

## Method of estimating the state of charge of a battery electric vehicle based on RS-SVM

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**Abstract.** Charging, discharge, maintenance and energy management technology for electric vehicle power battery is relatively backward, An advanced and reasonable method is presented for battery state of charge( SOC ), used simple rough set attribute ,simplified battery charging related parameters, the simplified data is processed by using the support vector machine (SVM) to predict charged state of the battery , and the service life of the battery is lengthened .This paper has important research value.

### Introduction

The phenomenon, the improper charging method leads to the car battery damage and the shortened life expectancy ,remains commonplace. According to the battery state of charge (SOC) , the effective method is proposed to guide the charge, discharge and battery reasonable collocation for energy-saving the battery life increasing.

Affected by many factors such as power rate,battery temperature, self-discharge rate, battery different working rate and so on, It is difficult for conventional method to correctly predict battery state of charge( SOC ).

At present, the main detection methods of SOC, such as counting method, resistance method, open circuit voltage method and neural network method and so on. can not meet the various needs of the working state of the battery, the SOC estimation error is large. A new method is presented based on RS-SVM. The method consists of two main processes: Data reduction, processed battery charging history data based on the rough set theory, constructed a new learning sample and test sample, dynamically predicted the state of charge of battery based SVM.

### rough set and support vector machine

Support vector machine (SVM) proposed by Vapnik , is a new machine learning method based on statistic learning theory - linear network ,is under the principle of structural risk minimization, According to the maximum classification interval output pattern recognition is developed , and the decision function is determined by the optimal classification hyper plane.However, it can't distinguish good data and bad data on processing to the training samples, thus, is likely to lower the SVM real-time prediction system.In order to solve this problem,preprocessed a large number of training sample data to eliminate redundant, useless information, high reliability training samples is provided for SVM, improved the efficiency of SVM prediction system. Rough set solved the problem.

Z.Pawlak pioneered the concept of rough set (RS), through the analysis of data uncertainty, and processing data by fuzzy knowledge.Attribute reduction and relative attribute reduction are a core of KDD.Rough sets [] can be expressed as: for the decision system $S=(U,C\cup D,V,f)$  , In the formula, domain $U=\{x_1,x_2\dots x_n\}$  represents a collection of n the research object; attribute set  $A=C\cup U(C\cup D=\phi)$  , C and D represent the condition attributes and the decision attributes; the

attribute domain  $V = \bigcup_{a_i \in A} V_{a_i}$  ;  $f$  is the mapping function of attribute domain object.  $(U,A,f)$  is a decision table.

Using the complementarity of rough sets and support vector machines, Prediction system of battery Soc based on RS-SVM is proposed, as shown in figure 1.

the preposition system

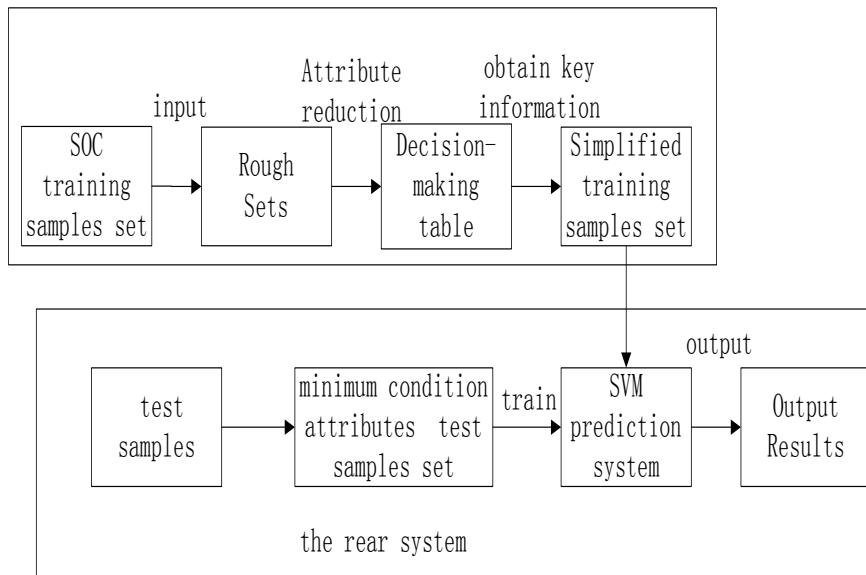


Figure 1 system structure diagram of battery SOC based on RS-SVM estimation

The system is composed of two parts, namely the front system and post system. Rough set network is the front system, includes the battery state of charge input sample, attribute reduction, decision table is established, the table data is obtained after simplification, is preprocessed data, The SVM network is the post information recognition system, training on reduced samples to get the forecasting result.

### Improved reduction algorithm based on mutual information heuristic attribute

For the decision system  $S, R \subseteq C$  The domain  $U$  is consistent in  $C$  compared with  $D$  ( $POS_i(D)=U$ ),  $B \subseteq C$ ,  $B$  is the relatively simple  $C$ , thus,  $I(B, D)=I(C, D)$ , that is, mutual information of reduced data remained unchanged.

