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Application of an effective strategy for optimizing the design of air curtains for open vertical refrigerated display cases

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ABSTRACT

This paper presents a novel strategy for optimizing the design of air curtains for open vertical refrigerated display cases which is based on an air curtain two-fluid of cooling loss (CLTF) model and a support vector machine (SVM) algorithm. A model for air curtain cooling loss, one important performance factor of display cases, is proposed. To verify the air curtain cooling loss and determine which design parameters significantly influence the performance of air curtains in open vertical display cases, the CLTF model was built to study the flow and transfer of heat through air curtains used in such display cases. After the object function for cooling loss is constructed, it is solved using an SVM algorithm with different input design parameter combinations. As a result, the predicted cooling loss is reduced by 19.6%. After being validated using experimental data, the TEC/TDA of optimum display case is found to be reduced by 17.1%. The experimental results show this strategy to be an effective method of optimizing the air curtain design.

1. Introduction

Open vertical display cases, despite being high consumers of energy are a common type of case which makes it possible to display large amounts of food within a small area in the store. Therefore, the open vertical case is probably one of the most important components in the supermarket system even though cases with permanent glass doors can reduce energy consumption by 50% [1].

Although many studies have been conducted on the performance of display cases [2–9], most of them only emphasize a few aspects by performing experiments or computational fluid dynamics (CFD) software simulations. As a result, few studies have presented systematic strategies for performance optimization by investigating the relationship between multiple parameters. Nevertheless, accurate optimization strategies will help manufacturers effectively and quickly design better display cases. This paper, attempts to fill this gap. In particular, we investigate strategies for the optimization of the air curtain in open vertical refrigerated display case based on the CLTF model and SVM algorithm.

The two-fluid model, proposed by Spalding [10–16], can be summarized as follows.

(1) Turbulent flow is considered as comprehensive motion for each fluid and interactions [17–19].
(2) There is respective volume fraction for the two fluids, i.e., the two fluids exist respectively with certain probability.
(3) The two fluids, whose motions respectively follow their controlled differential equations, infiltrate each other as a continuum.
(4) The dividing characteristics of two fluids are the concentration, temperature, or flow direction, etc.

Yu et al. [20,21] applied the two-fluid model to the simulation of the air curtain for vertical display cases, which successfully gained a better prediction of performance of the air curtain including the thermal field outside the case and the cold air overspill from the case to the store.

Recently, artificial neural algorithms have been a preferred method for modeling thermal applications [22]. Unlike traditional artificial neural algorithms which implement the ERM (empirical risk minimization) principle, modeling using the support vector machine (SVM) which implements the SRM (structured risk minimization) principle demands fewer samples to obtain a good level of performance which reduces the time and cost to obtain the experimental samples. Moreover, the SVM solution is unique, optimal and unlikely to generate local minima. The basic SVM deals with two-class problems, in which the data are separated by a hyper-plane defined by a number of support vectors. However,

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with the introduction of Vapnik's ε-insensitive loss function and kernel function, SVM has been extended to solve problems involving nonlinear regression estimation and noise characterization [23]. Based on the statistical learning theory, the SVM which is a novel method with good theoretical properties, has been developed and widely used recently in the HVAC and refrigeration field [24–28]. However, as a machine learning method, the SVM needs the output samples and input samples for training.

2. Materials and methods

2.1. The display case

The object of this investigation is an open vertical display case with a single chilled air curtain (Fig. 1). The dimensional features are: Length 2.45 m, height 2 m, depth 1.1 m and display opening height 1.63 m. The width of air curtain discharge opening is 82 mm, and the width of return opening is 88 mm with the width of grille 4 mm.

Experiments and heat balance investigations show the importance of the interaction between the interior condition in the case and the ambient condition in the store. The heat loads in a display case can be illustrated as follows:

$$Q = Q_{cur} + Q_{rad} + Q_{cond} + Q_{in} \tag{1}$$

where, Q_{cur} refers to the cooling loss from the refrigerated air in the air curtain; Q_{rad} refers to the radiation cooling loss from the case walls; Q_{cond} refers to the cooling loss from the case walls through conduction; and Q_{in} refers to heating power inside the case (including heating power of fans, lightings, etc.).

As shown in Fig. 2, for the open vertical display case, the heat from the external environment which enters by infiltration through the air curtain makes up the majority of the heat load in the display case [29]. In addition, when the temperature field inside the case reaches equilibrium, i.e., there is no heat transfer inside the case, all the heat consumption, called the air curtain cooling loss, is in the heat exchange between the case and the ambient air. Therefore, the air curtain cooling loss is the key factor affecting the performance of display cases. By decreasing the air curtain cooling loss, the performance of display cases can be improved, and the energy consumption can be decreased simultaneously (c.f. Part 3.3).

