Trade-off between Minimum Number of Wireless Sensors and the Accuracy of Temperature Profile in Cold Rooms: A Model-based Framework

Ji Ma[1,2], David Murphy[1], Gregory Provan[1], Michael Hayes[2], Cian O'Mathuna[2]
[1]Department of Computer Science and [2]Tyndall National Institute, University College Cork (UCC), Ireland.
mj3@cs.ucc.ie

Abstract: Evaluation of temperature distribution in cold rooms is an important consideration in the design of food storage solutions. Two common approaches used in both industry and academia to address this question are the deployment of wireless sensors, and modelling with Computational Fluid Dynamics (CFD). However, for a real-world evaluation of temperature distribution in a cold room, both approaches have their limitations. For wireless sensors, it is economically unfeasible to carry out large-scale deployment (to obtain a high resolution of temperature distribution); while with CFD modelling, it is usually not accurate enough to get a reliable result. In this paper, we propose a model-based framework which combines the wireless sensors technique with CFD modelling technique together to achieve a satisfactory trade-off between minimum number of wireless sensors and the accuracy of temperature profile in cold rooms. A case study is presented to demonstrate the usability of the framework.

1 Introduction

Quality and safety of food products stored in cold rooms are subjected to many factors e.g., heat and mass transfer [1]. In particular, one of the most important factors that need to be considered is the distribution of temperature. While uniform distribution of temperature will ensure the quality and safety of the food products in a reasonable level, uneven distribution of temperature can easily cause the deterioration of food through either increased respiration at higher temperature or by chilling or freezing injury at lower temperature. Therefore, good solutions to evaluate the distribution of temperature during the cooling process are necessary.

There are many papers that have been proposed to address this issue. In particular, wireless sensor, depending on its cheap cost, flexible deployment and reasonable accuracy, has gained more and more interest. Many studies have employed wireless sensor technique to monitor the environment or physical conditions [2][3]. However, the technique exists an obvious drawback. In order to obtain a high resolution monitoring data within a big space, a large number of wireless sensors have to be purchased. Although a single wireless sensor is inexpensive, purchase of such a large-scale wireless sensors is still economically unfeasible. Solutions that aim to reduce the number of wireless sensors while keeping the accuracy of the monitoring condition are desirable.

Another popular approach to solve such an issue is to use the mathematical modelling [1][4][5][6]. Different modelling approaches have been proposed to predict the

temperature distribution during cooling over past years. These approaches can be distinguished into three categories [5]. The first one is zonal method [7] in which a room is usually divided into a relatively small number of zones – typically on the order of tens to hundreds. The temperature in each zone is considered to be well mixed and simplified ordinary differential equations are used to describe mass and energy exchanges between zones. The second is namely Lattice Boltzmann Method (LBM). In this model, instead of solving the macroscopic Navier–Stokes equations a certain volume of fluid is represented by a collection of fictive particles; during motion particles can collide on a regular lattice obeying the fundamental conservation laws [8][9]. The third technique is CFD method. In CFD, the geometry is usually discretized into thousands of meshes and the governing equations of conversation of mass, momentum and energy is solved in each mesh. Compared to zonal method and LBM, CFD can be considered as a trade-off in terms of calculation time and accuracy and therefore it is the most primary choice. However, due to the extreme complexity of fluid dynamics in the real world, using CFD technique to solve and predict the temperature distribution in cold rooms is still unreliable. More advanced solutions which produce more reliable result are desirable.

In this paper, we propose a framework which combines the wireless sensor technique with CFD modelling technique together to address this issue. The organisation of the paper is as follows. Section 2 presents the concept of virtual sensor and model-based framework to achieve the trade-off between minimum number of sensors and the accuracy of the temperature profile in cold rooms. Section 3 describes a case study that includes a transient CFD model of an empty cold room and the sampled dataset from the temperature sensors to demonstrate the usability of the framework. Section 4 gives a concluding remark and future work is also pointed out.

2 Model-based Framework

2.1 Virtual Sensors

Virtual sensor, also known as “soft sensor”, “smart sensor” or “estimator” [10], has been widely applied in order to replace the real sensor, which may be expensive to be purchased or difficult to be deployed. They have became an important industrial tool and can be used for computationally estimating complex variable (usually quality variables) that otherwise should require very expensive equipments or laboratory tests that can consume many times before having a result.

