Temperature Estimation Accuracy Improvement of Computational Fluid Dynamic Simulation by Optimizing Multiple Parameters

Yuanzhi Huo*, Nobuo Funabiki, Xiang Xu, Kazuyuki Kojima, Yihan Zhao, and Wenchung Kao

***Abstract*—The computational fluid dynamic (CFD) model can be used to estimate temperatures of structures with complex dynamics. Currently, we are developing the CFD model for estimating temperatures in a room that has cooling and heating sources to optimize the air-conditioning guidance. Previously, only one parameter in the model was optimized using the parameter optimization algorithm, which results in insufficient estimation accuracy. In this paper, we present the improvement by optimizing the four parameters in the model and allowing different values to them by the temperature. The evaluation results show that the average difference between the estimated and measured temperature is reduced to 0.06℃ and the coefficient of determination R^2 is improved to 0.9994.**

***Index Terms*—CFD model simulation, parameter optimization algorithm, temperature estimation**

I. Introduction

Nowadays, heaters, air-conditioners, and fans are equipped in rooms in houses, schools, factories, and offices to offer comfortable environments for humans and machines. On the other hand, global warming has become serious due to overconsumptions of fossil fuels. The proper use of air-conditioning equipments is increasing its importance, which has motivated us to study the air-conditioning guidance (AC-Guide) in a room that has cooling and heating sources [1]. Usually, temperature or humidity sensors are used to monitor the current condition of a room. However, their locations are limited near the equipment due to the cost reason. Besides, they will be changed in certain time later after some actions are taken. As a result, persons in the same room may feel hot or cold depending on their locations and time.

The estimations and predictions of temperature and humidity distributions in the room using the simulation model can be solutions for them. The computational fluid dynamic (CFD) model has been used to estimate temperatures of structures with complex dynamics [2]. Therefore, we are developing a CFD model for estimating temperatures of several locations in a room, to improve the guiding accuracy of AC-Guide [3].

Manuscript received March 27, 2023; revised April 13, 2023; accepted June 19, 2023; published October 16, 2023.

Y. Huo, N. Funabiki, X. Xu are with the Department of Information and Communication Systems, Okayama University, Okayama, Japan. E-mail: funabiki@okayama-u.ac.jp (N.F.); xuxiang5012@gmail.com (X.X.)

K. Kojima, Y. Zhao are with the Department of Mechanical Engineering of Shonan Institute of Technology University, Kanagawa, Japan. E-mail: kojima@mech.shonan-it.ac.jp (K.K.); 22t1007@sit.shonan-it.ac.jp (Y.Z.)

W.-C. Kao is with Department of Electrical Engineering National Taiwan Normal University, Taipei, Taiwan. E-mail: jungkao@ntnu.edu.tw (W.C.K.)

*Correspondence: pa9h1fz9@s.okayama-u.ac.jp (Y.H.)

In our previous study, we have optimized only one parameter in the CFD model using the parameter optimization algorithm, which resulted in the insufficient estimation accuracy. A CFD model needs to simulate complex physical phenomena. A physical parameter such as the heat transfer coefficient may take a different value by the location in a room. The value should be optimized for each location. Besides, the optimization process takes very long CPU time on a conventional PC because it needs to repeatedly run CFD simulations with different parameter values while their optimizations.

In this paper, we present the improvement of the temperature estimation accuracy by optimizing the four parameters in the CFD model together by the parameter optimization algorithm and allowing to take different values to them by the temperature.

The application results show that the average difference between the estimated and measured temperature is reduced to 0.06℃ and the coefficient of determination R^2 is improved to 0.9994.

The rest of this paper is organized as follows: Section II introduce the necessary technique in this paper. Section III introduces the temperature estimation model for simulation. Section IV presents the experiment and analyzes the results. Section V introduce related work. Finally, Section VI provides concluding remarks with future work.

II. Background Technologies

In this section, we introduce necessary technologies for this study.

A. CFD

Computational fluid dynamics (CFD) is used to analyze and solve problems that involve fluid flows by using the numerical analysis and proper data structures. CFD is a branch of fluid mechanics. Computers are used to simulate the free-stream flow of liquids or gases, and the interactions of the fluid with surfaces defined by boundary conditions. By running it on a high-speed supercomputer, better solutions can be achieved, where it is often required to solve the largest and most complex problems.

