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Prediction of heat transfer rate of a Wire-on-Tube type heat exchanger: An Artificial Intelligence approach

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Abstract

In this paper, an innovative approach is used to predict the rate of heat transfer of a wire-on-tube type heat exchanger by utilizing the support vector machine model. Heat exchangers have been a well-studied subject over the past decades. Various approaches have been used to determine the heat transfer rate of heat exchangers. To solve this algorithm, a computer program was developed using MATLAB software. This helped us formulate an equation for the total heat transfer which gave minimal error when compared to traditional techniques. This model exhibits inherent advantages due to its use of the structural risk minimization principle in formulating cost functions and of quadratic programming during model optimization. A comparative study between the artificial neural network and the support vector machine approach is also illustrated. The paper then provides its conclusion.

Keywords: Artificial Neural Network(ANN); heat exchanger; kernel mapping; Support Vector Machines(SVMs)

1. Introduction

Wire-on-tube heat exchangers are more often used by refrigerator manufacturers [1] (as condensers) mainly due to their simple construction, ruggedness and low cost. This type of heat exchanger consists of a single steel tube, bent into serpentine parallel passes carrying the fluid, mainly refrigerant and solid steel wires are attached to the tube to increase the surface area. . The exchanger, tested by Lee et al. [2], is presented in Fig. 1. [3]The solid wires are spot welded on to diametrically opposite sides of the tubes as shown in Fig. 1.The refrigerant enters the tube in a vapor state and leaves the condenser in a liquid state thereby undergoing a phase change. The heat transfer takes place

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from the outer surfaces of the wires and tubes to the external environment either by free or by forced convection [4-5]. Hence it is very important to find out the heat transfer rate for this type of heat exchanger. One of the models used to predict the heat transfer rate of a wire-on-tube heat exchanger is the Artificial Neural Network model (ANN)[6].ANN's techniques inspired by biological nervous systems have been used to solve a wide variety of complex scientific, engineering and business problems [7]. However ANN's major drawbacks include its "black box" nature [8], greater computational burden, proneness to overfitting and the empirical nature of model development. To overcome these problems, we use another modeling technique called the Support Vector Machine (SVM). SVMs were first developed by Vapnik in 1992[9]. It was originated from the concept of statistical learning theory pioneered by Boser et al. in 1992. SVM is a machine learning technique that allows the combination of the simplicity and the uniqueness of linear models with the possibility of a highly nonlinear, kernel based, pre-processing into a possibly infinite dimensional extended feature space [10].This results in powerful models that can be applied to classification and regression problems [11-14]. While quite simple, SVM estimates the regression using a set of linear functions that are defined in a high-dimensional space. They require the selection of two structural parameters, the penalty term that is applied to margin slack values and, in the case of Support Vector Regression (SVR), the tolerance threshold under which the errors are not penalized [10]. The objective of this paper is to develop the required heat transfer rate equation (using SVM modeling technique) and to compare the actual output and the output obtained from ANN modeling technique. These experiments and their comparative results are discussed in the following sections, and finally the paper presents its conclusions.

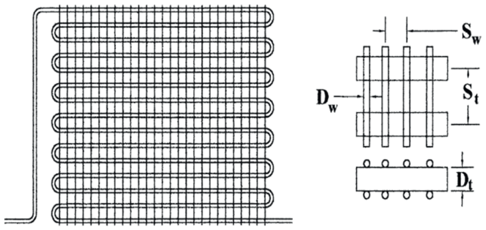

Fig. 1 Wire-on-Tube Heat Exchanger

Nomenclature

A	heat transfer surface area (m^2)
D	diameter (m)
G	volumetric flow rate (m^3/s)
L	length (m)
m	mass flow rate (kg/h)
q	heat transfer rate (watt)
s	spacing (m^3)
T	temperature (°C)
W	width (m)
Subscripts	
a	air
cond	condensation
emp	empirical
i	inlet
r	refrigerant
T	temperature
t	tube
w	wire

