	190.2642
10	0.4000	0.2000	209.2100

From Table 2 it is clear that the driving range of EV which is measured through simulation experimental is 209.21km. It is close to 204.49km that is derived from theoretical calculation and the error is 2.3%.

3.3 THE PROGRAM OF PSO SVM ALGORITHM

PSO parameters of SVM are run in the Matlab environment. Establish the PSO model according to the Figure 2. The specific implementation programs are as follows:

```
load A.txt;        % import sample data
load B.txt;
c1 = 1.7;          % set the acceleration constant
c2 = 1.6;
maxgen=200;  % the number of iterations
sizepop=20;                              % population size
popcmax=10^(2);
% set the scope of optimal parameters C
popcmin=10^(–1);
popgmax=10^(3);
% set the scope of optimal parameters g
popgmin=10^(–2);
k = 0.6;
Vcmax = k*popcmax;      % set extreme speed of C
s=3;
%% produce the initial particles and speed
for i=1:sizepop
pop(i,1) = (popcmax-popcmin)*rand+popcmin;
% generate initial population randomly
   pop(i,2) = (popgmax-popgmin)*rand+popgmin;
V(i,1)=Vcmax*rands(1);
% initialize speed
   V(i,2)=Vgmax*rands(1);
%% calculate the initial fitness value
   cmd = ['-s',num2str(v),' -c ',num2str( pop(i,1) ),
' –g ',num2str( pop(i,2) )];
   fitness(i) = svmtrain(trainx, train, cmd);
fitness(i) = -fitness(i);
end
 %% find extremum and extremum point
[global_fitness bestindex]=min(fitness);
% global extremum
local_fitness=fitness;
% initialize individual extremum
global_x=pop(bestindex,:);
% global extremum point
local_x=pop;
% initialize individual extremum point
```

Run the program of the above and the fitness curve is shown in Figure 6. As can be seen from Figure 6, the optimal fitness value is 0.91. The results show that the optimal parameters of SVM are $C = 2$ and $g = 0.25$ which are shown in Figure 7. The prediction results are evaluated by the mean square error and the square correlation coefficient. Mean square error:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2 , \tag{13}$$

Square correlation coefficient:

$$r^2 = \frac{(N\sum_{i=1}^{N} X_i Y_i - \sum_{i=1}^{N} X_i \sum_{i=1}^{N} Y_i)^2}{(N\sum_{i=1}^{N} X_i^2 - (\sum_{i=1}^{N} X_i)^2)(N\sum_{i=1}^{N} Y_i^2 - (\sum_{i=1}^{N} Y_i)^2)}, \quad (14)$$

where X_i refers to measured values. Y_i refers to prediction values. N refers to the number of prediction sample.

Establish the prediction model of SVM under the optimal parameters and predict the test data. The mean square error is calculated to be 0.005 according to Equation (13) and the square correlation coefficient is 0.98 according to Equation (14).