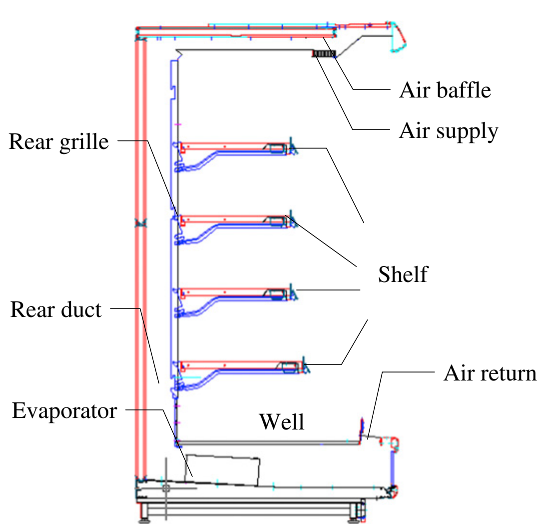

Fig. 1. Open vertical refrigerated display case.

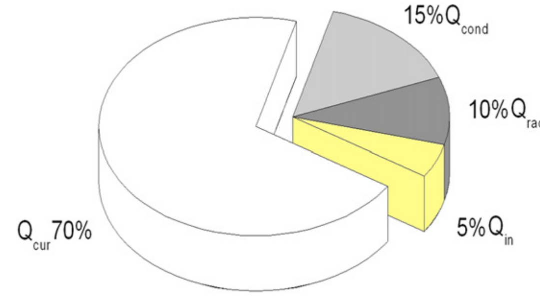

Fig. 2. Make up of display case heat load.

2.2. CLTF model

In order to apply the two-fluid model, the air curtain system is divided into the air curtain and the ambient air. The air exiting the back panel, the inner and the outer air curtains are defined as fluid 1 (the turbulent fluid), and the ambient air is defined as fluid 2 (the non-turbulent fluid).

Based on the initial two-fluid model, the CLTF model without gas diffusion is shown as follows.

$$\frac{\partial}{\partial t}(\rho_i\delta_i\phi_i) + div(\rho_i\delta_i\vec{u_i}\phi_i) = div(\delta_i\Gamma_{\phi i}grad\phi_i) + S_{\phi i} + L_{\phi i} \tag{2}$$

where the equation is made up of a transient term, a convection term, a diffusion term, the inside source term for each fluid, and the interaction source term of two fluids (cooling loss term); the subscript i is 1 or 2, denoting fluid 1 or fluid 2; δ denotes volume fraction of the fluid; ϕ denotes a general dependent variable (when ϕ is 1, the equation is corresponding to continuity equation; when ϕ is velocity, temperature, k, and ξ, the terms making up the equation respectively correspond to the momentum equation, energy equation, turbulent kinetic energy equation, and the dissipation rate equation.).

From the theoretical model, the governing equations of two fluids are derived. The derivation of these equations is described well in Yu et al.'s study [20,21]. In this paper, only the concrete expression of cooling loss term is presented in Table 1.

Because of the mutual entrainment of fluid 1 and fluid 2, the value of fluid mass transfer rate per unit volume m can be positive or negative. The expression of m in Table 1 is then given by [30]:

$$m = c_m\rho_1\delta_1\delta_2(\delta_2 - 0.5)\left|\vec{u_1} - \vec{u_2}\right|/h \tag{3}$$

It is considered that the momentum term I and energy term E are proportional to the volume fraction δ of the two fluids and the slip velocity $\vec{u}$. Meanwhile, they are inversely proportional to the Prandtl mixing length h. The momentum term I and energy term E are given by [20,21]:

$$I_{12} = c_I\rho_1\delta_1\delta_2\left(\vec{u_2} - \vec{u_1}\right)\left|\vec{u_1} - \vec{u_2}\right|/h \tag{4}$$

$$E_{12} = c_Ec_p\rho_1\delta_1\delta_2(T_2 - T_1)\left|\vec{u_1} - \vec{u_2}\right|/h \tag{5}$$

Table 1
Expression of cooling loss.