B. OpenFOAM

OpenFOAM is the popular open-source CFD software that has been developed primarily by OpenCFD Ltd. since 2,004 [4]. It can be used to simulate free-stream flows of liquids or gases or interactions of the fluid with surfaces defined by boundary conditions. The CFD simulation accuracy depends

DOI: 10.7763/IJMO.2023.V13.834

on the selected parameter values in the model.

OpenFOAM uses the finite volume method (FVM) and sets the boundary condition as patterns [5]. Each pattern has several parameters. The selection of the patterns and the parameter values have significant influences on simulation results. Therefore, their optimizations are very important.

C. Heat Flux Equation

In the temperature estimation model, the following heat flux equation is computed by using the discrete form in OpenFOAM:

$$q = \lambda \frac{\Delta T}{\Delta x} \tag{1}$$

where

- q represents the heat flux W/m^2.
- λ represents the thermal conductivity through a specified material, which is expressed as the amount of heat that flows per unit of time through a unit area with a temperature gradient of one degree per unit distance.
- ΔT represents the difference between the outside and inside temperatures of the wall *Kelvin (K)*.
- x represents the thickness of the wall (*meter(m)*).

D. Parameter Optimization Algorithm:paraOpt

In this section, we review the parameter optimization algorithm called *paraOpt*.

1) Symbols

First, we define the symbols to describe the procedure of *paraOpt* [6]. Among them, p_i^{init}, Δp_i, t_i, and $S(P)$ should be properly selected for the target algorithm/logic to achieve a better result.

- P: the set of the ${n}$ parameters for the algorithm/logic in the logic program whose values should be optimized.
- p_i:the value of the ith parameter in P ($1 \leqslant i \leqslant n$).
- p_i^{init}: the initial value of the ith parameter in P ($1 \leqslant i \leqslant n$).
- Δp_i: the change step for p_i.
- t_i: the tabu period for p_i in the tabu table.
- $S(P)$: the score of the algorithm/logic using P.
- P_{best}: the best set of the parameters.
- $S(P_{best})$: the score of the algorithm/logic where Pbest is used.
- L: the log of the generated parameter values and their scores.

2) Algorithm Procedure

The following procedure describes the steps of *paraOpt* to find the parameter values of P to minimize the score $S(P)$:

Algorithm1 parameter optimization tool

1: Clear the generated parameter log L.
2: Set the initial value in the parameter file for any p_i
In P, set 0 for any tabu period t_i
, and set a large value for $S(P_{best})$.
3: Generate the neighborhood parameter value sets for P by:
(a) Randomly selecting one parameter p_i for $t_i = 0$.
(b) Calculate the parameter values of p_i- and p_i+ by:

$$p_i- = p_i - \Delta p_i \text{ , if } p_i > \text{lower limit,}$$

$$p_i+ = p_i + \Delta p_i \text{ , if } p_i < \text{upper limit.}$$

(c) Generate the neighborhood parameter value sets $P-$ and $P+$ by replacing p_i by p_i- or p_i+:

$$P- = \{p_1, p_2, \ldots, p_i-, \ldots, p_n\}$$
$$P+ = \{p_1, p_2, \ldots, p_i+, \ldots, p_n\}$$

4: When P ($P-$, $P+$) exists in L, obtain $S(P)$ ($S(P-)$, $S(P+)$) from L. Otherwise, execute the logic program using P ($P-$, $P+$) to obtain $S(P)$ ($S(P-)$, $S(P+)$), and write P and $S(P)$ ($P-$ and $S(P-)$, $P+$ and $S(P+)$) into L.
5: Compare $S(P)$, $S(P-)$, and $S(P+)$, and select the parameter value set that has the largest one among them.
6: Update the tabu period by:
(a) Decrement t_i by -1 if $t_i > 0$.
(b) Set the given constant tabu period TB for t_i if $S(P)$ is the largest at 5 and p_i is selected at 3-(a).
7: When $S(P)$ is continuously largest at 5 for the given constant times, go to 8. Otherwise, go to 3.
8: When the hill-climbing procedure in 9 is applied for the given constant times HT, go to 10 as the state is converged. Otherwise, go to 9.
9: Apply the hill-climbing procedure:
(a) If $S(P) < S(P_{best})$, update P_{best} and $S(P_{best})$ by P and $S(P)$.
(b) Reset P by P_{best}.
(c) Randomly select p_i in P, and randomly change the value of p_i within its range and go to (3).
10: Terminate the algorithm.