3.4 PREDICTION RESULTS AND ANALYSIS

```
Vcmin = -Vcmax ;
Vgmax = k*popgmax        % set extreme speed of g
Vgmin = –Vgmax ;
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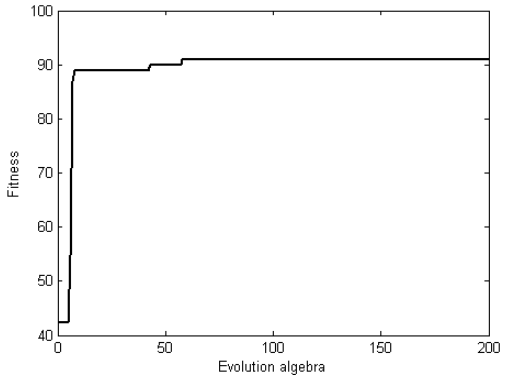

FIGURE 6 Fit curve of PSO

Name	Value	Min
V	<20x2 double>	-600
Vcmax	60	60
Vcmin	-60	-60
Vgmax	600	600
Vgmin	-600	-600
bestCVaccuarcy	90.9662	90.9662
bestc	2	2
bestg	0.2500	0.2500
bestindex	15	15
c1	1.7000	1.7000
c2	1.6000	1.6000

FIGURE 7 Diagram of C and g optimization results

BP neural network is a multilayer feed forward neural network. It is composed of input layer, hidden layer and output layer. There are two circulation signals between layer and layer, namely, the working signal and error signal. The working signal propagates forward after the input signal until the actual output signal at the output terminal. It is the function of the input signal and the weight. The error signal is the difference signal between actual output and expected output of neural network. It propagates back layer by layer through the output terminal [26,27].

Establish PSO-SVM algorithm prediction model according to the optimum parameters in section 2.3 and compare the prediction results between BP network model and PSO-SVM model.

From Figure 8, we can draw the conclusion that the change tends of SVM prediction, BP neural network prediction and the measured values is basically the same. But SVM prediction results are closer to the measured values. The prediction value of BP neural network has significant fluctuation. So its error is obvious. From Table 3, it is clear that the prediction results of SVM model are good. The maximum value of relative error of ten prediction samples is 1.91%. But the maximum value of relative error of BP neural network is 4.88%. So the prediction model of PSO parameters for SVM is reliable and reasonable and its accuracy rate is higher.

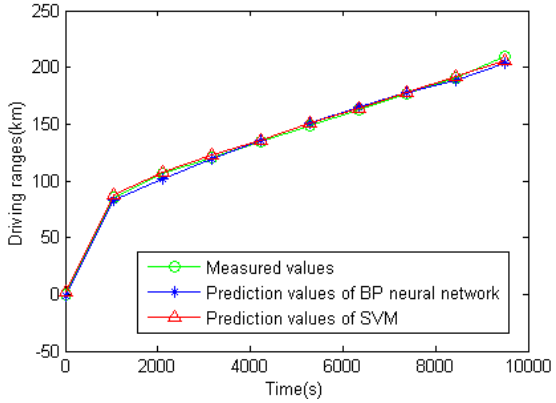

FIGURE 8 Results comparison diagram of between SVMand BP neural network driving ranges prediction

TABLE 3 Comparison of prediction results between SVR and BP neural network

NO.	Measured values	Prediction values of BP neural network model	Relative errors %	Prediction values of SVM model	Relative errors%
1	0.0102	2.6434	—	0.0082	—
2	85.5521	82.5505	-3.51	87.1834	1.91
3	106.9241	101.7097	-4.88	107.4154	0.46
4	120.8139	119.6689	-0.95	121.5251	0.59
5	134.7040	136.1486	1.07	135.7710	0.79
6	148.5938	151.1705	1.73	150.8951	1.55
7	162.4842	164.8946	1.48	163.9965	0.93
8	176.3737	177. 5508	0.67	177. 4479	0.61
9	190.2642	188.9525	-0.69	191.0705	0.42
10	209.2100	203.1256	-2.9	205.5227	-1.76

4 Conclusions

The paper proposes to predict the driving ranges of dual-energy PEV with SVM. It can overcome the local minimum phenomenon and overfitting phenomenon. At the same time, it can also address the uncertain hidden nodes of neural network.

The penalty coefficient and the width of radial basis function are optimized by particle swarm algorithm, then we establish SVM model. The comparison between SVM to BP neural network shows that the maximum relative error of SVM is less than 2%. But the maximum relative error of BP neural network is controlled within 5%. The results indicate that PSO parameters of SVM model have high fitting precision and are feasible for PEV with DESS to predict the driving ranges.

Acknowledgments

The authors are grateful to the Project of Scientific and Technical Development Plan of Jilin Province of China (No. 20080353) and the Young Start-up Funding Project of Jilin Agricultural University of Jilin Province of China (N0. 201233).

References

[1] Dinggen L, Jie D and Jun C 2008 A study of electric vehicle battery's state of charge estimation and its continued driving mileage *Industrial Instrumentation and Automation Device* (5) 91-4
