OPTIMIZATION OF THE AUTOMOTIVE AIR CONDITIONING SYSTEM USING RADIAL BASIS FUNCTION NEURAL NETWORK

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The defrosting performance of automotive air conditioners plays an important role in driving safety. This paper uses computational fluid dynamics (CFD) to simulate the internal flow field of the automobile numerically. Simulation results show that the flow distribution is unreasonable. The horizontal grilles are added at the outlets to improve the defrosting performance of the automobile. Airflow jet angle and the length of the air conditioning outlets \(L_1, L_2\) are selected as design variables based on the radial basis neural network to find the optimal combination scheme. The area of the defrosting dead corner has been reduced from 20% to 5% after optimization, and the frost layer of the front windshield has been completely melted in 25 min. The experiment test is conducted to verify the improvement of the defrosting performance of automotive air conditioners. The design methodology can be applied to the development of the air conditioner.

Key words: defrosting performance; automotive air conditioning; optimization; radial basis neural network

1. Introduction

Frosting and fogging of automobile windshields is a practical problem frequently encountered in the course of driving [1]. The defrosting performance of the front windshield affects the safety of drivers and passengers. Therefore, effectively improving the defrosting performance of automobile air conditioning systems has become a serious problem in the auto industry [2-4]. With the development of computer techniques, the computational fluid dynamics (CFD) technique has been widely used in the optimization research of defrosting performance [5-6].

A considerable amount of research has been conducted in this area in the past years. Ikeda et al. [7] simulated the airflow from the inlet of the air conditioner and compared their results with the experimental findings to verify the feasibility of CFD numerical analysis. Aroussi et al. [8] simulated the defrosting process of the vehicle side window and indicated the insufficient design of the experimental vehicle defrosting system. Swales et al. [9] described how to combine usage of CAE with a newly developed laser based technique and provided an excellent method for maximising defrost and demist performance. Kang et al. [10] studied the automotive defrosting system and verified the simulation results. They found that the airflow from the outlet is not uniform and does not cover the entire windshield area, thus affecting the defrosting efficiency. Karim et al. [11] found that the structural adjustment of defrosting ducts can improve the defrosting performance of vehicle windshields. Huang et al. [12] improved the internal structure of the defroster duct to improve the
defrost effect. Li et al. [13] used the resistance wire heating method to accelerate the defrosting of the bus air conditioner due to insufficient heat source, which affects the defrosting effect of the windshield. However, optimizations of the model are based on working experience. The optimization method is slightly inefficient and blind. Moreover, obtaining the best results is difficult using this method.

In recent years, response surface methodology (RSM) has been employed in many design fields. For example, Yang et al. [14] used RSM to optimize the centrifugal fan and reduce automobile noise. However, RSM also has certain limitations. Cho et al. [15] believed that RSM is best for two or fewer design variables, and optimizing multiple design variables simultaneously is difficult. In most cases, the object that must be modeled is a complex large system, and no explicit mathematical expression exists between the design variables and the target. Neural networks can capture the nonlinear relationship between variables and the target and solve the optimization problem of multiple design variables. Some researchers have successfully applied neural networks to optimization with multiple variables. Atuanya et al. [16] used neural networks to predict the mechanical properties of palm wood fiber-recycled low-density polyethylene composite. Selvam [17] and Esonye et al. [18] used RSM and neural networks to model the optimization with multiple variables and found that the neural network has a high modeling accuracy for the optimization with more than three variables. The neural networks introduce improved results for the optimization with multiple variables.

This paper aims to optimize the defrosting performance of automobiles. First, chapter 2 describes principle of the radial basis function neural network. Then, chapter 3 constructs the simulation model of air conditioning including automotive interior to realize the structure optimization from the perspectives of topology. With radial basis function neural network, chapter 4 establishes an approximate model between the parameters of air conditioning and the air flow velocity and realizes multiple variables optimization. Finally, the experiment is conducted to verify the optimization results.

2. Radial Basis Function Neural Network Principle

The neural network is a mathematical model that imitates the behavior of the biological neural network and performs the distributed parallel information processing. The neural network comprises many neurons that are connected. The structure of the neural network is changed in accordance with the input information. The modeling process mainly adjusts the weights between neurons. Up to now, the types of neural network models are quite rich and have developed to nearly 40 kinds [19-20]. Among the many networks, radial basis function neural network (RBFNN) has the advantages of simple structure and solid mathematical foundation; thus, this network is widely used in many fields.