Cooling loss term	Continuity equation	Momentum equation	Energy equation	Turbulent kinetic energy equation	Dissipation rate equation
$L_{\phi 1}$	m	$\vec{u_2}q + I_{12}$	$T_2q + E_{12}/c_p$	0	0
$L_{\phi 2}$	$-m$	$-\vec{u_2}q - I_{12}$	$-T_2q - E_{12}/c_p$	NA	NA

Fig. 3. Temperature test inside display case.

where c_m, c_l, and c_E are the empirical constants, 10.0, 0.05, and 0.05, respectively [30,31]; c_p is the specific heat of air at constant pressure.

2.3. Comparison of simulation and experiment results

The experimental display case system consists of three loops: the refrigerant loop, the condensing air loop and the evaporating air curtain loop. The refrigerant loop is a single-stage vapor compression plant, using R22 as working fluid, fundamental components of which are as follows: a reciprocating open type compressor, a thermostatic expansion valve, and a fin-tube condenser.

To validate the accuracy of the CLTF model presented, an experiment was conducted testing the temperature field inside the case which is loaded with M-packages. The following parameters were set in the experiments and CLTF model. The air supply temperature (T_s) is 0 °C, the air supply velocity (v_s) is 0.8 m s^{-1} (TESTO 435 with uncertainty of 0.5%), the ambient temperature (T_a) is 25 °C, the ambient relative humidity (φ_a) is 60% (with uncertainty of 1% of the full scale range), and the variation of the baffle position (Δh) is 0 mm. As shown in Fig. 3, six measuring points (T-type thermocouples with uncertainty of ±0.1 °C) are uniformly set up along the longitudinal direction of each shelf or well (the bottom shelf). All the measurements were recorded by a temperature acquisition logger at intervals of 60 s for a period of 12 h with the average value then calculated for comparison with the modeled predictions. In addition, the temperature of second shelf was not analyzed so as to comply with the European Standard EN ISO 23953-2 [32].

As shown in Fig. 4, the maximum and mean temperature deviation between the simulated results and results obtained experimentally were −0.8 °C and −0.4 °C, respectively. Meanwhile, the root mean squared deviation of the simulated results is 0.32 °C. The results show that the simulation data of the CLTF model coincide well with the actual temperature field.

2.4. Determination of air curtain cooling loss function

As shown in Fig. 5, the factors influencing the air curtain cooling loss derived by CLTF model can be determined by changing some parameters such as the air supply velocity. From an analysis of the simulated results, the factors which significantly influence the air curtain cooling loss are summarized as follows: air supply temperature (T_s), air return temperature (T_r), air supply velocity (v_s), ambient temperature (T_a), ambient relative humidity (φ_a), and air curtain baffle position. Usually, the formation of a complete air curtain is determined by the air supply velocity. As shown in Table 2, based on the formation of a complete air curtain, the

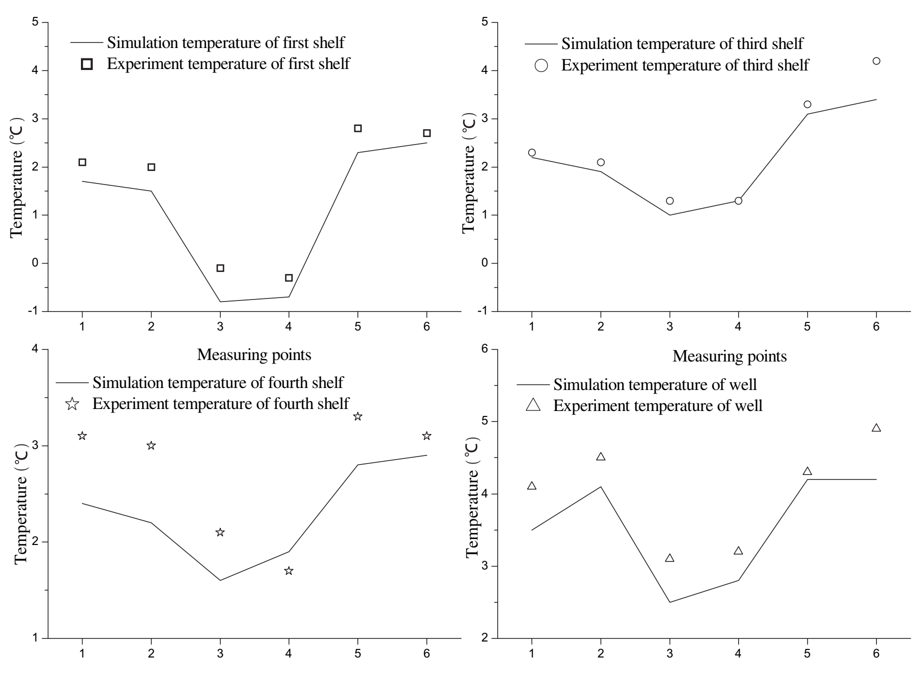

Fig. 4. Comparison of simulation and experiment temperature inside display case.