2. Description of selected model

2.1. Support Vector Machine

SVM has been used successfully in many engineering applications such as heat transfer correlation for two phase flow in vertical pipes [15], prediction of Lake water level [16], forecasting power output of photo-voltaic systems based on weather conditions [17] and optimization of biogas production process in a wastewater treatment plant [18]. SVM is a general learning method developed from Statistical Learning Theory with better performance than many other routine methods. Statistical Learning Theory is based on a set of rigid theory foundation that provides a united frame in order to solve the problem of limited sample learning [16]. In this paper, the SVM model from Haykin (1999) is described in detail, with an assumption that most readers might not have been exposed to this model before. Fig. 2 shows the basic architecture of SVM model. It shows the input and output parameters along with the hidden nodes. In this SVM model, we make use of radial basis function in the generation of a generalized equation. The basic idea of SVM applied to regression prediction is described as follows [16]: Let us consider a non-linear regressive model in which the dependence of scalar on a vector is described by

$$d = f(x) + v \quad (1)$$

where both the non-linear function $f(.)$ and the statistics of the additive noise v are unknown. This additive noise is statistically independent of the input vector. All the information we have is a set of training data $\{(x_i, d_i)\}_{i=1}^{N}$ where x_i = sample value of the input vector x and d_i = corresponding value of the target output d .

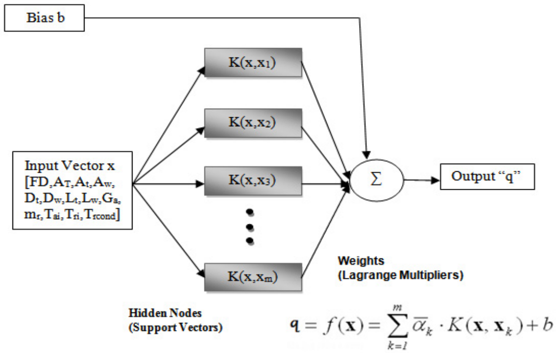

Fig. 2 Architecture of SVM

The problem is to provide an estimate of the dependence of d on x. In performing nonlinear regression we map the input vector x into a high-dimensional feature space in which we then perform linear regression. Let x denote the vector drawn from the input space, assumed to be of dimension m_0. Let $\{\varphi_j(x)\}_{j=1}^{m_1}$ denote the set of nonlinear transformations from the input space to the feature space: m_1 =dimension of the featured space, which is determined by the number of support vectors (a subset of input vectors). The architecture of SVM is shown in Fig. 2, where

$$K(x, x_i) = \varphi^T(x)\varphi(x_i), \; i = 1, 2, .., m_1 \quad (1)$$

It is assumed that $\varphi_j(x)$ is defined a priori for all j. Given such a set of nonlinear transformations, we may define an estimate of d, denoted by y as follows

$$y = \sum_{i=1}^{m_1} w_j \varphi_j(x) + b \tag{2}$$

where $\{w_j\}_{j=1}^{m_1}$ defines a set of linear weights connecting the feature space to the outer space; and $b =$ bias. We may simply matters by writing

$$y = \sum_{i=0}^{m_1} w_j \varphi_j(x) \tag{3a}$$

$$y = w^T \varphi(x) \tag{3b}$$

where it is assumed that $\varphi_0(x) = 1$ for all x, so that w_0 denotes the bias b. Equation (3) defines the regression equation computed in the feature space in terms of linear weights of the machine. The quantity $\varphi_j(x)$ represents the input supplied to the weights w_j through the feature space where

$$\varphi(x) = \left[\varphi_0(x), \varphi_1(x), \varphi_2(x), .., \varphi_{m_1}(x)\right]^T \tag{4a}$$

And $w = \left[w_0, w_1, w_2, .., w_{m_1}\right]^T$ (4b)

The optimal regression function is obtained by minimizing the empirical risk

$$R_{emp} = \frac{1}{N} \sum_{i=1}^{N} L_s(d_i, y_i) \tag{5}$$

Subject to the inequality

(6)

where $c_0 =$ constant and $L_\varepsilon(d, y)$ is called the ε-insensitive loss function, originally proposed by Vapnik (1995, 1998) and described in Haykin (1999) as follows

$$L_\varepsilon(d, y) = \begin{cases} |d - y| - \varepsilon \; for \; |d - y| \geq \varepsilon \\ 0 otherwise \end{cases} \tag{7}$$

where ε =prescribed parameter. The loss function is equal to the absolute value of the deviation minus ε if the discrepancy between the predicted and actual value is less than ε and is equal to zero otherwise. The above constrained optimization problem may be reformulated by introducing two sets of nonnegative slack variables $\{\xi_i\}_{i=1}^{N}$ and $\{\xi_i\}_{i=1}^{N}$ representing upper and lower constraints on the outputs of the system, defined as follows

$$d_i - w^T\varphi(x_i) \le \varepsilon + \xi_i \tag{8}$$

$$w^T\varphi(x_i) - d_i \le \varepsilon + \xi_i^{'} \tag{9}$$

$$\xi_i \ge 0 \; i = 1,2,..,N \tag{10}$$

$$\xi_i^{'} \ge 0 \; i = 1,2,..,N \tag{11}$$

The constrained optimization problem may therefore be viewed as equivalent to that of minimizing the cost functional

$$\Phi(w,\xi,\xi_i) = c\left(\sum_{i=1}^{N}\left(\xi_i + \xi_i^{'}\right)\right) + \frac{1}{2}w^T w \tag{12}$$

