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CLASSIFICATION ALGORITHM OF REGRESSION SUPPORT VECTOR MACHINE AND ITS APPLICATION TO ENHANCE ANTIFREEZE HEAT TRANSFER CAPABILITY IN GROUND SOURCE HEAT PUMP SYSTEM

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ABSTRACT

To enhance the heat transfer capability of antifreeze mixture in ground source heat pump systems, the paper improved the existing proximal support vector machines [1], constructed a classification algorithm model of regression Support Vector Machine (SVR), and further applied it to a new classification method of mixed antifreeze heat transfer capability on the basis of analyzing antifreeze [2] heat transfer capability of ground source heat pump systems.

Keywords: *Ground Source Heat Pump, Heat Transfer Capability, Classification Algorithm of Regression Support Vector*

1. INTRODUCTION

Ground source heat pump [3] is a highly efficient air conditioning system which takes advantage of shallow underground geothermal resource (also known as Ground Energy, including groundwater, soil or surface water) to provide both heat and cooling energy. It transfers heat energy from low temperature to high temperature by inputting a little amount of high-grade energy (e.g. electricity). In ground source heat pump systems, geothermal energy is used as the heating source of heat pumps in winter and the cooling source of air conditioning in summer. Ground source heat pump does not emit any exhaust gas, water and waste residues and thus is considered as an ideally green technology with renewable energy as well as a sustainable development technology. To trace its origin, it was first proposed and named as ″Ground Source Heat Pump″ by Zoelly from Swiss in 1912. As the name suggests, ground source heat pump is one type of heat pump, similar to air source heat pump. "Ground Source" is the low level heat of heat pump which is from ground. Ground source heat pump is classified into Ground-coupled heat pump (GCHP) and Water-source Heat Pump (WSHP) based on different ways of using low level heat.

Ground source heat pump system depends on the stability of shallow surface temperature. In winter, water temperature of core system is in general between 10 and 15 degrees; the return water temperature is between 6 to 10 degrees supplied by underground pipes. Theoretically there is no need to fill an antifreeze solution into ground source heat pump system in normal circumstance [4]. But in practice, it is rarely to achieve an idealized state. It is subjected to the area limitation of system heat transfer and the volume as well as depth of underground drilling pipes. Another limitation depends on construction conditions. For instance, to explore a well with 100-meter depth, it could hardly go beyond 60 meters due to underground rock structure. Thus, it is necessary to fill an antifreeze solution into ground source heat pump system. The most common antifreeze solutions are water, sodium chloride, calcium chloride, ethanol, ethylene glycol, methanol, potassium acetate and potassium carbonate, etc. For various regions and types of ground source heat pump systems, one or more kinds of antifreeze solutions should be considered in order to economically reduce pollution and equipment corrosion on the premise of standard thermal conductivity. This brings up an optimal choice problem. Here, we apply a new data mining method - support vector machine - to do the

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optimization research and experiment to solve this problem.

2. THE FEASIBILITY ANALYSIS OF SUPPORT VECTOR MACHINE AND ITS APPLICATION TO IMPROVE ANTIFREEZE HEAT TRANSFER CAPACITY OF GROUND SOURCE HEAT PUMP SYSTEM

2.1. Support Vector Machine

Support Vector Machine (SVM), which is a new data mining method, was brought up by Cortes and Vapnik in 1995 and has already been one significant achievement [5] on Machine Learning Research in recent years. The theoretical foundation of SVM is Statistical Theory [6] and Optimization Theory [7]. It has been successfully applied to the military, economy and other fields in developed countries such as the United States to solve problems including pattern classification, regression analysis, estimation function, etc. Common principles are concluded from existing observation samples and utilized to predict future data or data that cannot be observed or collected. In other words, Support Vector Machine is a process where, given a training set, an optimization model is built to obtain optimized solutions for creating a decision function which can be applied to practical problems to make optimal decisions.