E. Model Room for Experiments

In this study, we evaluate the accuracy of the temperature estimation result of the CFD simulation using *OpenFOAM* with the measured ones in the model room. In a real room in a conventional building, it is very difficult or impossible to freely change the temperature or humidity to be the required one in the experiments under various weathers or seasons.

To solve this problem, a small-sized model room for expe-riments in Figure 1 is assembled for this study. The size of this room is 1m × 1m × 1m and is covered by the outer box whose size is 2m × 2m × 1.5m. The walls of this box are insulated by the 30mm thick insulation. In the model room, temperature-controlled air using an air conditioning unit can be supplied. Besides, at the bottom of the model room, heaters are mounted to raise the temperature in the room. To measure the temperature distribution of the room, 27 temperature sensors are installed at the equal interval in the room.

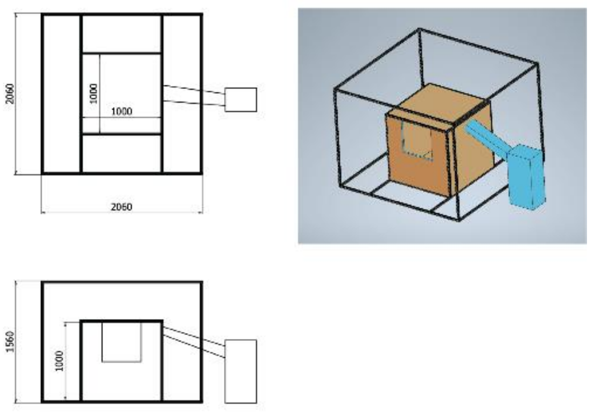

Fig. 1. Model room for experiments.

III. Proposal

In this section, we present the temperature estimation model for the model room and the optimization of its multiple parameters.

A. Temperature Estimation Model

To estimate the temperature distribution in the model room, the 3D mesh model in Figure 2 is made for *OpenFOAM* to represent the alternative room. The size for this model is the same as that for the real one.

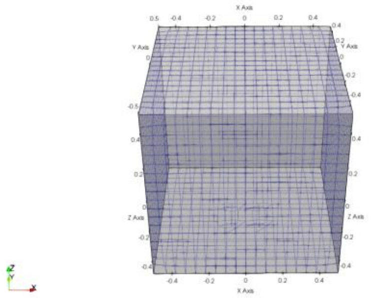

Fig. 2. 3D mesh model.

Before starting the *CFD* simulation using *OpenFOAM*, the boundary conditions for the walls and the heaters need to be set properly, since they strongly influence the simulation results. The boundary condition of the wall is given by the heat flux in the following subsection.

B. Parameters for Optimization

Table I shows the parameters for the boundary conditions related to heat flux whose values are optimized in this study.

TABLE I: Parameters for Boundary Conditions

parameter	description
Q	power of heater
T_h	temperature of heater
h	heat transfer coefficient
T_w	temperature of wall

Then, at each wall, the following heat flux q is transferred to the wall from the chamber:

$$q = h(T_f - T_w) \quad (2)$$

where

- q represents the *heat flux* (W/m^2).
- h represents the heat transfer coefficient $W/(K{\bullet}m2)$ [7].
- T_f represents the temperature of the fluid along the wall at a certain moment (*Kelvin*(K)).
- T_w represents the temperature of the wall (*Kelvin*(K)).

C. Score Function

The boundary condition of the wall may have the large influence on the temperature changes in the room. To accurately predict the temperature changes, the values of the boundary condition parameters in *OpenFOAM* should be optimized. For this purpose, in *paraOpt*, the following score function $S(P)$ is calculated from the given simulation heat flux values P and the measured temperatures by the following procedure:

(1) Record the simulation temperature every five seconds for one hour.

