Measurement-based strategies for high-fidelity thermo-fluid dynamics simulation of an automotive heat exchanger

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Abstract
A heating ventilation and air conditioning (HVAC) unit is an essential unit to adjust temperature for passenger’s comfortability in an automotive cabin. For efficient and reliable design and development of the HVAC unit, the interior thermal flow needs to be simulated and the performance needs to be evaluated with low cost and high fidelity. Hence, this paper develops measurement-based strategies for high-fidelity thermo-fluid dynamics simulation of an HVAC heat exchanger. These strategies tune up the parameters of a porous media model in the governing equations, which model the interaction between the heat exchanger and the surrounding thermal flow field and are conventionally fixed to certain constants, by functionalization or data assimilation with actual measurement data. The present results show that both strategies are able to reduce discrepancies between the simulation and the actual measurements, and improve fidelity to simulate the temperature field without sacrificing the simulation cost very much. Especially, the data assimilation strategy is more effective to yield more accurate simulation results only with the measurement data while the functionalization strategy needs to derive theoretical correlations. It demonstrates that data assimilation is helpful to assist reliable and efficient design and development of an HVAC unit regardless of designer’s professional skills or knowledge.

Keywords: Heating ventilation and air conditioning (HVAC) unit, Heat exchanger, Computational fluid dynamics (CFD), Porous media model, Functionalization, Data assimilation

1. Introduction
A car air conditioner is indispensable for adjusting temperature and maintaining comfort inside the passenger compartment. It is referred to a heating ventilation and air conditioning (HVAC) unit which consists of a blower unit that sends out wind and a heater unit that adjusts temperature. In recent years, as the number of electric cars increases, the demands for reducing the electric power consumption, maintaining comfort, and expanding the passenger compartment space are increasing (Iguchi, 2010). Now it is required to develop a compact and low-load HVAC unit satisfying the demands.

It usually takes a huge human effort to develop such an HVAC unit. Hence, computer aided engineering (CAE) technologies, such as computational fluid dynamics (CFD) and optimization, have been used to design the HVAC unit efficiently. For examples, Kitamura et al. (2018) conducted CFD simulation for an HVAC heater unit and modified the interior wall position to reduce the ventilation resistance. Iwamoto et al. (2015) suggested that an HVAC heater unit with straight flow channels is effective to enhance heat performance, pressure loss reduction, and noise reduction at the same time. Moreover, Kamada et al. (2019) optimized the shapes of multi-blade fan and scroll in an HVAC blower unit using a CFD solver based on the Reynolds-averaged Navier-Stokes (RANS) equations and a genetic algorithm. The optimized design outperformed the baseline design in terms of both total pressure efficiency and noise level.
Compared to RANS-based CFD, higher-fidelity CFD like large eddy simulation (LES) is sometimes needed to simulate complex thermal flow and evaluate performance of an HVAC unit accurately. In fact, Onodera and Ito (2010) predicted noise with a peak at a certain frequency in an HVAC unit by LES, which resulted in good agreement with the actual measurements. However, such high-fidelity simulation usually costs a large amount of time, which is not acceptable for the HVAC product development in the real world. Thus, CFD is required to keep a balance between fidelity and cost.

For example, the heat exchanger in an HVAC unit is often replaced with a porous media model (this is formulated in Eq. 1 and will be explained in more details later). Once the model parameters ($\alpha$ and $\beta$ in Eq. 1) are given somehow (e.g., empirically), the porous media model is included in the RANS equations to simulate the interaction between the heat exchanger and the surrounding thermal flow field in a simple way. In fact, Okada et al. (2000), Yano et al. (2004), and Patidar et al. (2009) applied the porous media models to the RANS-based CFD for HVAC units, and demonstrated drastic reduction in time for the HVAC product development. However, Okada et al. (2000) and Yano et al. (2004) also suggested that conventional CFD with globally fixed model parameters is still insufficient for good consistency with the actual measurements.