2.2. The Feasibility Analysis of Support Vector Machines Applied to Ground Source Heat Pump System and Enhancement of Antifreeze Heat Transfer Capability

Ground source heat pump system employs a great variety of antifreeze solutions, including water, sodium chloride, calcium chloride, methanol, ethanol, ethylene glycol, potassium acetate, potassium carbonate, etc. Each antifreeze solution has its own characteristics, such as heat transfer performance, corrosion, price, toxicity on human body, leakage and potential risk. Under some actual condition, different users mix different proportion of antifreeze solutions. No related research studied how to determine the concentration proportion of antifreeze solutions to achieve the best effect before since a variety of factors are required to be involved into the research and difficulty exists in quantitative analysis with traditional techniques and approaches.

Here, a new data mining method - support vector machine is created to solve this problem. N kinds of antifreeze solutions are denoted as a_1, a_2, ..., a_n. a_i refers to the i-th type of antifreeze solution and also represents the amount of the i-th antifreeze solution with certain concentration. Thus, a n-dimensional vector $(a_1,a_2,...,a_n)$ is constructed. For each component, given some concentration and amount, there will be L number of n-dimensional vectors. A standard denoted by A on heat transfer capability of antifreeze solutions is set based on design requirements of a ground source heat pump system and geographic conditions (such as surface temperature, ground corrosion resistance, etc.) . If a result is higher than or equal to A, the concentration proportion is considered to be eligible; if lower than A, it is not eligible. In the experiment of L number of n-dimensional vectors, the number of results more than and equal to A is recorded as l1 and each result is labeled as +1, while results less than A are counted as l_2 and each result is labeled as -1. In this way, we get L training points including l_1 positive points and l_2 negative points, which constitute a training set $T=\{(x_1,y_1),...,(x_l,y_l)\}$, where $x_i=(a_{i1},a_{i2},...,a_{in})$, $y_i=\pm1$, i=1,2,...,l. To find the optimal proportion, a decision function f(x) is derived from support vector machines and the optimal solution can be given from this function f(x). In other way, SVM-based decision function f(x) is the key to solve for figuring out the optimal proportion of antifreeze mixture with strong heat transfer capability, low cost and weak corrosion.

3. SVR MODEL OF SOLVING CLASSIFICATION PROBLEMS

As classification problem is one special form of regression problem, we are attempted to construct classification algorithm through Support Vector Machine (SVM). The purpose is to find an optimization model easy to be solved. The training set is given as,

$$T=\{(x_1,y_1),\cdots,(x_l,y_l)\}\in(\mathrm{X}\times\mathrm{Y})^l \qquad (1)$$

Here, $x_i\in\mathrm{X}=R^n, y_i\in\mathrm{Y}=\{1,-1\}, i=1,\cdots,l$. Given any mode x, the corresponding value y can be derived from the decision function

$$f(x)=\mathrm{sgn}(g(x)) \qquad (2)$$

Here, $g(x)$ is a real-valued function, $\mathrm{X}=R^n$.

When comparing the definition above with regression problem definition, classification problem can be considered as a special regression problem. Thus, it is able to be solved with Support Vector Regression Machine.

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3.1. The Original Optimization Problem and the Dual Problem

Considering classification problem as a regression problem, Gaussian loss function is selected instead of ε-insensitive loss function since y_i takes value from $\{1,-1\}$. The original form of optimization problem is

$$\min_{w,\xi,b} \ \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{l}\xi_i^2 \tag{3}$$

$$s.t. \quad ((w\cdot x_i)+b)-y_i \le \xi_i, i=1,2,\cdots,l \tag{4}$$

$$y_i-((w\cdot x_i)+b) \le \xi_i, i=1,2,\cdots,l \tag{5}$$

$$\xi_i \ge 0, i=1,2,\cdots,l \tag{6}$$

Problem (3)-(6) is equal to

$$\min_{w,\xi,b} \ \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{l}\xi_i^2 \tag{7}$$

$$s.t. \quad \xi_i \ge |((w\cdot x_i)+b)-y_i|, i=1,2,\cdots,l \tag{8}$$

Apparently constraints in the problem can be formulated as equalities. Then problem (7) and (8) is equal to

$$\min_{w,b} \ \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{l}(y_i(w\cdot x_i)+b)-1)^2 \tag{9}$$