The structure of the RBFNN is a three-layer forward network (Fig. 1), which includes input, hidden, and output layers. The first layer is the input layer, which comprises the signal source node; this layer only serves to transmit signals; the second layer is the hidden layer, and the number of hidden layer nodes is determined by the problem described. The transformation function (radial basis function) of neurons in the hidden layer, as a local response function, is a non-negative linear function with radial symmetry and attenuation to the center point. The third layer is the output layer, which responds to the input [21-22].
The Gaussian function is commonly used as the activation function of RBFNN. The expression of the Gaussian function is presented in Eq. (1).

$$R(x_p - c) = \exp \left( -\frac{1}{\delta_i^2} \|x_p - c_i\|^2 \right), p = 1, 2, \ldots, n; i = 1, 2, \ldots, m,$$

where $R(x_p - c_i)$ is the output of the $i$-th hidden layer node, $\|x_p - c_i\|$ is the Euclidean norm, $x_p$ is the $p$-th input sample, and $c_i$ is the $i$-th Gaussian function center of the hidden layer. $\delta_i$ is the variance of the Gaussian function, which is also called the width or expansion constant of the Gaussian function, $m$ is the number of hidden layer nodes, and $n$ is the number of hidden layer nodes.

The output layer has only one node, which is the prediction result. The output can be expressed as shown in Eq. (2).

$$y_p = \sum_{i=1}^{m} \omega_i R(x_p - c_i) + b_i, p = 1, 2, \ldots, n; i = 1, 2, \ldots, m,$$

where $\omega_i$ is the weight of the hidden layer to the output layer, and $b_i$ is the bias term.

### 3. Topology Analysis

#### 3.1. Mathematical models of defrosting

The Realizable K-Epsilon turbulence model [23] was adopted in the article, which can simulate rotary shear flow, free flow and submerged water jet well, as well as the velocity and direction of airflow generated in the flow field. Its governing equations are given by

$$\frac{\partial (\rho k)}{\partial t} + \frac{\partial (\rho ku_i)}{\partial x_i} = \frac{\partial}{\partial x_j} \left[ \mu_s \frac{\partial k}{\partial x_j} \right] + G_k + G_b - \rho \varepsilon - Y_M + S_k$$

$$\frac{\partial (\rho \varepsilon)}{\partial t} + \frac{\partial (\rho \varepsilon u_i)}{\partial x_i} = \frac{\partial}{\partial x_j} \left[ \mu_s \frac{\partial \varepsilon}{\partial x_j} \right] + \rho C_{1\varepsilon} \varepsilon \bar{e} - \rho C_{2\varepsilon} \frac{\varepsilon^2}{k} + \frac{\varepsilon^3}{k} + C_{3\varepsilon} \frac{\varepsilon}{k} + G_b + S_\varepsilon$$

where, $k$ is turbulent kinetic energy; $\varepsilon$ is turbulent dissipation rate; $\rho$ is airflow density; $x_i$ and $x_j$ are position vectors; $u_i$ is velocity; $\mu_s$ is turbulent viscosity coefficient, $\mu_l$ is the molecular viscosity; $\sigma_k$, $\sigma_\varepsilon$ are turbulent Prandtl number of turbulent kinetic energy and turbulent dissipation rate, which are 1.0 and 1.3 respectively; $G_k$ is the turbulent kinetic energy caused by average velocity gradient; $G_b$ is the turbulent kinetic energy caused by buoyancy; $Y_M$ Contribution of compressible velocity turbulent pulsation expansion; $C_{1\varepsilon}$, $C_{2\varepsilon}$ and $C_{3\varepsilon}$ are constants; $S_k$, $S_\varepsilon$ are user-defined source items.
The defrosting of automobile windshield is the melting process of frost layer under the hot air flow and the energy equation can be expressed

$$\frac{\partial}{\partial t} \left( \rho H \right) + \nabla \left( \rho \vec{v} H \right) = \nabla \left( k \nabla T \right) + S$$  \hspace{1cm} (3)

where $H$ is the enthalpy, $\vec{v}$ is the fluid velocity, $S$ is active phase shown by the follow

$$S = \frac{1 - \beta^2}{\beta^2 + \sigma} A_{mub} (\vec{v} - \vec{v}_p)$$  \hspace{1cm} (4)