Kitada et al. (2000) and Ito et al. (2017) proposed the functionalization of model parameters, which allows the model parameters to vary in space depending on local flow properties, for the improvement in CFD simulation accuracy. They considered the turbulent Prandtl number in the RANS equations as a function of local flow variables, which was manually constructed based on theory and experiments, and applied it to CFD simulation for an actual HVAC. As a result, their CFD successfully improved the accuracy to simulate the temperature field in turbulent mixing flow without additional cost.

The model parameter functionalization is similar to optimizing the model parameters, which is well known as data assimilation. This is the method that can automatically tune up the model parameters to fit reference data (e.g., actual measurements). Thus, data assimilation is considered more effective and versatile to improve the accuracy of CFD simulation than the model parameter functionalization. It is famous that data assimilation is applied to a numerical model for weather forecast (e.g., Japan Meteorological Agency non-hydrostatic model: JMA-NHM reviewed by Saito et al. (2007)). In addition, Kikuchi et al. (2018) developed a wind nowcasting algorithm, which combines ensemble weather forecasting data and flight data through data assimilation, for safe and efficient aircraft operation. As other applications, Kato et al. (2016) simulated back step flow accurately by assimilating the turbulence model parameters in RANS-based CFD with the measurement data. Yamakawa et al. (2015) applied the data assimilation to the porous media model and improved the accuracy of the heat exchanger air flow in a home appliance air conditioner.

In this study, we endeavor to improve the accuracy of the RANS-based thermo-fluid dynamics simulation for an HVAC heat exchanger. This paper works on developing the high-fidelity simulation models by functionalization or data assimilation with actual measurement data, and compare and discuss the effects of each strategy on the simulation results.

2. Setup

This study considers the HVAC heat exchanger shown in Fig. 1(a). Since it is difficult to observe the flow properties inside the actual HVAC unit, we construct a simple assembly, which consists of the heat exchanger and a duct, as shown in Fig. 1(b) for the present CFD and actual measurements. The experimental conditions of the heat exchanger are listed in Table 1 (in total, $1 \times 2 \times 3 \times 6 = 36$ patterns of experimental conditions). Dividing the outlet section of the heat exchanger into $N_{cell} = 5 \times 4 = 20$ cells, the average temperature $T_{air, out}$ [°C] and velocity $u_{air, out}$ [m/s] are measured at 10 mm downstream of each cell center.
Table 1 Experimental conditions of the HVAC heat exchanger

| Inflow water | Inflow air |
|--------------|-----------|
| Temperature  | Volume flow rate | Temperature  | Volume flow rate |
| $T_{\text{water, in}}$ [$^\circ$C] | $m_{\text{water}}$ [L/min] | $T_{\text{air, in}}$ [$^\circ$C] | $m_{\text{air}}$ [m$^3$/h] |
| 85           | 6          | 10           | 5            |
|              | 12         | 20           | 350          |
|              |            | 235          | 150          |
|              |            |              | 100          |

3. Simulation methods

3.1. Governing equations with a porous media model

For the present thermo-fluid dynamics simulation for the HVAC heat exchanger, the governing equations are the three-dimensional steady RANS equations. In the heat exchanger zone, which is colored yellow in Fig. 2, a porous media model is activated. This model approximates the pressure drop of flow passing through the fins, $-\frac{dp}{dx}$, as

$$-\frac{dp}{dx} = \alpha u + \beta u|u|,$$

where $u$ is the velocity component in the $x$-direction, and $\alpha$ and $\beta$ are the model parameters related to viscous drag and inertial drag, respectively. In addition, the present model considers the heat transfer between air and water, $Q$, which is given by

$$Q = h (T_{\text{air}} - T_{\text{water}}),$$

where $h$ is the heat transfer coefficient, $T_{\text{air}}$ is the air temperature, and $T_{\text{water}}$ is the water temperature. The present system of governing equations activates Eq. 1 in the momentum equation and Eq. 2 in the energy equation once the values of $\alpha$, $\beta$, and $h$ are assigned to each mesh node in the heat exchanger zone.