(2) Calculate the absolute value of difference simulation temperature between measurement actual temperature.

(3) Calculate $S(P)$ by:

$$S(P) = \sum_{i=0}^{N} \left| T_s^i - T_m^i \right| \quad (3)$$

where T_s^i does the *i-th* simulated temperature at every five seconds, T_m^i does the *i-th* measured temperature saved at every five seconds, and N does the total number of temperature-s. In the parameter optimization algorithm, tabu $t_i = 10$.

IV. Experiment

In this section, we present experiment results for evaluati-ons. In experiments, First, we switch on the heater within 1 h our to increase the indoor temperature and measure temperat ure in coordinates (0, 0, 0). Second, simulation and optimi-za tion.

TABLE II: Initial Parameter Values for paraOpt

parameter	unit	initial value	range
Q	W	1	1~30
T_h	K	345	300~350
h	$W/(K{\bullet}m^2)$	1	1~30
T_w	K	345	300~350

A. Evaluation Setup

Table II shows the parameter values for *paraOpt*. The init -ial temperature of the room at both the inside and the outsid- e of the wall is 26.76◦C.

To evaluate the difference between the estimated tempera-ture and the measured one. the coefficient of determination R^2 is calculated by the following equation. R^2 becomes closer t o 1 as the difference becomes smaller.

$$R^2 = 1 - \frac{\sum_{i=0}^{m} \left(y_i - \hat{y}_i \right)^2}{\sum_{i=0}^{m} \left(y_i - \bar{y}_i \right)^2} \quad (4)$$

where:

- y represents the measured temperature (◦C).
- $\hat{y}_i$ represents the estimated temperature (◦C).
- $\bar{y}_i$ represents the average measured temperature (◦C).

B. One Parameter Optimization Result

First, we evaluate the model estimation accuracy when only one parameter Q is optimized by *paraOpt*.

Fig. 3 shows the estimated and measured temperature results. The difference between them is large. Table III shows the value of Q after optimization, and the average difference and the coefficient of determination between the estimated and measured temperature results. The result suggests one parameter optimization is not sufficient.

TABLE III: Results by One Parameter Optimization

parameter	after proposal	temperature difference	R^2
Q	2	6.23℃	0.5414

C. Four Parameters Optimization Result with Constant Value

Next, we evaluate the model estimation accuracy when all of the four parameters in Table II are optimized and their values are fixed.

Figs. 4–5 show the estimated and measured temper-ature results using the training data and the validation data, respectively. The average temperature difference between es-timated and measured during one hour is 0.79◦C and 0.68◦C. The difference becomes much smaller.

However, when the temperature becomes high as the time elapses, the difference increases. To improve it, the paramet-er values should be changed at the high temperature of 341K.

TABLE IV: RESULTS BY FOUR PARAMETERS OPTIMIZATION WITH CONSTANT VALUE.

parameter	after proposal	temperature difference	R^2
Q	10	0.79◦C	0.9878
T_h	345		
h	3		
T_w	321		

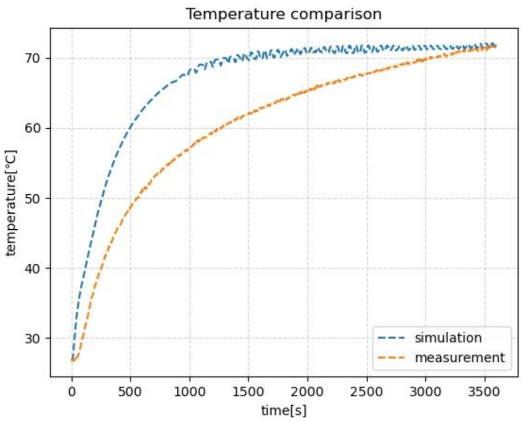

Fig. 3. Temperature results by one parameter optimization.

Table IV shows their optimized values, and the average difference and the coefficient of determination between the estimated and measured temperature results. The result sug-gests the four parameters optimization can improve the accuracy, but is still not sufficient.