where $\sigma = 0.001$ to avoid a denominator of 0, $A_{mub} = 10^3$, $\vec{v}_p$ is the velocity of ice-water mixture, $\beta$ is the liquidus fraction. $\beta = 0$ when the frost temperature $T$ is lower than the solidus temperature $T_{solidus}$; $\beta = 1$ when $T$ is higher than the liquid temperature $T_{liquidus}$; when $T$ is between $T_{solidus}$ and $T_{liquidus}$,

$$\beta = \frac{T - T_{solidus}}{T_{liquidus} - T_{solidus}}.$$

### 3.2. Numerical Simulation

Fig. 2 shows the simulation model of the automobile. The model includes a cabin, a glass layer, a frost layer, a defrosting duct, and a seat. The front windshield is divided into $A$, $A'$, and $B$ areas [24].

![Figure 2. Physical model of the automobile.](image)

The entire computational domain is divided by tetrahedral meshes. The mesh is refined near the defroster duct and the frost and glass layers. The glass and frost layers each have five layers [25], as shown in Fig. 3.

![Figure 3. Grids of simulation domain.](image)
The airflow is assumed to be incompressible and the environmental pressure is standard atmosphere. The inlet and outlet are set as mass flow inlet and pressure outlet respectively. The air temperature changes with time, the initial temperature is -18 °C, and the final temperature is 47.3 °C. Ansys Fluent software was used for CFD modelling and solution [26]. Simple algorithm in pressure-velocity coupling is adopted as the solution method and the second-order upwind difference scheme is used in the discrete differential algorithm. During the solutions, the convergence precision of the continuity and momentum equations are within $10^{-4}$, and that of the energy equation is less than $10^{-5}$.

Tab. 1 shows the flow distribution of each outlet after computation convergence. The flow rate of the driver’s side outlet accounts for 10.96% and that of the passenger side is 11.04%; the flow distribution of the two outlets is reasonable. The flow rate of the central outlet accounts for 38.56%, the left side outlet is 19.44%, and the right outlet is 20%. The flow rate of the central outlet is approximately the sum of the left and right outlets, and the flow distribution of the three outlets are unreasonable.

**Table 1. Flow distribution of each outlet.**

<table>
<thead>
<tr>
<th>Outlet</th>
<th>Flow rate (kg/s)</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left outlet</td>
<td>0.0243</td>
<td>19.44</td>
</tr>
<tr>
<td>Central outlet</td>
<td>0.0482</td>
<td>38.56</td>
</tr>
<tr>
<td>Right outlet</td>
<td>0.0250</td>
<td>20.00</td>
</tr>
<tr>
<td>Driver-side outlet</td>
<td>0.0137</td>
<td>10.96</td>
</tr>
<tr>
<td>Passenger-side outlet</td>
<td>0.0138</td>
<td>11.04</td>
</tr>
<tr>
<td>Total</td>
<td>0.125</td>
<td>100</td>
</tr>
</tbody>
</table>

**3.3. Topological improvements**

Fig. 4 shows the defrosting duct structure. The left, central, and right outlets are responsible for the defrosting operation of the front windshield. The driver- and passenger-side outlets are responsible for the side windshields.

![Figure 4. Defrosting duct structure and outlet position.](image)

The structural topology scheme aims to add horizontal grilles at the outlets, as shown in Fig. 5. The horizontal grille can increase the resistance in the defrosting duct and squeeze the airflow of the central outlet to the left and right outlets, thus resulting in reasonable flow distribution. The horizontal grille also helps the even distribution of airflow over the windshield to improve defrosting efficiency.
4. Optimization Based on RBFNN

4.1. Design strategies

The RBFNN is used for the optimization of the air conditioning structure to improve the defrosting performance of the automobile. Fig. 6 shows the optimization process.

The air flow velocity on the A, A’, and B areas of the front windshield f is chosen as the optimization objective. The optimization objective can be expressed as shown in Eq. (3).

$$Max f = \omega_1 v_A + \omega_2 v_{A'} + \omega_3 v_B,$$  \hspace{1cm} (3)

where \( v_A, v_{A'}, \) and \( v_B \) are respectively surface weighted average air flow velocity of the A, A’, and B areas. \( \omega_1, \omega_2, \) and \( \omega_3 \) are weight coefficients. The defrosting work in A area was completed first, followed by the A’ and the B areas; thus, \( \omega_1, \omega_2, \) and \( \omega_3 \) are respectively set to 0.5, 0.3, and 0.2.