Let

$$\eta_i = 1-y_i((w\cdot x_i)+b) \tag{10}$$

then, the above problems can be expressed as

$$\min_{w,\xi,b} \ \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{l}\eta_i^2 \tag{11}$$

$$s.t. \quad y_i((w\cdot x_i)+b) = 1-\eta_i, i=1,2,\cdots,l \tag{12}$$

It is changed into the original optimization problem in the Least Squares Support Vector Machine.

Next, solution properties of the resulting problem above and its dual problem are studied in order to create an algorithm.

Theorem 3.1.1 The Dual problem of problem (11)-(12) is

$$\min_{\alpha} \ \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j((x_i\cdot x_j)+\frac{\delta_{ij}}{C}) - \sum_{i=1}^{l}\alpha_i \tag{13}$$

$$s.t. \ \sum_{i=1}^{l}\alpha_i y_i = 0 \tag{14}$$

Where,

$$\delta_{ij} = \begin{cases} 1 & i=j \\ 0 & i\ne j \end{cases} \tag{15}$$

Proof Introducing the Lagrange function of problems (11)-(12)

$$L(w,b,\eta,\alpha) = \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{l}\eta_i^2 - \sum_{i=1}^{l}\alpha_i(y_i((w\cdot x_i)+b)+\eta_i-1) \tag{16}$$

where $\alpha \in R^l$ is the Lagrange multiplier vector. Finding the minimum of Lagrange function with respect to w,b,η to get the following KKT conditions:

$$w = \sum_{i=1}^{l}\alpha_i y_i x_i \tag{17}$$

$$\sum_{i=1}^{l} y_i\alpha_i = 0 \tag{18}$$

$$\eta = \frac{\alpha}{C} \tag{19}$$

$$y_i((w\cdot x_i)+b)+\eta_i-1=0, i=1,2,\cdots,l \tag{20}$$

Substituting the above conditions into the Lagrange function and finding the maximum of α, the dual problem (13) and (14) are obtained.

Regarding to relations between solution of original problem (11)-(12) and that of dual problem (13)-(14), there are theorems below:

Theorem 3.1.2 The solution (w^*,b^*,η^*) of original problem (11)-(12) exists and the solution is unique.

Theorem 3.1.3 Suppose (w^*,b^*,η^*) is the solution of original problem (11)-(12), then dual problem (13)-(14) must have solution $\alpha^* = (\alpha_1^*,\cdots,\alpha_l^*)^T$ to satisfy

$$w^* = \sum_{i=1}^{l}\alpha_i^* y_i x_i \tag{21}$$

Proof Concluded from Theorem 3.1.1 and Wolfe Theorem, if (w^*,b^*,η^*) is the solution of original problem (11)-(12), and the dual problem (13)-(14) must have the solution which satisfies equation (21).

Theorem 3.1.4 Suppose $\alpha^* = (\alpha_1^*,\cdots,\alpha_l^*)^T$ is an arbitrarily solution of dual problems (13)-(14), then the solution to (w,b) of original problem (11)-(12) exists and must be unique,

$$w^* = \sum_{i=1}^{l}\alpha_i^* y_i x_i \tag{22}$$

$$b^* = y_i(1-\frac{\alpha_i^*}{C}) - \sum_{j=1}^{l}\alpha_j^* y_j(x_j\cdot x_i) \tag{23}$$