When the condition attributes small affects decision attribute, mutual information gain rate is larger, thus, the selected decision attribute is not the most important, based on this, the attribute importance measurement can be defined as:

$$SGF(a, R, D) = (I(R \cup \{a\}, D) - I(R, D)) / I(a, D) \quad (2)$$

This measurement method not only considers the increment of mutual information after adding attributes in the attribute  $R$ , but also considers the mutual information of his own.

According to equation (2), the improved attribute reduction algorithm is established. This algorithm takes the core attributes of decision table as a starting point, selects successively, adds the largest non core condition attribute to the relative core set  $SGF(a, R, D)$ , until a termination condition is satisfied  $I(R, D) = I(C, D)$

Input: decision system  $S = (U, C \cup D, V, f)$

Onput: Feature subset  $R$  of decision table information system.

① calculate attribute information between condition attributes and decision  $I(C, D)$ ;

② calculate  $R_0 = Core(C)$ ,  $I(R_0, D)$ , if  $I(R_0, D) = I(C, D)$ , turn ⑤ else if continue,

③ if  $R = R_0$ ,  $C = C - R$ , calculate  $C$  according formula (2), and select  $SGF(a, R, D)$ , form the greatest attribute set  $a$ ;

- ④  $R = R \cup \{a\}$ ;
- ⑤  $I(R, D) = I(C, D)$ , terminate, otherwise turn step③。

### the parameters of support vector machine establish

In the practical application, important parameters influencing SVM are: the penalty factor C and kernel function and its value. In the battery charging process, through comprehensively analysis all parameters to judging battery SOC, Prediction method of battery SOC is described for the terminal voltage, SOH% and residual capacity. Parameters distribution diagram of battery charging 20 times is shown in Figure 1。

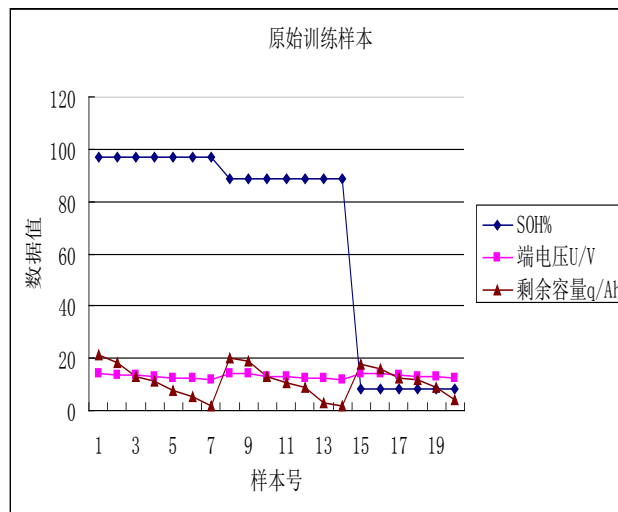


Figure 1 parameters distribution diagram of battery charging 20 times。 the K-fold cross validation method was used. four kinds of kernel functions :

(1) Polynomial:  $K(x, x_i) = [(x, x_i) + 1]$

(2) Gauss Function:  $K(x, x_i) = \exp\left\{-\frac{|x - x_i|^2}{2\sigma^2}\right\}$

(3) Radial Basis Function (RBF)  $K(x, x_i) = \exp(-|x - x_i|^2 / \sigma^2)$

(4) Sigmoid Function:  $K(x, x_i) = \tanh[v(x \bullet x_i) + c]$

The training set consisted of the parameters data of 20 times of charging, was divided into 20 groups, used grid-search, GA and PSO to find the optimal combination of C and gamma value of the penalty parameter. The forecast effect produced is shown in table 1-3.

Table1 battery terminal voltage correlation coefficient R

	Grid-search/%	GA/%	PSO/%
Linear	94.5265	96.7625	94.3018
Polynomial	86.3489	87.3487	86.7213
RBF	94.2431	97.7586	95.0456
Sigmoid	93.4325	95.7102	93.4709

Table2 SOH% correlation coefficient R

	Grid-search/%	GA/%	PSO/%
Linear	92.4789	98.4723	93.5238
Polynomial	86.8810	87.6813	84.6712
RBF	95.2213	97.3452	96.6724
Sigmoid	93.3647	96.7813	94.2672

Table3 residual capacity correlation coefficient R

	Grid-search/%	GA/%	PSO/%
Linear	91.3217	95.4017	92.4931
Polynomial	84.4078	86.0432	86.1089
RBF	93.0780	95.3452	95.2127
Sigmoid	92.2974	92.0431	93.3005

Table 1 to table 3 shows that the epsilon-SVR-RBF-Genetic Algorithm model, called ERGA model, compared with other models, the prediction set the highest goodness of fit, the terminal voltage prediction accuracy reached 97.7586%, the SOH prediction accuracy reaches 97.3452%, the residual capacity reached 95.3452%. In conclusion, The SOH% and terminal voltage is less interfered in the normal charge and discharge cases, higher forecasting accuracy is reached, however, the residual capacity in the process of charge and discharge is influenced by the different charging method, which is low.