![Fig. 2 CFD simulation domain for the HVAC heat exchanger](image)

3.2. Flow solver

We employ a commercial CFD software STAR-CCM+ 13.06.012 (Siemens, 2020). The semi-implicit method for pressure-linked equations (SIMPLE) is used to solve the governing equations discretized by a finite volume method. A second-order upwind scheme, the least squares cell-based gradient scheme, and the $k$-$\epsilon$ turbulence model are chosen here. A polyhedral mesh with 199,074 cells is generated in the simulation domain as shown in Fig. 2. As the boundary conditions, velocity and temperature are fixed at the inlet, which are given from Table 1, while atmospheric pressure is imposed at the outlet.

3.3. Model parameter assignment

There are three parameters $\alpha$, $\beta$, and $h$ to be assigned in the porous media model (Eqs. 1 and 2). This paper investigates the following three strategies, (1) fixed parameters, (2) functionalization, and (3) data assimilation, for the model parameter assignment.
3.3.1. Fixed parameters
Conventionally, the model parameters are often assumed to be constant. In this strategy, we simply fix $\alpha = 3000$, $\beta = 500$, and $h = 100$ at all mesh nodes in the heat exchanger zone.

3.3.2. Functionalization
Now $dp/dx$ and $h$ are assumed to be functions of local flow properties and assigned to $N_{\text{cell}} = 20$ heat exchanger cells (denoted in Fig. 1(b)) individually. First, regarding $dp/dx$, the equation of state for ideal gas leads to the following correlation as

$$dp = \frac{m_{\text{air}} R T_{\text{air,in}}}{A} \left( \ln \frac{T_{\text{air,out}}}{T_{\text{air,in}}} - \ln \frac{u_{\text{air,out}}}{u_{\text{air,in}}} \right),$$

where $R$ is the gas constant and $A$ is the area of the heat exchanger projected to the $x$-direction. Dividing Eq. 3 by the heat exchanger thickness as $dx$ gives the functional form of $dp/dx$. We experiment with the test bench, which is shown in Fig. 3, under different conditions (in this study, all 36 patterns listed in Table 1) and calculate $dp/dx$ by Eq. 3 for each heat exchanger cell. This test bench is designed to control the inflow water volume rate $\dot{m}_{\text{water}}$, the inflow air temperature $T_{\text{air,in}}$, and the inflow air volume rate $u_{\text{air}}$ independently (Ito et al., 2017). Curve fitting to the measurement data results in the following function:

$$\frac{dp}{dx} = f_1(T_{\text{air,in}}) \frac{\exp [g_1(T_{\text{air,in}}) u^*]}{T_{\text{air,in}}}$$

(4)

where $u^* = u_{\text{air,out}}/u_{\text{air,in}}$, $T^* = (T_{\text{air,out}} - T_{\text{air,in}}) / (T_{\text{water,in}} - T_{\text{air,in}})$, and

$$f_1(T_{\text{air,in}}) = 1197.4 T_{\text{air,in}} + 687.28,$$

(5.a)

$$g_1(T_{\text{air,in}}) = -0.0324 T_{\text{air,in}} - 0.1484.$$  

(5.b)

Fig. 3 Test bench of the HVAC heat exchanger

Next for $h$, the heat conservation law gives

$$h = \frac{m_{\text{air}} C_{\text{air}} (T_{\text{air,out}} - T_{\text{air,in}})}{A_{\text{air}} \Delta T_{\text{LMTD}}},$$

(6)

where $C_{\text{air}}$ is the air heat capacity, $A_{\text{air}}$ is the air passage sectional area per heat exchanger cell, which is provided by the specifications of the heat exchanger, and

$$\Delta T_{\text{LMTD}} = \frac{(T_{\text{water,out}} - T_{\text{air,in}}) - (T_{\text{water,in}} - T_{\text{air,out}})}{\ln \left( \frac{T_{\text{water,out}} - T_{\text{air,in}}}{T_{\text{water,in}} - T_{\text{air,in}}} \right)}.$$  