Proof**:** Let

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$$H = (y_i y_j((x_i \cdot x_j) + \frac{\delta_{ij}}{C}))_{l\times l}, e = (1,\cdots,1)^T,$$

$$\alpha = (\alpha_1,\cdots,\alpha_l)^T, y = (y_1,\cdots,y_l)^T$$

The dual problem becomes

$$\min_\alpha \quad W(\alpha) = \frac{1}{2}\alpha^T H\alpha - e^T\alpha \tag{24}$$

$$s.t. \quad \alpha^T y = 0 \tag{25}$$

Suppose α^* is the solution of problem (13)-(14), as a result, the Lagrange multiplier b^* must exist and satisfy

$$\alpha^{*T} y = 0 \tag{26}$$

$$H\alpha^* - e + b^* y = 0 \tag{27}$$

Let $w^* = \sum_{i=1}^{l} y_i \alpha_i^* x_i$. According to equation (27), we can get

$$y_i((w^* \cdot x_i) + b^*) = 1 - \eta_i^*, i = 1,2,\cdots,l \tag{28}$$

where

$$\eta_i^* = \frac{\alpha_i^*}{C} \tag{29}$$

Therefore, (w^*, b^*, η^*) is a feasible solution satisfying the original problem (11)-(12).

Furthermore, according to the equation (26)-(27), we can get

$$-\frac{1}{2}\|w^*\|^2 - \frac{C}{2}\sum_{i=1}^{l}\eta_i^{*2} = \frac{1}{2}\alpha^{*T}H\alpha^* - e^T\alpha^*$$

It manifests that the dual problem (13)-(14) and the original problem (11)-(12) have the same objective function value. Accordingly, (w^*, b^*, η^*) is one solution of original problems. Because the solution of the original problem to w is unique, w^* is the unique solution.

Based on KKT condition equation (27), the threshold b^* can be calculated directly,

$$b^* = y_i(1-\eta_i^*) - (w^* \cdot x_i) = y_i(1 - \frac{\alpha_i^*}{C}) - \sum_{j=1}^{l} a_j^* y_j (x_j \cdot x_i)$$

and b^* is unique.

3.2. The SVR Algorithm of Solving Classification Problems

For general nonlinear problems, put the input space R^n into a single mapping $\Phi(\cdot)$, which can transform it to a high-dimensional Hilbert space. In this space, the original optimization problem is constructed and its dual problem is obtained.

$$\min_\alpha \quad \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j (\Phi(x_i)\cdot\Phi(x_j) + \frac{\delta_{ij}}{C}) - \sum_{i=1}^{l} a_i \tag{30}$$

$$s.t. \quad \sum_{i=1}^{l} a_i y_i = 0 \tag{31}$$

The kernel function $K(x_i, x_j)$ is introduced to replace the inner product $(\Phi(x_i)\cdot\Phi(x_j))$ in the dual problem, and then the dual problem becomes,

$$\min_\alpha \quad \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j (K(x_i, x_j) + \frac{\delta_{ij}}{C}) - \sum_{i=1}^{l} a_i \tag{32}$$

$$s.t. \quad \sum_{i=1}^{l} a_i y_i = 0 \tag{33}$$

For $K(x_i, x_j) + \frac{\delta_{ij}}{C}$ in the objective function, it can also be represented by a kernel function

$$\hat{K}(x_i, x_j) = K(x_i, x_j) + \frac{\delta_{ij}}{C} \tag{34}$$

In Hilbert space, Theorems 3.1.2-3.1.4 still hold for the relationship between the solution of dual problem and that of the original problem. Then the formula of the solution to b^* becomes

$$b^* = y_i(1 - \frac{\alpha_i^*}{C}) - \sum_{i=1}^{l} a_i^* y_i K(x_j, x_i) \tag{35}$$

According to theorem 3.1.4, the following algorithm is established:

Algorithm 3.2.1 The SVR Algorithm for Solving Classification Problems

(i) Assume a known training set

$T = \{(x_1, y_1),\cdots,(x_l, x_l)\} \in (X \times Y)^l$, here, $x_i \in X = R^n, y_i \in Y = \{-1,1\}$, $i = 1,2,\cdots,l$