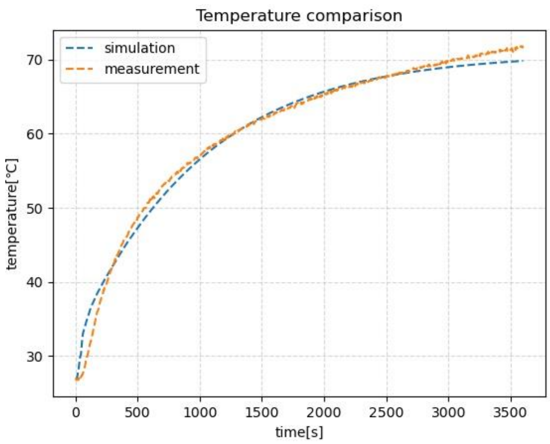

Fig. 4. Temperature results by four parameters optimization with constant value for training.

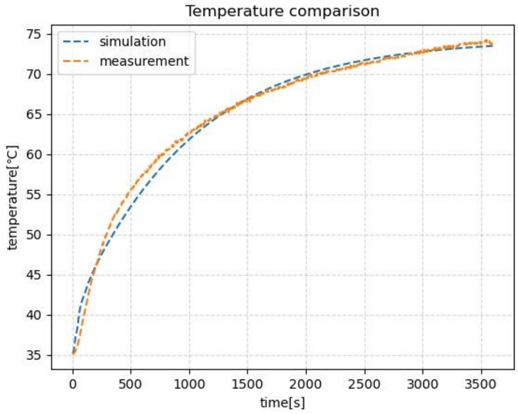

Fig. 5. Temperature results by four parameters optimization with constant value for validation.

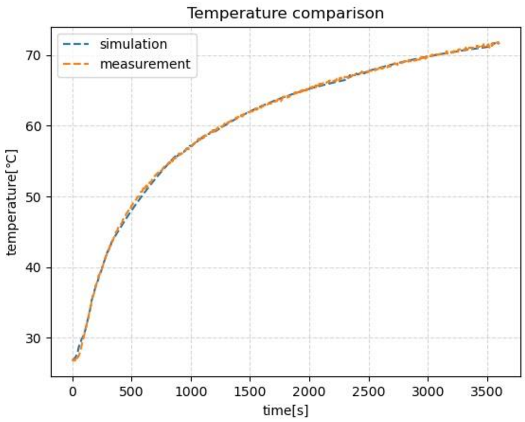

Fig. 6. Temperature results by four parameters optimization with changed value for training.

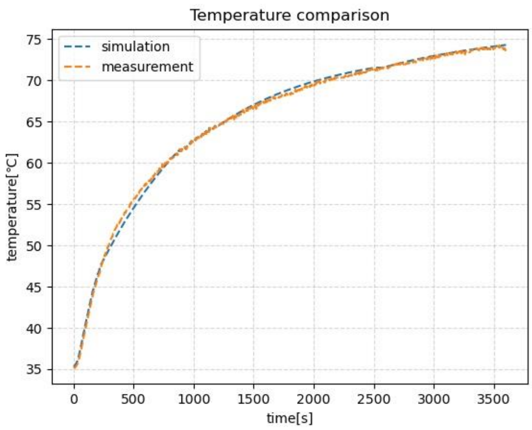

Fig. 7. Temperature results by four parameters optimization with changed value for validation.

D. Four Parameters Optimization Result with Changed Value

Last, we evaluate the model estimation accuracy when all of the four parameters are optimized and their values can be changed by the temperature. Here, the different values can be given to each parameter by the temperature range of 300 − 317K, 317 − 341K, and 341 − 346K. These ranges are also optimized by the parameter optimization tool.

Figs. 6 and Figs.7 show the estimated and measured temper-ature results using the training data and the validation data, respectively. The average temperature difference is 0.06◦C a nd 0.31◦C. The difference becomes small at any temperature and is not increasing as the temperature increases. Table V shows the optimized values, and the average difference and t-he coefficient of determination between the estimated and measured temperature results. The result suggests the four p-arameters optimizations with changed values can improve the accuracy sufficiently.