Subject to the constraints of Eq. (8 – 11)

Incorporation of the term $\frac{1}{2}w^T w$ in the cost functional dispenses with the need for the inequality constraints of Eq. (6). The constant in Eq. (12) (Lagrangian function) is constructed from both the objective function and the corresponding constraints as follows

$$J(w,\xi,\xi^{'},\alpha,\alpha^{'},\gamma,\gamma^{'}) = C\left(\sum_{i=1}^{N}\left(\xi_i + \xi_i^{'}\right)\right) + \frac{1}{2}w^T w - \sum_{i=1}^{N}\alpha_i\left[w^T\varphi(x_i) - d_i + \varepsilon + \xi_i\right] - \sum_{i=1}^{N}\alpha_i^{'}\left[d_i - w^T\varphi(x_i) + \varepsilon + \xi_i^{'}\right] - \sum_{i=1}^{N}\left(\gamma_i\xi_i + \gamma_i^{'}\xi_i^{'}\right) \tag{13}$$

where α_i and $\alpha_i^{'}$ Lagrange multipliers. The last term on the right-hand side of Eq. (13), involving γ_i and $\gamma_i^{'}$ is included to ensure that the optimality constraints on the Lagrange multipliers α_i and $\alpha_i^{'}$ assume variable forms. The requirement is to minimize $J(w,\xi,\xi^{'},\alpha,\alpha^{'},\gamma,\gamma^{'})$ with respect to the weights vector w and slack variables ξ and $\xi^{'}$; it must also be maximized with respect to α and $\alpha^{'}$ as well as to γ and $\gamma^{'}$. The partial derivatives of Lagrangian function with respect to those variables have to vanish for optimality, producing the following results

$$w = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^{'} \right) \varphi(x_i)$$

(14) $\gamma_i = C - \alpha_i$ (15)

And $\gamma_i^{'} = C - \alpha_i^{'}$ (16)

The optimization of $J(w, \xi, \xi^{'}, \alpha, \alpha^{'}, \gamma, \gamma^{'})$ just described is the fundamental problem in nonlinear regression. We may obtain the corresponding dual problem after substituting Eq. (14 - 16) In Eq. (13), which can be written in the convex functional form after some simplification as follows

$$Q(\alpha_i, \alpha_i^{'}) = \sum_{i=1}^{N} d_i \left(\alpha_i - \alpha_i^{'} \right) - \varepsilon \sum_{i=1}^{N} \left(\alpha_i + \alpha_i^{'} \right) - \frac{1}{2} \sum_{\substack{1 \le i \le N \\ 1 \le j \le N}} \left(\left(\alpha_i - \alpha_i^{'} \right) \left(\alpha_j - \alpha_j^{'} \right) K\left(x_i, x_j \right) \right)$$

(17)

where $K\left(x_i, x_j\right) =$ inner-product kernel defined as follows

$$K\left(x_i, x_j\right) = \varphi^T(x_i)\varphi(x_j) \quad (18)$$

The solution to that constrained optimization problem is thus obtained by maximizing $Q(\alpha, \alpha^{'})$ with respect to the Lagrange multipliers α and $\alpha^{'}$ subject to a new set of constraints described below that incorporates the constant C included in the definition of the function $\Phi(w, \xi, \xi^{'})$ in Eq.(12).

We may now state the dual problem for nonlinear regression using SVM as follows:
Given the training sample $\{x_i, d_i\}$, find the Lagrange multipliers α_i and $\alpha_i^{'}$ that maximize the objective function in Eq.(17) subject to the following constraints:

$$\sum_{i=1}^{N} \left(\alpha_i - \alpha_i^{'} \right) = 0 \text{ and}$$

$$0 \le \alpha_i \le C \quad i = 1, 2, .., N$$

and $0 \le \alpha_i^{'} \le C \quad i = 1, 2, .., N$

where $C =$ user-specified constant. The constraint in Eq.(1) arises from optimization of the Lagrangian with respect to the bias $b = w_0$ for $\varphi_0(x) = 1$. Thus, having obtained the optimum values of α_i and $\alpha_i^{'}$, we may then use Eq.(14) to determine the optimum value of the weight vector w for a prescribed map $\varphi(x)$. The data points for which $\alpha_i \neq \alpha_i^{'}$ define the support vectors for the machine, and the approximating regression function is given by

$$y = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^{'} \right) K(x, x_i) \tag{19}$$

$$K(x, x_i) = \exp\{-\frac{(x_i - x)(x_i - x)^T}{2\sigma^2}\} \tag{20}$$

the two parameters ε and C must be selected by user, and the choices of ε and C control the complexity of the regression.