(ii) Choose a suitable positive C and a kernel $K(x, x')$;

(iii) Construct the problem and find the solution of

$$\min_\alpha \quad \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j (K(x_i, x_j) + \frac{\delta_{ij}}{C}) - \sum_{i=1}^{l} a_i \tag{36}$$

$$s.t. \quad \sum_{i=1}^{l} a_i y_i = 0 \tag{37}$$

The optimum solution is obtained $a^* = (a_1^*, \cdots a_l^*)^T$

(iv) Create a decisive function

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{l} a_i^* y_i K(x_i, x) + b^*) \tag{38}$$

Here b^* is given by equation (35).

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3.3. The Numerical Experiments

In order to verify the proposed Algorithm3.2.1, a test is conducted on Iris data set [3]. The Iris data set is a standard data set used to test the performance of classification algorithms. The data set contains 150 sample points divided into three categories: I(Iris-setosa), II(Iris-versicolor) and III(Iris-virginica). Each category contains 50 sample points and each sample point has four properties [8].

There are three two-class classification problems: Class I and II are considered as positive classes and Class III is a negative class; Class I and III are positive classes when Class II is a negative class; or Class II and III are positive classes when Class I is a negative class. In each of the two-class classification problems there are 150 sample points. These sample points are randomly grouped into training set and testing set. The training set contains 50 positive points and 25 negative points, while the testing set contains 50 positive points and 25 negative points. The trainings are conducted by using Algorithm 3.2.1 and standard C-SVM. During the training process, the RBF Kernel function is adopted for the two algorithms. The parameter C is set to be 0.1, l, 10, 100, 1000, 10000 and so on. The decisive functions gained in each training session are tested, and each testing result is recorded. Finally by computing and comparing the average testing accuracy, results are shown in the table 1.

Table 1. Result Comparison Table

Classification	C-SVC	Algorithm 3.2.1
{I, II} - III	95.6%	96.1%
{II, III} - I	100%	100%
{I, III} - II	97.5%	97.2%

From the above comparison results, obviously testing accuracy rates from Algorithm 3.2.1 and C-SVC are close to equal.

4. THE APPLICATION OF CLASSIFICATION ALGORITHM OF REGRESSION SUPPORT VECTOR MACHINE ON ENHANCING THE THERMAL CONDUCTIVITY OF ANTIFREEZE SOLUTIONS

In running ground source heat pump system, eight kinds of antifreeze solutions are mixed with different proportions, that is to take n = 8. 1000 trials of mixed antifreeze solutions are tested, that is to take l=1000. Each one is labeled as qualified (+1) or not (-1), so that the training set is $T=\{(x_1,y_1),...,(x_{1000},y_{1000})\}$, where $x_i=(a_{i1},a_{i2},...,a_{i8})$, $y_i=\pm1$, i=1,2,...,1000. From here, the actual training decision-making is processed and the decision-making information system is built based on Classification Algorithm of Regression Support Vector Machine.

4.1. Data Preprocessing

It can be seen from observing data that some indicator values are small and some indicator values are large. Therefore, data values should be standardized first. The standardization method used here is minimum-maximum standardization method and the formula is:

$$[x_j]_i' = ([x_j]_i - \min_{j=1,...,100}([x_j]_i)) / (\max_{j=1,...,100}([x_j]_i - \min_{j=1,...,100}([x_j]_i))) \quad (39)$$

With this method, the dataset can be standardized into D'.

Then the dataset D' is divided into 2 parts according to the proportion of seven to three randomly, in which one part is Training Set T and the amount of training points into it is recorded as l (l=700 here); the other part is Testing Set S and the amount of training points into it is recorded as m (m=300 here). Let the amount of positive points in the training set be T_+, the amount of negative points be T-, the amount of positive points in the Testing Set be S_+, and the amount of negative points be S-. From observing data, it can be seen that the amount of negative points which do not satisfy requirements, is 260, while the amount of positive points which are eligible is 440. The positive and negative point counts are not equal. Therefore, different penalty parameters C_+ and C_- are given to these two type of points. The penalty parameters C_+ and C_- are derived from the following formulas:

$$c_+ = c\times\frac{T_-}{l}, \quad c_- = c\times\frac{T_+}{l} \quad (40)$$

Here, C>0 is given.