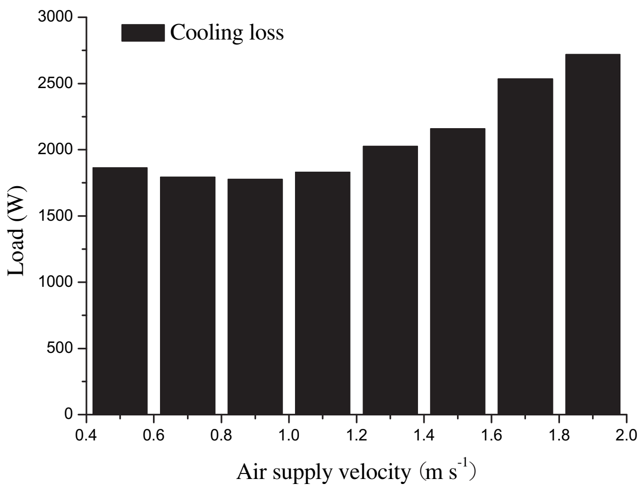

Fig. 5. The influence on cooling loss with different air supply velocity.

variation of the baffle position (Δh) has a decisive influence on the air curtain performance.

Based on the experience from the development process of medium temperature display cases [33–35] and the actual situation of the presented display case, the range of design parameters values mentioned above can be presented as in Table 3. Based on the range of the design parameters values, the objective function of the air curtain cooling loss is expressed as Eq. (6).

$$L_\phi = \phi(v_s,(T_a-T_s),(T_a-T_r),\varphi_a,\Delta h)$$
$$0.3 \le v_s \le 1.5, 14 \le (T_a-T_s) \le 31, 4 \le (T_a-T_r) \le 22,$$
$$0.4 \le h_a \le 0.8, -10 \le \Delta h \le 10 \qquad (6)$$

2.5. The objective function of the cooling loss as based on SVM algorithm

From Eq. (6), the cooling loss is seen to be a function of v_s, $(T_a - T_s)$,$(T_a - T_r)$,φ_a and Δh. However, the objective function is nonlinear in the range of parameter values above. Whether experimental, or CFD simulation optimization methods were chosen, a lot of time, manpower and material resources would be required to solve the objective function of the cooling loss corresponding to all possible parameter combinations. Therefore, it could be faster and more effective to deal with the nonlinear relationship between variables of the cooling loss equation through the use of an algorithm, such as SVM.

For regression problems, SVM nonlinearly maps the input data into a higher-dimensional feature space (Hilbert space) to yield and solve a linear regression problem in the feature space. The presented objective function describing the cooling loss as based on the SVM algorithm can be established by the following steps.

(1) Collection of data samples.

$$L = \left\{(x_1,y_1),(x_2,y_2),\cdots,(x_i,y_j)\right\}\in R^n \times R \qquad (7)$$

where x_i is the input sample, y_i is the output sample.

Table 2
The influence on cooling loss with the variation of baffle position.

	Initial position	Decreased by 5 mm	Decreased by 3 mm
Cooling loss (W)	1863	1790	1752

Table 3
The value ranges of design parameters.

Parameters	v_s (m s^{-1})	T_a (°C)	φ_a (%)	T_s (°C)	T_r (°C)	Δh (mm)
Range	0.3–1.5	16–27	40–80	−4 to 2	5–12	(−10)[a] to 10

[a] The minus means the baffle position is descending.

(2) Standardized pretreatment of data samples is performed to eliminate dimensional influences and improve the model's training.

(3) Construction of linear function in the Hilbert space.

$$L(x) = a\Omega(x_i) + b \qquad (8)$$

(4) Based on the structural risk minimization principle, the weight coefficient (a) and threshold (b) are determined to make $|L - a\Omega(x_i) - b| \le \varepsilon$, which is equivalent to: $\min_{a,b}\frac{1}{2}\|a\|^2 + C[\sum_{i=1}^{l}(\xi_i+\xi_i^*)]$, and

$$a\Omega(x_i)+b_i-y_i \le \varepsilon+\xi_i, -a\Omega(x_i)-b_i+y_i \le \varepsilon+\xi_i^*, \quad \xi_i,\xi_i^* \ge 0,$$
$$i = 1,2,\cdots,m \qquad (9)$$

where C is the penalty coefficient which determines the trade-off between the empirical risk and the regularization term of the model when an error occurs, ε is the loss coefficient (pre-set parameter near zero [36]) which controls the width of the ε-intensive zone used to fit the training data, ξ_i and ξ_i^* are both the relaxation factors.