3. Collection of data

As far as, air flow in wire-on-tube type heat exchanger is concerned; it can be classified into the following three categories based on how each part contacts air flow:

- All cross (AC): the air passes through both the tubes and the wires.
- Wire cross (WC): the air passes through the wires, whereas it passes along the tubes.
- Tube cross (TC): the air passes through the tubes, whereas it passes along the wires.

The experiments were conducted for single layer samples of wire-on-tube type heat exchanger. The mathematical background, the procedures for training and testing the ANNs, and an account of its history can be found in the book by Simon Haykin [19-22].Test conditions and results are given in Table 1. In developing the SVMs model, the available data set is divided into 2, one to be used for training of the network (73.8% of the data), and the rest for testing the performance [20]. The training process is carried out by comparing the output from the network to the given data. The data is then normalized between 0-1 for further calculation.

Table 1. Training data set for the SVM model

Test no.	Flow Direction	A_T	A_t	A_w	D_t	D_w	L_t *	L_w	G_a	m_r	T_{ai}	T_{ri}	T_{rcond}	q
1	AC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.901	3.96	29.4	63.1	36.8	88.6
2	AC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.553	3.99	29.5	63.4	36.8	76.0
3	AC	0.32	0.16	0.16	4.76	1.53	10.9	158	0.924	3.99	29.6	63.5	36.7	52.1
4	TC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.920	3.98	29.4	64.8	36.7	79.9
5	TC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.408	3.97	29.7	64.6	36.8	70.0
6	TC	0.32	0.16	0.16	4.76	1.53	10.9	158	0.924	3.95	29.4	64.7	36.8	55.0
7	WC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.939	3.99	29.7	63.2	36.8	77.9
8	WC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.212	3.99	29.8	63.1	36.8	58.9
9	WC	0.32	0.16	0.16	4.76	1.53	10.9	158	0.897	4.03	29.7	63.3	36.8	50.6
10	AC	0.30	0.10	0.20	4.76	1.53	06.8	142	1.920	3.93	29.6	63.9	36.8	87.4
11	AC	0.30	0.10	0.20	4.76	1.53	06.8	142	1.510	3.96	29.8	63.9	36.8	74.7
12	AC	0.30	0.10	0.20	4.76	1.53	06.8	142	0.790	3.89	29.7	63.9	36.8	52.0
13	AC	0.39	0.13	0.26	4.76	1.53	08.8	142	1.910	4.04	29.6	65.9	36.8	95.9
14	AC	0.39	0.13	0.26	4.76	1.53	08.8	142	0.907	4.01	29.8	66.1	36.8	61.3

Table 2. Testing data set for the SVM model

Test no.	Flow Direction	A_T	A_t	A_w	D_t	D_w	L_t *	L_w	G_a	m_r	T_{ai}	T_{ri}	T_{rcond}	q
1	AC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.210	3.97	29.6	63.4	36.8	64.4
2	TC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.692	3.94	29.5	64.7	36.8	76.7
3	WC	0.32	0.16	0.16	4.76	1.53	10.9	158	1.551	3.95	29.4	63.1	36.7	66.9
4	AC	0.30	0.10	0.20	4.76	1.53	06.8	142	1.250	3.99	29.6	64.0	36.7	69.1
5	AC	0.39	0.13	0.26	4.76	1.53	08.8	142	1.207	4.00	29.7	65.9	36.8	70.9

4. Performance of Training and Testing Data

The graphs (Fig 3) plotted below depict the performance of the training and the testing data using Radial Basis Function (RBF). The value of coefficient of Correlation (R) is found out to be 0.9995 and 0.9997 for the training data and testing data respectively. The graph (Fig. 4) plotted between the beta values and the training data set is drawn below. The Table 3 illustrates the values of the beta and the corresponding values of heat transfer rate (q). These figures are later on used in the results and discussion.