4.2. Model Selection

Aiming at the classification problems above, first we need to determine a proper arithmetic model. Here there are three Support Vector Machine (SVM) models. The first one is Weighted Proximal SVM. The problem to be solved is

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$$\min_{\alpha} \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j (K(x_i, x_j) + \frac{\delta_{ij}}{C}) - \sum_{i=1}^{l} a_i \quad (41)$$

$$s.t. \sum_{i=1}^{l} a_i y_i = 0 \quad (42)$$

The second one is Weighted Transductive SVM model. The third one is Weighted Standard SVM model [9]. After these three models are confirmed, the corresponding parameters are selected including kernel function $k(x, x')$ and C, C*, and parameters in kernel function. We choose the kernel function as the radial base kernel function[10].

$$k(x, x') = \exp(-\frac{\left\|x - x'\right\|^2}{\sigma^2}) \quad (43)$$

The parameters to be selected are C, C*and σ.

According to lattice method, the optimum parameters are needed to choose for each model. The value range of C and C* is {0.1,1,10,100,1000,10000} and the numeric area of σ is {0.1,0.2,0.5,1,2,5} so that the parameter group (C, C^*, σ) is constituted to calculate LOO error. The parameter group $(\overline{C}, \overline{C}^*, \overline{\sigma})$ satisfying the minimum LOO error is the optimum value. In the application, the optimum parameter group values are equal to $(\overline{C} = 10, \overline{\sigma} = 1.5)$ for the Weighted Proximal SVM model. The Weighted Transductive SVM model corresponds with the optimum parameter group $(\overline{C} = 100, \overline{C}^* = 100, \overline{\sigma} = 2)$. The Weighted Standard SVM model has the optimum parameter $(\overline{C} = 10, \overline{\sigma} = 5)$.

4.3. Result

These three groups of optimum parameters are applied to three Support Vector Machine models respectively in order to get final decision functions and to measure the points in the Testing Set S. The results are shown in the table 2.

Table 2 Result Comparison

Testing Result	C-SVC	TSVC	Algorithm 3.2.1
Detection Precision	83%	87%	89%
Error Rate	3%	0%	1%
Detection Rate	67%	68%	86%

C-SVC in this diagram is the weighted standard support vector machine; TSVC is the weighted transductive support vector machine.

Here, detection precision is the ratio of the number of the correctly detected samples in the Testing Set over the total number of samples in the Testing Set[11]; Error rate is the ratio of the number of positive points detected falsely to be negative over the total number of positive points; detection rate is the ratio of the number of detected negative points over the total number of negative points.

The result above indicates that the classification algorithm of regression support vector machine performs the highest detection precision in solving the problem of antifreeze thermal conductivity. In ground source heat pump system, given certain antifreeze mixing proportion ratio, we can confirm if this ratio is optimal by inputting sample data into the decision-making system. If the output is equal to +1, it is feasible and executable; if the output equals -1, the antifreeze concentration or dosage is to be adjusted (starting with those antifreezes with low prices and small corrosion) until the decision-making system outputs +1. This ratio is the optimal mixing proportion ratio.

5. CONCLUSION

In summary, it is feasible to apply support vector machines to determine the optimal proportion of antifreeze solutions and thus maximize the thermal conductivity of ground source heat pump systems. A variety of support vector machine models improve the decision-making process on different levels, while specific models should be decided based on actual situations to achieve the highest precision. As shown above, support vector machines can provide optimal decision-making solutions to classification-related problems. The results from three years of research and experimentation manifest that the optimized decision-making system based on a support vector machine model provide significant decision-making effects in management and economic benefits to enterprises.

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