(7)

Here $T_{\text{water,out}}$ is obtained for each heat exchanger cell by

$$T_{\text{water,out}} = T_{\text{water,in}} - \frac{m_{\text{air}} (T_{\text{air,out}} - T_{\text{air,in}})}{\dot{m}_{\text{water}}}. $$

(8)

Similar to the functionalization for $dp/dx$, $h$ is calculated by Eq. 6 for each heat exchanger cell, and the following function is obtained by curve fitting:

$$h = f_2(u^*) \exp [g_2(u^*) T^*],$$

(9)
where $u^* = u_{air,in}/u_{air,in,min}$ ($u_{air,in,min}$ is the minimum value of $u_{air,in}$ among the actual measurements) and

$$f_2(u^*) = 0.793u^{*2} - 0.1907u^* - 0.8089,$$

$$g_2(u^*) = 0.8989u^{*2} - 6.1304u^* + 13.417.$$  

(10.a)  

(10.b)

In this strategy, simulation is conducted in the heat exchanger zone by replacing the original form of $dp/dx$ (Eq. 1) and the fixed $h$ (= 100) with the functions formulated in Eqs. 4 and 9, respectively.

### 3.3.3. Data assimilation

We use the ensemble Kalman filter (EnKF) (Evensen, 2003) for data assimilation. Figure 4 shows the flowchart of the present EnKF for CFD simulation. The state vector $x$ consists of the flow quantities (pressure $p$, velocity component $u$, and temperature $T$) calculated at $N_{\text{flow}}$ mesh nodes in the whole simulation domain (currently, $N_{\text{flow}} = 199,074$) and the model parameters ($\alpha$, $\beta$, and $h$) given at $N_{\text{model}}$ mesh nodes in the heat exchanger zone (currently, $N_{\text{model}} = 10,706$) as

$$x = \left[ p_1, u_1, T_1, p_2, u_2, T_2, \ldots, p_{N_{\text{flow}}}, u_{N_{\text{flow}}}, T_{N_{\text{flow}}}, \alpha_1, \beta_1, h_1, \alpha_2, \beta_2, h_2, \ldots, \alpha_{N_{\text{model}}}, \beta_{N_{\text{model}}}, h_{N_{\text{model}}} \right]^T,$$

(11)

and the observation vector $y$ consists of $u$ and $T$ obtained at 10 mm downstream of $N_{\text{cell}}$ heat exchanger cells as

$$y = \left[ u_1, T_1, u_2, T_2, \ldots, u_{N_{\text{cell}}}, T_{N_{\text{cell}}} \right]^T.$$  

(12)

![Flowchart of the EnKF for CFD simulation](image)

First in the flowchart, an initial ensemble of $N_{\text{ensemble}}$ state vectors, $x^{(i)}_{n=0}$ ($i = 1, 2, \ldots, N_{\text{ensemble}}$), is generated randomly. In this study, $N_{\text{ensemble}} = 40$ and the initial ensemble follows to the normal distribution around the fixed parameters, i.e., $\alpha \sim \text{Norm}(3000, 10)$, $\beta \sim \text{Norm}(500, 10)$, and $h \sim \text{Norm}(100, 10)$. Starting with $n = 0$, CFD is conducted for the $i$-th ensemble member $x^{(i)}_{n=0}$ to predict the state vector at the next assimilation step, $x^{(i)}_{n+1|i}$, and the corresponding observation vector, $y^{(i)}_{n+1|i}$, which is linearly obtained through a mapping matrix $H$ as

$$y^{(i)}_{n+1|i} = Hx^{(i)}_{n+1|i}.$$  

(13)

Next, EnKF generates a new ensemble, $x^{(i)}_{n+1|i+1}$, as

$$x^{(i)}_{n+1|i+1} = x^{(i)}_{n+1|i} + K_{n+1}(y_{n+1|i} - Hx^{(i)}_{n+1|i} + w).$$  