The length of the left and right outlets is the same due to the structural symmetry of the left and right outlets. The lengths of the left outlet \( L_1 \) and the central outlet \( L_2 \) and the airflow jet angle \( \alpha \) are chosen as design variables. The range of values of \( L_1, L_2, \) and \( \alpha \) is \( 170mm \leq L_1 \leq 350mm, \)

\( 0mm \leq L_2 \leq 150mm, \) and \( 0^\circ \leq \alpha \leq 90^\circ, \) respectively. Thirty groups of analytic models are created using
the Latin hypercube sampling method for the selection of sample points. The concrete parameters of each group and the final simulated values are presented in Tab. 2.

**Table 2. Concrete parameters and final values in each group.**

<table>
<thead>
<tr>
<th>Groups</th>
<th>Design variables</th>
<th>Simulated value</th>
<th>Predicted value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$L_1$ (mm)</td>
<td>$L_2$ (mm)</td>
<td>$\alpha$ (°)</td>
</tr>
<tr>
<td>1</td>
<td>255</td>
<td>17</td>
<td>89</td>
</tr>
<tr>
<td>2</td>
<td>204</td>
<td>51</td>
<td>71</td>
</tr>
<tr>
<td>3</td>
<td>170</td>
<td>102</td>
<td>58</td>
</tr>
<tr>
<td>4</td>
<td>238</td>
<td>34</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>221</td>
<td>68</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>340</td>
<td>119</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>187</td>
<td>17</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>170</td>
<td>51</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>187</td>
<td>68</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>306</td>
<td>34</td>
<td>7</td>
</tr>
<tr>
<td>11</td>
<td>221</td>
<td>85</td>
<td>6</td>
</tr>
<tr>
<td>12</td>
<td>272</td>
<td>68</td>
<td>2</td>
</tr>
<tr>
<td>13</td>
<td>238</td>
<td>119</td>
<td>3</td>
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<tr>
<td>14</td>
<td>323</td>
<td>68</td>
<td>5</td>
</tr>
<tr>
<td>15</td>
<td>306</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>16</td>
<td>204</td>
<td>85</td>
<td>4</td>
</tr>
<tr>
<td>17</td>
<td>255</td>
<td>85</td>
<td>2</td>
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<tr>
<td>18</td>
<td>238</td>
<td>102</td>
<td>0</td>
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<tr>
<td>19</td>
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<tr>
<td>20</td>
<td>187</td>
<td>51</td>
<td>6</td>
</tr>
<tr>
<td>21</td>
<td>289</td>
<td>85</td>
<td>8</td>
</tr>
<tr>
<td>22</td>
<td>306</td>
<td>17</td>
<td>4</td>
</tr>
</tbody>
</table>
4.2. Approximate model construction

An approximate model was constructed by RBFNN. First, the 30 sets of sample points are merged into a data set, where \( L_1 \), \( L_2 \), and \( \alpha \) are independent input parameters. The approximate model generated a related parameter, that is, the air flow velocity on the front windshield \( A \), \( A' \), and \( B \) areas. The accuracy of the approximation model is verified by the coefficient of determination \( R^2 \) and correction factor \( R^2_{adj} \). The coefficient of determination \( R^2 \) measures the predicted value of the sample on the total variation proportion of the average value \( \bar{y} \). The ideal model is one that can reflect all variabilities. \( R^2 \) is a number between 1 and 0. The analytic model will be improved when the number is close to 1. The model is considered sufficiently good to be accepted when \( R^2 \) is between 0.95 and 1. The model is considered and then checked further with the modified \( R^2_{adj} \) when the number is between 0.9 and 0.95. The formulas for \( R^2 \) and \( R^2_{adj} \) are respectively presented in Eqs. (4) and (5).

\[
R^2 = \frac{\sum_{i=1}^{n}(\bar{y} - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \tag{4}
\]

\[
R^2_{adj} = 1 - \frac{N - 1}{N - k - 1}(1 - R^2), \tag{5}
\]

where \( N \) is the number of design points, \( k \) is the number of variables in the approximate model, \( y_i \) is the simulation value, \( \bar{y} \) is the predicted value, and \( \bar{y} \) is the average of the simulated values.