(5) Based on the kernel function $K(x,y)$ of the original data space which replaces the dot product of the Hilbert space, the complexity of the calculation process is reduced [37]. Here, the Gaussian radial basis function (RBF) kernel function, which is more accurate [38], is employed.

$$K(x_i,x_j) = \exp(-\gamma\|x_i-x_j\|^2) \qquad (10)$$

where γ represents the bandwidth of RBF kernel.

(6) Construction and solution of optimization problem then becomes:

$$\min\frac{1}{2}\sum_{i,j=1}^{m}(a_i^*-a_i)(a_j^*-a_j)K(x_i,x_j)+\varepsilon\sum_{i=1}^{m}(a_i^*+a_i)$$
$$-\sum_{i=1}^{m}y_i(a_i^*-a_i), \text{ and } \sum_{i=1}^{m}(a_i^*-a_i) = 0,$$
$$0 \le a_i,a_i^* \le \frac{C}{m} i,j = 1,2\cdots,m \qquad (11)$$

The samples of $\overline{\alpha}_i$ and $\overline{\alpha}_i^*$, which generally exist in the position of the violent function variation, are the support vectors.

(7) The cooling loss function, as based on the SVM then becomes:

$$L(x) = \sum_{i,j=1}^{m}(\overline{\alpha}_i^*-\overline{\alpha}_i)K(x_i,x_j)+\overline{b} \qquad (12)$$

When $\overline{\alpha}_i$ or $\overline{\alpha}_i^*$ is chosen in the open interval $(0,C/m)$, and $\overline{b}$ is calculated as follows:

$$\overline{b} = y_i - \sum_{i,j=1}^{m}(\overline{\alpha}_i^*-\overline{\alpha}_i)K(x_i,x_j) \pm \varepsilon \qquad (13)$$

After the output samples are obtained, the cooling loss, and other parameters, will be obtained through a reduction process.

(8) For the SVM model, there exists no standard procedure to determine the free parameters C and γ. Here, the technique of

cross-validation and grid-search [39] was applied to obtain the SVM parameters of C and γ from which the optimal solution $\overline{a} = (\overline{a}_1, \overline{a}_1^*, \overline{a}_2, \overline{a}_2^*, \cdots, \overline{a}_m, \overline{a}_m^*)$ is obtained. Once the free parameters (Here, $C = 512$, $\gamma = 1.1$, $\varepsilon = 0.001$) have been obtained, the SVM models are developed.

2.6. The algorithm flow for determining the cooling loss function as based on SVM

The algorithm flow for the cooling loss function as based on the SVM algorithm is shown in Table 4. Refer to Eq. (12), the calculation model is established by using the cooling loss as the output and air supply velocity, ambient relative humidity, and the variation of the baffle position et al. as the input. In addition, scaling the features is very important before applying SVM. The main advantage of scaling is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. Large attribute values might cause numerical problem because kernel values usually depend on the inner products of the feature vectors, so another advantage of it is to avoid numerical difficulties during the calculation. It is recommended to linearly scale each attribute to the range $[-1, 1]$ or $[0, 1]$.

Table 4
The algorithm flow of cooling loss function based on SVM algorithm.