[2] Wenle X 2012 Forecasting the driving range of pure electric vehicles based on RBF neural network *Transport of Portage College of Beijing Jiaotong University* Beijing.
[3] Wanxing Z 2012 Forecasting for power battery remaining capacity and driving range of electric vehicle *Vehicle engineering College of Hefei University of Technology*
[4] Taylor J W, Buizza R 2002 Neural network load forecasting with weather ensemble predictions *IEEE Transactions on Power Systems* **17**(3) 626-32
[5] Zhaoqi B, Gongxue Z 2010 *Pattern Recognition* Tsinghua University press: Beijing 73-89
[6] vanajakshi L, Rilett L R 2004 A comparison of the performance of artificial neural networks and support vector machines for the prediction of traffic speed *IEEE Intelligent Vehicles Symposium* USA: Texas 194-9
[7] Vapnik V, Levin E, Le C Y 1994 Measuring the VC-dimension of a learning machine *Neural computation* **6**(5), 851-76.
[8] Alhusaini A H, Prasanna V K, Raghavendra C S 2000 A framework for mapping with resource coallocation in heterogeneous computing systems *Proceedings of the 9th Heterogeneous Computing Workshop* 273-86
[9] Vapnik V N 1998 *Statistical learning theory* New York: *Wiley* 21
[10] [Fen W, Tao M, Xu M 2012 Gold price forecasting model based on regression with support vector machine for particle swarm optimization *Journal of Lanzhou University of Technology* **39**(3) 65-9
[11] Cortes C, Vapnik V 1995 Support vector networks *Machine Learning* **20** 273-97
[12] Jian W, Yang Z and Rui H 2013 Fault detection and diagnosis of EMB sensor system based of SVR *Journal of Jilin University (Engineering and Technology Edition)* **43**(5) 1178-83
[13] Zhiliang M 2009 Applied research of mixture kernel support vector machine in modeling for fermentation process *Jiangnan University*
[14] Xuesong W, Yuhu C 2009 Theory, method and application of the machine learning *Science press: Beijing* 82-3
[15] Eberhart R, Kennedy J A new optimizer using particle swarm theory 1995 *Proceedings of the Sixth International Symposium on Micro Machine and Human Science* 39-43
[16] Kennedy J, Eberhart R 1995 particle swarm optimization 1995 *IEEE International Conference on Neural Networks* 1942-8.
[17] Poli R, Kennedy J, Blakwell T 2007 Particle swarm optimization *Swarm Intelligence* **1**(1) 33-57
[18] Donghui L, Jianpeng B, Ping F, Zhiqing L 2009 Study on the choice optimum parameters of support vector machine *Journal of Hebei University of Science and technology* **30**(1) 58-61
[19] Xu Z B, Dai M W, Meng D Y 2009 Fast and Efficient Strategies for Model Selection of Gaussian Support Vector Machine *IEEE Transactions on Systems Man and Cybernetics Part B-Cybernetics* **39**(5) 1292-307
[20] Hongying L 2009 Research of kernels in support vector classifying Machine *Chongqing University*
[21] Guojun D, Limulati H, Maiti M, Hui Y 2009 Algorithms of optimizing SVM's kernel parameters with RBF kernel *Journal of Xinjiang University(Natural Science Edition)* **26**(3) 355-63
[22] Dkarimi M, Mokhtari H, IravaniM R 2000 Wavelet based online disturbance detection for power quality applications 2000 *IEEE Transactions on Power Delivery* **15**(14) 1212-20
[23] Yuliang T 2013 Analysis of performance and research of driving ranges of pure electric vehicle *Bus technology and research* (1) 9-11
[24] Guiming W 2010 Electric vehicle and its performance optimization *Machinery Industry Press: Beijing*
[25] Kaiwen Z 2012 Research on key technologies of the composite power based on the electric vehicles *Automatic College of Wuhan University of Technology*.
[26] Yun S 2010 Matlab implementation of BP neural network *Journal of Xiangnan University* **31**(5) 86-8
[27] Houlin L, Xianfang W, Yong W 2012 Power prediction for centrifugal pumps at shut off condition based on BP neural network 2012 *Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE)* **28**(11) 45-9

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