Tab. 2 shows the final predicted values of the approximate model. The regression coefficients of training, test, validation, and overall model developed using RBFNN are shown in Fig. 7. The value on the X-axis is the simulated value. The value on the Y-axis is the predicted value of the approximate model by the developed RBFNN. The high regression value reveals that the predicted values are substantially close to the simulated values for all data sets, which is an indication of the successful development of the RBFNN model. The best performance validation is obtained at the 6th iterations as shown in Fig. 8. Eqs. (4) and (5) show that the value of \( R^2 \) is calculated to be 0.983, and the value of
The fitting effect of the approximate model is satisfactory. The optimal value for the response \( f \) is 4.623 m/s. The optimal combination of parameters is as follows: \( L_1=340\,mm \), \( L_2=119\,mm \), and \( \alpha=62^\circ \).

![Figure 7. Regression coefficients of training, test, validation, and overall model.](image)

4.3. Analysis of optimization

Tab. 3 shows the flow distribution before and after optimization. Excessive flow in the central outlet is distributed to the left and right outlets after optimization. The flow rate at the central outlet was reduced by 9.93\%, the flow rate at the left outlet was increased by 3.90\%, and the flow at the right outlet was increased by 4.16\%.
Table 3. Flow distribution before and after optimization.

<table>
<thead>
<tr>
<th>Outlet Type</th>
<th>Before (%)</th>
<th>After (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left outlet</td>
<td>19.44</td>
<td>23.34</td>
</tr>
<tr>
<td>Central outlet</td>
<td>38.56</td>
<td>28.63</td>
</tr>
<tr>
<td>Right outlet</td>
<td>20.00</td>
<td>24.16</td>
</tr>
<tr>
<td>Driver's side outlet</td>
<td>10.96</td>
<td>11.86</td>
</tr>
<tr>
<td>Passenger's side outlet</td>
<td>11.04</td>
<td>12.01</td>
</tr>
</tbody>
</table>

Fig. 9 shows the streamline distribution of the front windshield. The streamlines in the \( A \) and \( A' \) areas are relatively concentrated before optimization; thus, both areas can achieve an improved defrosting effect. Streamlines are absent in the lower left and right corners of the \( B \) area, thus achieving poor defrosting effect. The streamlines completely cover the \( A \), \( A' \), and \( B \) areas after optimization, and the defrosting effect is improved.

Fig. 10 shows the steady-state air flow velocity. The white area means that the air flow velocity is larger than 1.5 m/s and demonstrates an improved defrosting effect. The defrosting effect of the \( A \) and \( A' \) areas is remarkable before the optimization. The lower left and right corners of the \( B \) area have poor defrosting effects and are called defrosting dead corners. The defrosting dead corner accounts for approximately 20% of the \( B \) area. The defrosting dead corner is reduced from approximately 20% to 5% after optimization, and the defrosting effect is improved. This finding is consistent with the conclusions drawn in Fig. 9.

Fig. 10. Steady-state air flow velocity near the wall: (a) Before optimization, (b) After optimization.
5. Experimental Verification

5.1. Verification of the frost layer melting effect

In the experiment, the test instruments include the BBK drum test stand (Burke Porter Group Company), spray gun, thermometer, engine tachometer, stopwatch, anemometer, voltmeter and camera. The environmental temperature is \(-18 \pm 3 ^\circ C\), and the horizontal component of air velocity is less than 2.2m /s. First, the test vehicle enters the low temperature chamber and needs to be parked for at least 10 hours; Then, the spray gun sprays water on the outer surface of the windshield to form a uniform ice layer. Spray velocity is 0.044g /cm², the nozzle is 200 mm~250 mm away from the glass surface, whose direction is perpendicular to the windshield. After the formation of uniform ice, the car still has to be parked in the low temperature chamber for 30 to 40 minutes. Then start the engine and open the defrost system at the same time, which means the defrost test begin. The test personnel recorded the defrost status every 5 min and took photos. Fig.11 compares the simulation results with the experimental results.

![Figure 11](image1.png)

Figure 11. Frost melting effect: (a) 0, (b) 10, (c) 20, and (d) 25 min.