Definition:
L = number of training samples under each condition;
M = number of conditions;
$m = 5$, number of elements in each sample;
$n = L \times M$, number of all the training samples;
$i = 1, 2, \ldots, M$, serial number of conditions;
$j = 1, 2, \ldots, M$, serial number of training samples under each condition;
$y_{\min}$ = the minimum sample output, i.e., minimum cooling loss;
$X_{\min} = (x_{1\min}, x_{2\min}, \cdots, x_{m\ \min})$ = the sample corresponding to minimum cooling loss.
Pretreatment:
Step1: Original samples input
$X = [X_{11} \quad X_{21} \ldots X_{ML}]^T = [X_1 \quad X_2 \ldots X_n]^T$,
$X_i = (x_{1i}, x_{2i}, \cdots, x_{mi})^T$, $i = 1, 2, \ldots, n$
Step2: Sample normalization
$\widehat{X}_{ij} = (x_{ij} - x_{\min})/(x_{\max} - x_{\min})$, $\widehat{y}_{ij} = (y_{ij} - y_{\min})/(y_{\max} - y_{\min})$
Step3: New training sample set
$\widehat{\Omega}_i = ((\widehat{X}_{i1}, y_{i1}), \ldots, (\widehat{X}_{ij}, y_{ij}))$, $\quad i = 1, 2, \ldots, M;\ j = 1, 2, \ldots, L$
Establishment of cooling loss function:
The priority of conditions is assumed to $C_1 \rightarrow C_2 \rightarrow \cdots \rightarrow C_M$, which is corresponding to $(\widehat{X}_{i1}, y_{i1}) \rightarrow (\widehat{X}_{i2}, y_{i2}) \rightarrow \cdots \rightarrow (\widehat{X}_{iM}, y_{iM})$
Step4: Training of samples $(\widehat{\Omega}_i)$
Step5: if $i = 1$(layer 1, pattern C_1), then $\widehat{\Omega}_i = \widehat{\Omega}_1 = \widehat{\Omega}_i$
if $i = 2$(layer 2, pattern C_1), then $\widehat{\Omega}_i = \widehat{\Omega}_2 = \widehat{\Omega}_i - \widehat{C}_1$
....
if $i = M - 1$(layer $M - 1$, pattern C_M), then $\widehat{\Omega}_i = \widehat{\Omega}_{M-1} = \widehat{\Omega}_{M-2} - \widehat{C}_{M-2}$
Step6: Definition of the kernel function $K(x_i, x_j)$
Step7: Establishment of function based on SVM
for $i = 1{:}M - 1$,
Solve Eqs. (11–13) for $\overline{a}$ and $\overline{b}$
end
Form the function SVM[i]
end
Calculation of cooling loss function:
Step8: Data acquisition
Step9: Data normalization
Step10: Sample set input of the function SVM[i]
Result output:
Step11: Minimum sample output data acquisition
for $i = 1{:}M$,
if $y[i] > y[i+1]$, then $y_{\min} = y[i+1]$,
$X_{\min}[\,] = (x_{1i+1}, x_{2i+1}, \cdots x_{mi+1})^T$
end
Step12: Output of minimum cooling loss and correlative parameter input parameters
print $y_{\min}$, $X_{\min}[\ ]$
end

Likewise, before testing, the same way is applied to scale the testing data.

3. Results and discussion

3.1. Flow chart of the optimization strategy

The flow chart of the optimization strategy is shown in Fig. 6. Using the verified CLTF model, the design parameters significantly influencing the air curtain cooling loss were confirmed. Then the SVM algorithm was trained by the confirmed design parameters (v_s, $(T_a - T_s)$, $(T_a - T_r)$, φ_a and Δh) and their corresponding cooling loss obtained from the CLTF model. Next, different design parameter combinations were input into the trained SVM algorithm to calculate the cooling loss. With the design parameters corresponding to the minimum cooling loss, the prototyping test was designed, and then, the TEC/TDA was tested to validate the optimization result.

3.2. Output results

In the constrained range of Eq. (6), 243 groups of typical parameter combinations (After each constrained range of variables is uniformly divided into 2 intervals, with 3 divided points of these intervals selected as typical parameters) and their corresponding cooling loss, as obtained from the results based on CLTF model, are selected as training samples for the SVM algorithm. Moreover, another 70 groups of parameter combinations and their corresponding cooling loss were selected to validate the accuracy of trained SVM algorithm. As shown in Fig. 7, with a 95% confidence interval, the discrepancy between the CLTF and the SVM results is less than 5% for the cooling loss.

The relative sensitivity of the model's output to variation in input parameter values was determined by the samples being input as the mode of one variable which was changed while the others were kept fixed. If the output varied by more than 20% as this input parameter was changed over the range of interest, the cooling loss

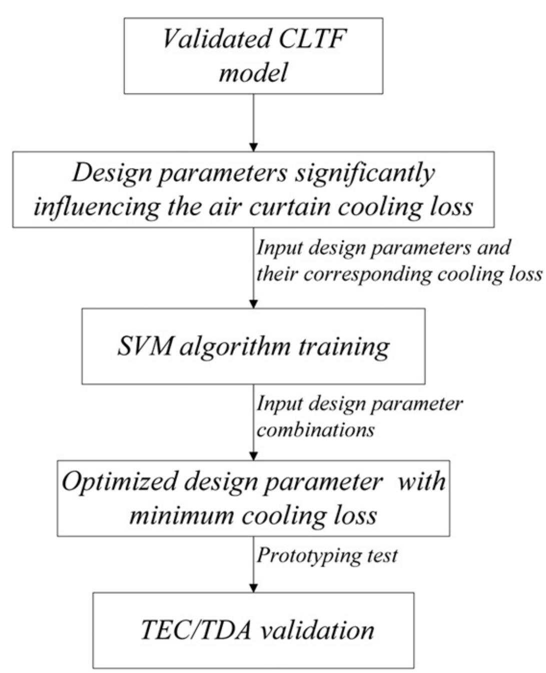

Fig. 6. Diagram of the optimization strategy.