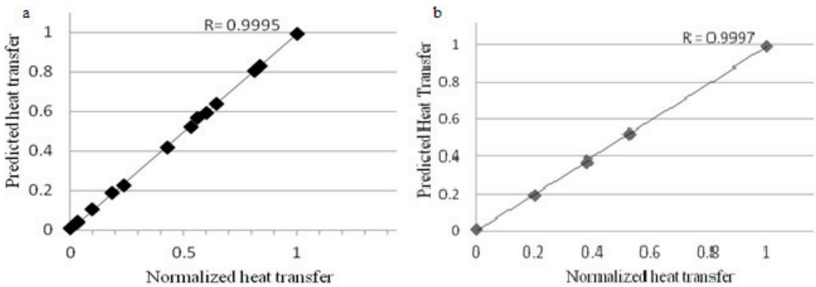

Fig. 3. (a) Performance of training data using RBF; (b) Performance of testing data using RBF

i	$\alpha_i - \alpha_i^*$	$q_{predicted}$	i	$\alpha_i - \alpha_i^*$	$q_{predicted}$
1	0.8479	88.19447	8	0	59.22059
2	-0.3069	76.40741	9	-0.0826	51.0077
3	-0.0192	52.50713	10	0.6903	86.99402
4	0.5817	79.49234	11	0.2263	74.2919
5	0.4101	69.59429	12	-0.0982	52.40747
6	-0.158	55.40633	13	0.9556	95.4923
7	0.3364	77.49008	14	0.1033	60.89216

Table 3. Predicted Heat Transfer and Beta values

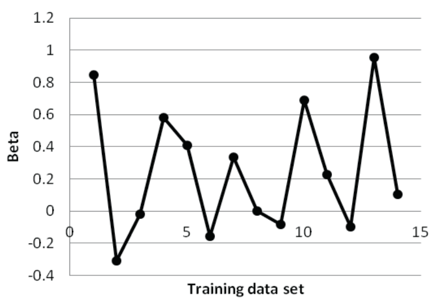

Fig. 4 Beta values for Training Data Set

Fig. 5. Comparison between ANN and SVM

5. Results and Discussion

In the design of the system we took the prescribed parameter ε =0.009, the user specified constant $C = 200$ and σ =0.5. The selection of these constants helped us design a system with a Coefficient of Correlation(R) = 0.9997 for testing data and R=0.9995 for the training data as shown in Fig 3. Overfitting is present if the difference in the value of R in case of training and testing data is very large. Since the value of R is almost the same in both training as well as testing performance, we can say that our model is not prone to overfitting and thus is a good model. Also a system with **R** =1 is a perfect system hence our system with **R** =0.9997 close to being perfect. The performance of the training and the testing data are shown in the graphs above. The straight line proves that our system is a good one and is close to the predicted value of the heat transfer rate. The bar chart (Fig. 5) plotted between % relative error and the type of neural network depicts that the relative error in case of SVM is much lesser when compared to ANN. A significant advantage of SVMs is that whilst ANNs can suffer from multiple local minima, the solution to an SVM is global and unique. SVMs generate an equation which can be used for further calculations whereas in case of ANNs, it does not generate any sort of equation. The equation in this case is

$$q = \sum_{i=1}^{14} \left(\alpha_i - \alpha_i^*\right) \exp\{-\frac{(x_i - x)(x_i - x)^T}{0.5}\} \tag{21}$$

6. Comparison

Table 4 below lays out the different values of the heat transfer calculated by ANN and SVM model respectively and compares the value with the actual heat transfer value that has been determined by experimental techniques. Table 5 on the other hand calculates the percentage relative error. The histogram (Fig. 5) plotted thereafter compares the relative errors calculated from the ANN and SVM modeling techniques.

Table 4 Comparison between ANN and SVM

Test no-flow direction	q (kcal/h) (experimental results)	q (kcal/h) (ANN result)	q (kcal/h) (SVM results)
3-AC	64.40	61.88	64.5107
6-TC	76.70	76.71	76.5893
10-WC	66.90	71.97	66.78989
15-AC	69.10	68.74	68.98913
18-AC	70.90	76.53	70.78985

Table 5 Percentage Relative Error

Test no-flow direction	ANN vs. Q	SVM vs. Q
3-AC	3.91	0.1719
6-TC	0.02	0.1443
10-WC	7.59	0.1646
15-AC	0.53	0.1604
18-AC	7.94	0.1554

7. Conclusion

This above article describes SVM modelling approach towards the determination of the rate of heat transfer in case of a wire-on-tube type of heat exchanger. A comparison between the two different types of modelling techniques SVM and ANN is illustrated. As seen in the results table, the relative error in the prediction of heat transfer rate is higher in the ANN modelling technique. Thus the SVM modelling approach gives us a better performance and a more accurate result. The developed equation can thereby be used by the user for the prediction of the rate of heat transfer in a wire-on-tube type of heat exchanger.

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