The frost layer began to melt in 10 min. The defrosting area in \(A\) area reached 80% at 20 min, and the defrosting area in \(A'\) area reached 65%. The frost layers in \(A\), \(A'\), and \(B\) areas were all melted at 25 min, and the defrosting work was almost completed. Comparing the simulation and the experimental results, the position of the initial melting is the same, but the experimental melting area is slightly larger than the simulation. Fig.12 shows the variation of the outlet air temperature per second. From 0 to 12 minutes, the inlet air temperature of the vehicle increases from \(-18^\circ C\) to approximate \(10^\circ C\). Early experiments reveal that the internal temperature of the front windshield increased, but the heat exchange between the glass and frost layer is not obvious. From 10 to 25 minutes, there has been a significant difference between the internal and external temperature of the front windshield, and as time passes, the heat transfer becomes better. From 25 to 40 minutes, the air temperature has reached more than \(30^\circ C\), during which time the defrost efficiency is getting faster and faster. in the 40th minute, the frost layer on the front windshield had been completely removed.
5.2. Verification of airflow temperature

The left and right outlets are structurally symmetrical. Thus, monitoring the airflow temperature at the left and central outlets is necessary. Fig. 13 compares the optimized simulation values with the experimental values. The results show that the experimental airflow temperature is always higher than that of the simulation; thus, the experimental melting area is slightly larger than the simulated melting area. The airflow is heated as it passes through the defrosting duct due to the generated heat during the experiment, while the simulation ignores the effects of convective heat transfer between the engine and the airflow. The temperature difference gradually decreases with the increase in time, and the experimental melting area tends to be consistent with the simulated melting area. This result is in accordance with the conclusions drawn in Fig. 11.

6. Conclusions

A simulation analysis of the original automotive air conditioning system is conducted, and the simulation results revealed that the flow distribution is unreasonable. A structural topology scheme for additional horizontal grilles at the outlets is proposed to solve this problem. The following optimization parameters of the air conditioning are then determined: the length of the left outlet $L_1$, the length of the central outlet $L_2$, and the airflow jet angle $\alpha$. The RBFNN is used to identify the optimal combination scheme of these parameters. The optimal combination of these parameters is as follows: $L_1 = 340\, mm$, $L_2 = 119\, mm$, $\alpha = 62^\circ$. 
The flow of each outlet is rationally distributed after optimization: the flow rate of the central outlet is reduced by 9.93%, the flow rate of the left outlet is increased by 3.90%, and the flow rate of the right outlet is increased by 4.16%. The defrosting dead corner is reduced from 20% to 5%, and the defrosting performance is improved. The optimized model is verified by experiments. The defrosting area reached 80% at 20 min, and the defrosting area reached 65%. The frost layers were melted at 25 min. The experimental results are consistent with the simulation results, which verifies the effectiveness of the optimization model.

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Nomenclature

- $x_p$ = The $p$-th input sample
- $c_i$ = The $i$-th Gaussian function center of the hidden layer
- $\delta_i$ = Variance of the $i$-th Gaussian function
- $\omega_i$ = Weight of the hidden layer to the output layer
- $b_i$ = Bias term
- $k$ = Turbulent kinetic energy [m$^2$s$^{-2}$]
- $\varepsilon$ = Turbulent dissipation rate
- $x_i, x_j$ = Position vectors [m]
- $u_i$ = Velocity [ms$^{-1}$]
- $\mu_t$ = Turbulent viscosity coefficient [kg m$^{-1}$s$^{-1}$]
- $\mu_i$ = Molecular viscosity
- $\sigma_k, \sigma_\varepsilon$ = Turbulent Prandtl number of turbulent kinetic energy and turbulent dissipation
- $G_k$ = Turbulent kinetic energy caused by average velocity gradient [m$^2$s$^{-2}$]
- $G_b$ = Turbulent kinetic energy caused by buoyancy [m$^2$s$^{-2}$]
- $Y_M$ = Contribution of compressible velocity turbulent pulsation expansion
- $H$ = Enthalpy [J]
- $\rho$ = Density [kgm$^{-3}$]
- $\bar{v}$ = Fluid velocity [ms$^{-1}$]
- $\bar{v}_p$ = Velocity of ice-water mixture [ms$^{-1}$]
- $T$ = Temperature [K]
- $\beta$ = Liquidus fraction
- $N$ = Number of design points
- $n$ = Number of variables in the approximate model
- $y_i$ = Simulation value
- $\bar{y}$ = Predicted value
- $\bar{y}$ = Average of the simulated values
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