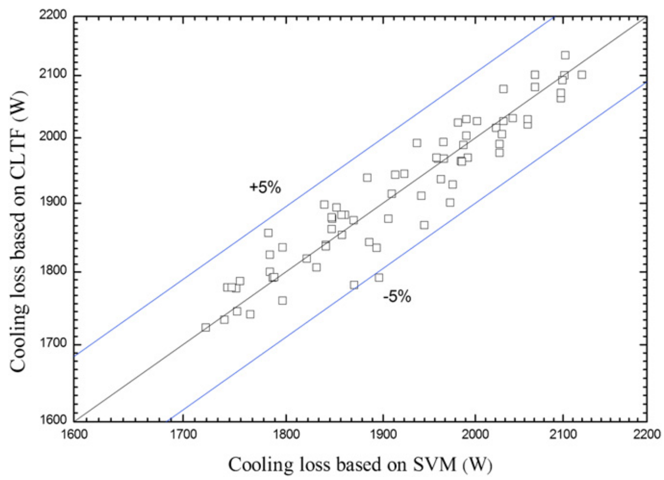

Fig. 7. SVM algorithm validation.

was identified as being particularly sensitive to the value of this input parameter. The results obtained show that these parameters include v_s, $(T_a - T_s)$ and $(T_a - T_r)$. In addition, some control parameters belong to partially sensitive parameters, i.e., the cooling loss changes greatly when variation in the input parameters exceed a certain range (such as $\varphi_a > 60\%$ and $\Delta h > 6$ mm). As shown in Table 5, the simulation results for the effect of the changing parameters are summarized.

The minimum values for the objective function describing the cooling loss in the constrained range of the input parameters is presented in Table 6, i.e., the best energy-saving results can be achieved by the application of these parameters which were found to reduce the cooling loss by 19.6%.

3.3. Method validation

After the air curtain of display case was designed using the optimum set of parameters obtained through the optimization strategy presented above, a verification test for 24 h was carried out using the 3M1 standard (Under an ambient temperature of 25 °C and an ambient humidity of 60%, the temperature inside case is achieved from −1 °C to 5 °C). Refer to the European Standard EN ISO 23953-2 [32], the display case performance was evaluated from the level of daily energy consumption per m^2 display area which was determined as follows:

$$\mathrm{TEC/TDA} = (\mathrm{REC} + \mathrm{DEC})/\mathrm{TDA} \tag{14}$$

where TEC is the total energy consumption in kW h per 24 h period, TDA is the total display area, REC is the refrigeration electrical energy consumption in kW h per 24 h period, and DEC is the direct energy consumption in kW h per 24 h period (including fan, lighting, heaters et al.).

As shown in Fig. 8, the TEC/TDA curve for the optimal display case is better than the non-optimized display case. When the following control parameters are used (the temperature inside case is achieved from −1 °C to 5 °C, air supply temperature −2 °C, air supply velocity 0.8 m s^{-1} and air return temperature 5.5 °C), the TEC/TDA for the optimal display case can reach 10.34 kW h m^{-2} 24 h^{-1}, which is a decrease of 17.1%.

Table 5
Parameters used in the sensitivity analysis and their sensitivity in the SVM algorithm.

Parameters	v_s (m s^{-1})	$(T_a - T_s)$ (°C)	$(T_a - T_r)$ (°C)	φ_a (%)	Δh (mm)
Base case	0.7	18	8	50	−6
Variable case	1.2	23	13	70	6
ΔL_ϕ (%)	53.2	43.7	37.3	18.1	17.0

Table 6
Compare of cooling loss and correlative parameters.