(14)

$K_{n+1}$ is the Kalman gain given by

$$K_{n+1} = \hat{V}_{n+1|i}H^T(H\hat{V}_{n+1|i}H^T + R)^{-1},$$  

(15)

where $\hat{V}_{n+1|i}$ is the ensemble covariance matrix given by

$$\hat{V}_{n+1|i} = \frac{1}{N_{\text{ensemble}} - 1} \sum_{i=1}^{N_{\text{ensemble}}} \left( x^{(i)}_{n+1|i} - \bar{x}_{n+1|i} \right) \left( x^{(i)}_{n+1|i} - \bar{x}_{n+1|i} \right)^T,$$

(16.a)

$$\bar{x}_{n+1|i} = \frac{1}{N_{\text{ensemble}}} \sum_{i=1}^{N_{\text{ensemble}}} x^{(i)}_{n+1|i}.$$  

(16.b)

In addition, $w$ is the observation error vector, which is currently set as $w \sim \text{Norm}(0, R)$ with $R = 0.1I$ ($I$ is the identity matrix). The current value of the observation error is tentatively employed for successful data assimilation. Although
we also tried the data assimilation employing the actual measurement errors in the test bench, its solution failed to be assimilated with the actual measurement data. We guess that, in real world, the observation error changes depending on a quantity of interest (temperature, velocity, etc.). Nevertheless, accuracy of the present data assimilation is governed by the model itself, which will be discussed in Section 4, rather than the observation error. This process is repeated \((n = n + 1)\) until the following cost function \(J\) is converged (hopefully, the predicted \(y\) approaches the actual measurement data in the test bench, \(y_{\text{actual}}\), for one standard pattern among the 36 patterns):

\[
J = \frac{1}{2} (y - y_{\text{actual}})^T (y - y_{\text{actual}}).
\]  

Finally, in this strategy, we conduct CFD with the model parameters \(\alpha_1, \beta_1, h_1, \alpha_2, \beta_2, h_2, \ldots, \alpha_{\text{Nmodel}}, \beta_{\text{Nmodel}}, h_{\text{Nmodel}}\) estimated by the EnKF.

4. Results and discussion

At the standard condition of the HVAC heat exchanger unit \((T_{\text{water,in}} = 85 \, ^\circ\text{C}, m_{\text{water}} = 10 \, \text{[L/min]}, T_{\text{air,in}} = 5 \, ^\circ\text{C}, \) and \(m_{\text{air}} = 235 \, \text{[m}^3/\text{h}]\)), we conduct CFD for the HVAC heat exchanger assisted by each of the three strategies for the model parameter assignment.

First, Fig. 5 compare the CFD results (temperature \(T\) and velocity component \(u\)), which are obtained at 20 locations corresponding to 10 mm downstream of the 20 heat exchanger cells, with the actual measurement data. Compared to the fixed parameters strategy, the functionalization strategy and the data assimilation strategy output higher values of \(T\) as seen in Fig. 5(a), which lead to the improvement in CFD accuracy. The average errors between CFD and the actual measurements are 1.30 °C for the data assimilation 3.04 °C for functionalization. Note that, even based on all the 36 patterns of actual measurement data, the functionalization strategy cannot adapt well to the actual measurement at the standard condition considered here. Hence, it indicates that the data assimilation strategy is most suitable for the RANS-based CFD to be consistent with the actual measurements in the HVAC heat exchanger unit.

Figure 6 compare the spatial distributions of a parameter (heat transfer coefficient \(h\)) estimated by the functionalization strategy and the data assimilation strategy. The functionalization strategy (Fig. 6(a)) constructs a smooth distribution of \(h\), which is higher than the fixed parameter strategy \((h = 100)\) in almost the whole heat exchanger domain, while the data assimilation strategy (Fig. 6(b)) is involved with a non-smooth distribution with locally higher \(h\) (note that the maximum of the color range in Fig. 6(b) is much higher than that in Fig. 6(a) by two orders). Higher \(h\) enhances heat exchange between air flow and the water flow in the heat exchanger. Thus, as seen in Fig. 5(a), the functionalization strategy shifts up \(T\) for all the heat exchanger cells while the data assimilation strategy increases \(T\) for each cell adaptively. From the physical point of view, however, the non-smooth distribution seems unrealistic (in other words, overfitting to the standard condition considered here). This is an issue to be addressed in future work, which will be stated in Section 5.