### Experimental results analysis

Through the rough set method to remove redundant information, simplified the SVM complexity, improved the training speed. overcome noise sensitive defects of the rough set, makes the evaluation model has good performance. The experimental samples is shown in Table 4, the experimental and the predicted results and error analysis are shown in table 5. Training samples is In Table 4 , residual capacity is estimated using SR-SVM

Table 4 10 charging process samples

Sample No.	1	2	3	4	5
SOH%	96.8	96.8	96.8	96.8	89.1
Terminal voltageU/V	14.12	13.72	12.53	12.32	13.79
Residual Capacityq/Ah	20.21	16.89	6.61	4.79	17.28
Sample No.	6	7	8	9	10
SOH%	89.1	89.0	83.1	83.1	82.6
Terminal voltageU/V	13.63	12.41	14.61	13.59	12.49

Residual					
Capacityq/Ah	15.69	6.22	17.81	13.41	6.78

algorithm, the prediction results is shown in Table 5, the predicted curve is shown in Figure 3, the error is very small, the measuring accuracy is high, Results is satisfactory.

Table 5 predicted results and error analysis

Sample No.	1	2	3	4	5
Predicted results	20.18	16.66	6.54	4.83	17.36
Error %	0.15	1.36	1.05	0.83	0.46
Sample No.	6	7	8	9	10
Predicted results	15.75	6.21	18.78	13.38	6.81
Error %	0.38	0.16	0.54	0.22	0.44

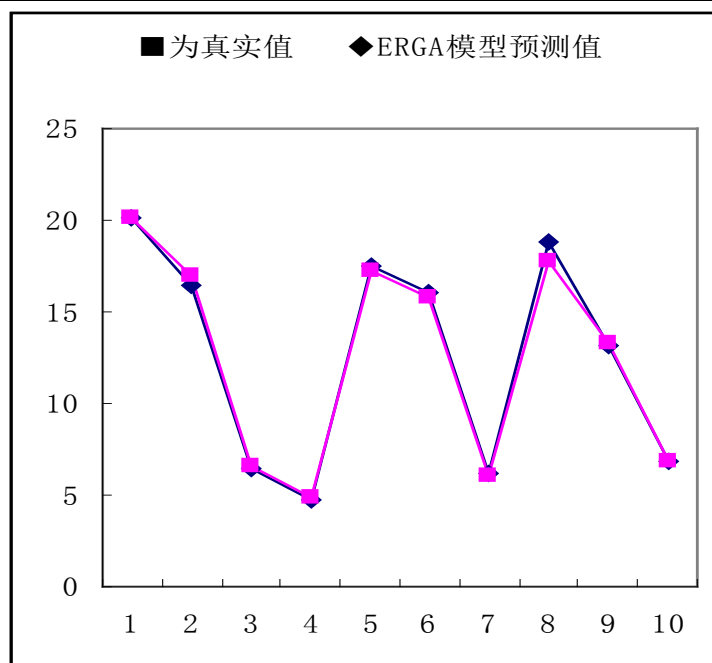


Figure 3 RS-SVM predicted results based on ERGA

## Conclusions

In the paper, the method of combining rough set with support vector machine to predict battery SOC is adept ,By the improved reduction algorithm based on mutual information heuristic attribute , reduce system data, Minimum attribute reduction set is classified by SVM.The experimental and predicted results show that the forecast effect applied in the terminal voltage, SOH% and residual capacity is good, The RS-SVM method has important research value.

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## References

- [1] Dj.M. Maric, P.F. Meier and S.K. Estreicher: Mater. Sci. Forum Vol. 83-87 (1992), p. 119
- [2] M.A. Green: High Efficiency Silicon Solar Cells (Trans Tech Publications, Switzerland 1987).
- [3] Y. Mishin, in: Diffusion Processes in Advanced Technological Materials, edited by D. Gupta Noyes Publications/William Andrew Publishing, Norwich, NY (2004), in press.
- [4] G. Henkelman, G.Johannesson and H. Jónsson, in: Theoretical Methods in Condensed Phase Chemistry, edited by S.D. Schwartz, volume 5 of Progress in Theoretical Chemistry and Physics, chapter, 10, Kluwer Academic Publishers (2000).
- [5] R.J. Ong, J.T. Dawley and P.G. Clem: submitted to Journal of Materials Research (2003)
- [6] P.G. Clem, M. Rodriguez, J.A. Voigt and C.S. Ashley, U.S. Patent 6,231,666. (2001)
- [7] Eman, O.E., Interactive bi-level multi-objective integer non-linear programming problem. Applied Mathematical Sciences, 5(65), 3221-3232, 2011.