Parameters	v_s (m s^{-1})	$(T_a - T_s)$ (°C)	$(T_a - T_r)$ (°C)	φ_a (%)	Δh (mm)	L_ϕ (W)	ΔL_ϕ (%)
Original model	1.1	27.5	17	60	0	2124	−19.6
Optimal model	0.8	27	19.5	60	−3	1708	

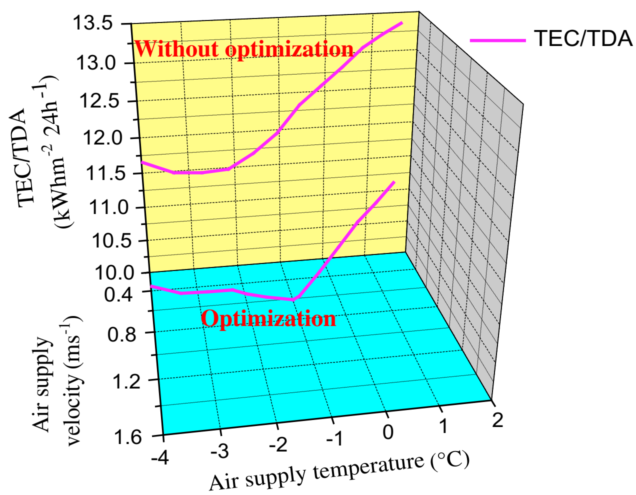

Fig. 8. Compare of TEC/TDA.

4. Conclusions

An effective strategy has been developed to optimize the air curtain for open vertical refrigerated display cases. In order to deal with the nonlinear relationship between control parameters, which leads to highly complex objective functions and a large mount of time and energy being required to solve to the optimization problem through the use of conventional design methods, the CLTF model and SVM algorithm are introduced in establishing and solving the objective function for the air curtain cooling loss. Verification and evaluation of the optimization strategy is then carried out using experimental data. The results obtained show that the air curtain cooling loss and energy consumption by the optimized model are decreased by 19.6% and 17.1%, respectively.

From the optimal controlled parameters achieved, some guidelines can be generalized as follow. Firstly, within certain operating conditions and given enough condensing capability, the lower the air supply temperature, the worse the performance (the energy consumption) of refrigerated display cases is. Secondly, the air supply velocity is one of the parameters which were used to control the cooling loss of refrigerated display cases. If the air supply velocity exceeds one certain threshold value (about 0.9 m s^{-1}), the cooling loss would go higher with the air supply velocity increasing. Thirdly, appropriately decreasing the variation of the baffle position can improve the performance of the refrigerated display cases. Finally, the ambient condition has great influence on the performance of the refrigerated display cases (e.g. the performance would deteriorate with the increase in ambient temperature and ambient relative humidity).

This study also reveals that the optimization strategy presented which uses the CLTF model and SVM algorithm has a high degree of accuracy. Usually, the equipments with the same type have the similar structure and design condition. Therefore, if the prototype optimization was finished, the improvement could be applied to the total equipments with the same type. It is found that these models can be used by the manufacturers to design an effective and energy-saving optimization strategy for the air curtain of display cases.

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Nomenclature

Δh: variation of baffle position (mm)
c: empirical constant
C: penalty coefficient
c_m, c_l, c_E: empirical constants
c_p: specific heat at constant pressure (J kg^{-1} K^{-1})
CFD: computational fluid dynamics
CLTF: two-fluid of cooling loss
DEC: direct energy consumption (k Wh 24 h^{-1})
E: fluid heat flux (J m^{-3} s^{-1})
ERM: empirical risk minimization
h: Prandtl mixing length (m)
I: fluid friction force per unit volume (N m^{-3} s^{-1})
k: turbulent kinetic energy (m^2 s^{-2})
L: air curtain cooling loss (W)
m: fluid mass transfer rate per unit volume (kg m^{-3} s^{-1})
Q: heat transfer rate (W)
RBF: radial basis function
REC: refrigeration electrical energy consumption (k Wh 24 h^{-1})
S: intra-fluid sources
SRM: structured risk minimization
SVM: support vector machine
T: temperature (°C)
TDA: total display area (m^2)
TEC: total energy consumption (k Wh 24 h^{-1})
$\vec{u}$: velocity vector (m s^{-1})
v: velocity (m s^{-1})

Greek symbols

γ: free parameter (the bandwidth of RBF kernel)
Γ: within-phase diffusion coefficient (m^2 s^{-1})
δ: volume fraction
ε: loss coefficient
ξ: dissipation rate of turbulent energy (m^2 s^{-3})

ξ_i, ξ_i^*: relaxation factors
ρ: density (kg m^{-3})
φ_a: ambient relative humidity (%)
ϕ: general dependent variable

Subscripts

1: the air exiting the back panel, the inner and the outer air curtains (the turbulent fluid)
2: the ambient air (the non-turbulent fluid)
a: ambient
cond: walls heat conduction
cur: air curtain
i, j: serial numbers
in: inside the case
min: minimum
r: air return
rad: walls radiation
s: air supply