Next, Fig. 7 shows the history of the cost function in the data assimilation strategy. It indicates that the data assimilation leads to the converged CFD solution, which is consistent with the actual measurements of \(T\) as seen in Fig. 5(a). Regarding \(u\) shown in Fig. 5(b), on the other hand, there is still a residual error even by the data assimilation strategy. This is because the present porous media model is still simple and not suitable for real-world heat exchanger geometry with microstructures (e.g., fins). Such structures disturb the flow field around the heat exchanger sensitively and yield a noisy velocity profile (like the actual measurements in Fig. 5(b)), which is hard to be resolved by CFD without considering the microstructures. For further improvement in CFD accuracy assisted by the data assimilation, therefore, the porous media models needs to be constructed in a more highly resolved mesh system. As additional information, we have checked that the residual error seen in Fig. 5(b) does not disappear by the data assimilation strategy even with different ranges of the parameters in the porous media model. In addition, the residual error seems independent of the choice of the three strategies. Hence, we think that the discrepancy mainly comes from the simulation model itself.

Here note that the present data assimilation strategy with good accuracy in temperature prediction is satisfactory for practical use in the design and development of an HVAC unit. This is because the HVAC unit needs to work in several different modes (not only air-conditioner but also defroster and fogger), which can be switched through precise temperature control. In addition, the present data assimilation strategy can be implemented only with the measurement data while the functionalization strategy needs to derive theoretical correlations. Moreover, the present data assimilation with \(N_{\text{ensemble}} = 40\) has taken 60 hours for 29 iterations on a parallel computing system with 16 cores. It is computationally quite reasonable within the period of design and production (in general, around one year). Hence, the data assimilation helps any designers efficiently regardless of their professional skills or knowledge.
Fig. 5  CFD results assisted by different model parameter assignment strategies compared with the actual measurements.

Fig. 6  Spatial distributions of an estimated parameter (heat transfer coefficient $h$).

Fig. 7  History of the cost function in the data assimilation strategy.
As another issue, the current number $N_{\text{cell}} = 20$ is given due to a limitation on the actual measurement capability in the test bench. In the data assimilation strategy, the residual error in velocity (Fig. 5(b)) is expected to be reduced as $N_{\text{cell}}$ increases (i.e., richer reference data is available). In the functionalization strategy, on the other hand, larger $N_{\text{cell}}$ is not effective because the current functions (Eqs. 5.a and 5.b) used to estimate $dp/dx$ mainly depends on temperature. Instead, the functionalization strategy may be improved if these functions are given in more complex forms depending on both temperature and velocity. To sum up, the data assimilation strategy has a higher possibility to be further improved in an easier way.

5. Conclusions

This paper developed strategies for high-fidelity RANS-based thermo-fluid dynamics simulation for an HVAC heat exchanger. Tuning up the parameters in a porous media model by functionalization or data assimilation, we improved the simulation accuracy without sacrificing the simulation cost very much. Especially, it was demonstrated that the data assimilation strategy is most effective for RANS-based simulation to simulate the temperature field consistent with the actual measurements. Consequently, the data assimilation is promising to enhance high fidelity as well as low cost in real-world product design and development of an HVAC unit.

In this paper, data assimilation was performed at a certain single condition. It may not only improve the simulation accuracy but also overfit to the reference data given at the single condition. For the universal use of data assimilation, therefore, our future work will develop a new data assimilation strategy to avoid such overfitting. We are thinking of a possibility to combine artificial intelligence technologies with data assimilation performed at several different conditions.

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