TABLE V: RESULTS BY FOUR PARAMETERS OPTIMIZATION WITH CHANGED VALUE

parameter	after proposal			temperature difference	R^2
Q	300-317 K	317-341K	341-346 K	0.06◦C	0.9994
	10	10	10		
T_h	300-317 K	317-341K	341-346 K		
	317	341	346		
h	300-317 K	317-341K	341-346 K		
	5.5	3	0.5		
T_w	300-317 K	317-341K	341-346 K		
	300	317	341		

V. RELATED WORK

In [8], Xi et al. proposed a smart hill-climbing algorithm based on RHC to configure the parameters in the server that can influence the server response automatically. They formulated the problem of finding the optimal configuration for a given application as the black-box optimization problem. They carried out extensive experiments with an online br-okerage application running in a WebSphere environment. The results demonstrated that the algorithm is superior to traditional heuristic methods.

In [9], Ghadimi *et al*. proposed an algorithm to optimize the shape of the centrifugal blood pump based on the genetic algorithm. They applied the proposal to optimize the parame-ters of the CFD simulation to improve the performance. Th-e results showed that hydraulic efficiency was improved 11.1% and the hemolysis index was reduced 11.8% by using th-e optimized shape of the centrifugal blood pump.

In [10], Noor et al. presented the non-Newtonian fluid sim-ulations via OpenFOAM. They focus on the implementation and functionality of the code of the non-Newtonian power l-aw equations and used the finite volume method (FVM). The simulation results were shown with graphs and animate-d videos. The flow analysis states the behavior of the velocit-y field when the fluid hits the obstacle. The animated video-s further include the behavior of velocity in the leaving zon-e of the cylinder obstacle. A clear view of fluid flow can be seen far from the cylindrical object.

VI. CONCLUSION

This paper presented the improvement by optimizing the four parameters in the *CFD* model together by the parameter optimization algorithm and allowing different values to them by the temperature. The evaluation results show that the average difference between the estimated and measured temperature is reduced to 0.06℃ and the coefficient of determination R^2 is improved to 0.9994. In future works, we will further improve the accuracy by optimizing other parameters in the model and evaluate the accuracy under different experiments.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Y. Huo conducted the research and wrote the paper; N. Funabiki, K. Kojima and W.Kao reviewed and finalized the paper; X. Xu and Y. Zhao analyzed the data. All authors had approved the final version.

ACKNOWLEDGMENT

We would like to thank all the authors they conducted the measurement, analyzed the data and wrote the paper.

REFERENCES

[1] M. Sakagami, N. Funabiki, Y.-Z. Huo, K. Kojima, and W.-C. Kao, "A study of ventilation guidance function in air-conditioning guidance system," in *Proc. ICCE*, Jan. 2022.

[2] Computational fluid dynamics. [Online]. Available: https://en.wikipedia.org/wiki/

[3] Y. Zhao, K. Kojima, Y. Huo, and N. Funabiki, "CFD parameter optimization for air-conditioning guidance system using small room experimental model," in *Proc. LifeTech*, pp. 252–253, March 2022.

[4] Open FOAM. [Online]. Available: https://www.openfoam.com/. [Accessed: 19-Dec-2022].

[5] Finite volume method. [Online]. Available: https://en.wikipedia.org/wiki/Finite_volume_method

[6] Y. Huo, P. Puspitaningayu, N. Funabiki, K. Hamazaki, M. Kuribayashi, and K. Kojima, "A proposal of the fingerprint optimization method for the fingerprint-based indoor localization system with IEEE 802.15.4 devices," *Information*, vol. 13, no. 211, April 2022.

[7] Heat Transfer Coefficienz. [Online]. Available: https://en.wikipedia.org/wiki/Heat_transfer_coefficient

[8] B. Xi, Z. Liu, M. Raghavachari, C. H. Xia, and L. Zhang, "A SMART hillclimbing algorithm for application server configuration," in *Proc. 13th conference on World Wide Web – WWW'04*, 2004.

[9] B. Ghadimi, A. Nejat, S. A. Nourbakhsh, and N. Naderi, "Shape optimization of a centrifugal blood pump by coupling CFD with Metamodelassisted genetic algorithm," *Journal of Artificial Organs*, vol. 22, no. 1, pp. 29–36, 2018.

[10] N. Muhammad, "Finite volume method for simulation of flowing fluid via openfoam," *Europe. Physic. J. Plus*, vol. 136, no. 10, 2021.