Different approaches have been proposed to create the virtual sensor over past years. Here we distinguish them into three categories. The first approach is to abstract data from the real sensors, like described in [11]. In this approach, a virtual sensor is built based on one or more real sensor(s) and the virtual reading of the virtual sensor is derived from the real sensor(s). The second approach is to make use of neural network (NN) technique [12]. In such an approach, the NN is set up to predict certain value(s) of variable(s) desired. A set of pre-obtained dataset called training set is provided to

train the NN. After the repetitive training, the intelligence of the NN increases and consequently, one or more virtual sensor(s) is created. The third approach is by means of mathematical modelling technique to build the virtual sensor(s) [13], namely, model-based method. A famous example is the weather forecast model. Obviously, the accuracy of the virtual sensor(s) depends on the mathematical model constructed. With extremely complexity of certain real-world problems, the construction of such mathematical model can be very challenged and time-consuming.

2.2 Model-based Framework

In this section, we introduce the model-based framework which combines CFD modelling technique and wireless sensor technique together to evaluate the temperature profile in cold rooms. Figure 1 presents the flow chart of the framework. The actual framework can be outlined into the following three steps. First of all, we construct an initial CFD model. Secondly, we employ the sampled dataset obtained from the real temperature sensors to calibrate the model. After such a step, we generate the valid virtual sensors which are capable to predict the temperature distribution in cold rooms within a reasonable accuracy. Thirdly, we adopt an algorithm. The inputs of the algorithm are the sampled dataset of temperature from the real temperature sensors, the virtual sensors from the CFD model and the target accuracy of the temperature profile specified by the user. The outputs of the algorithm are the minimum number and positions of the real temperature sensors necessary to achieve the target accuracy of temperature profile. The algorithm is described as follows.

(1) We record the absolute difference between the time-average value from the virtual sensor with the time-average value from the sampled temperature sensor in every corresponding position into a table, named absolute difference table.

(2) We calculate the Root Mean Square Error (RMSE) based on the absolute difference table.

(3) We compare the RMSE with the target accuracy of the temperature profile specified by the user TG_{error}. If the RMSE > TG_{error}, we pick up the position where there is the maximum absolute difference, and use the time-average value from real sensor to replace the time-average value from the virtual sensor at the position. Consequently, the absolute difference at the position is 0 which means there is no error at such a position. We update the absolute difference table and then go back to step (2) to re-calculate the RMSE; if the RMSE <= TG_{error}, we go to step (4).

(4) We summarise the current value of RMSE and output the number and positions of real temperature sensors which we have used to replace the virtual sensors.

As a result, given target accuracy from the user and a known CFD model with certain accuracy, the user can get to know the minimum number of real sensors necessary and their positions of deployment, in order to achieve the desired target.

3 Case Study

A case study is present here in order to demonstrate the usability of the framework. In this case study, we only consider the distribution of temperature in an empty cold room. However, it is possible to apply the framework to evaluate the distribution of temperature under other environmental settings.

3.1 Modelling

A transient CFD model has been developed to simulate the behaviour of the cooling system as well as the temperature distribution inside an empty cold room for 20 minutes. The purpose of the model intends to be simple so that it is affordable in terms of computation time on a personal laptop. The modelling software we adopted for the CFD simulation is the commercial code CFX from Ansys.

3.1.1 Description of the Cold Room

The cold room we used in this study is located in the Department of Food and Nutritional Science, UCC. The dimension of it is 4.5m x 2.05m x 2.8m (length x width x height), with a door placed on the north wall and is closer to the east wall. A heat exchanger is positioned in the centre of the cold room and a monitoring temperature sensor is mounted on the top of the west wall.

The entire cooling system of the cold room consists of two components: a heat exchanger and a condensing unit. The heat exchanger includes two fans, which run constantly to circulate the airflow inside the cold room. The condensing unit is comprised of one fan and a compressor. It is controlled by the simplest form of temperature control device - an on/off controller to switch its status between on and off.

The upper and lower limit of the temperature values allowed in the cold room is 5.9°C and 3.8°C respectively. When the value of temperature sensed by the monitoring sensor is above the upper limit, the condensing unit will be switched on to cool down the cold room. And when the value of temperature sensed by the monitoring sensor is below the lower limit, the condensing unit will be switched off to stop cooling.

3.1.2 CFD Model

3.1.2.1 Governing Equations

The governing equations based on the conservation of mass, momentum and energy of a Newtonian fluid flow and applied to an infinitesimal small volume in a Cartesian coordinate system are:

$$\frac{\partial \rho}{\partial t}+\nabla\bullet(\rho U)=0$$

$$\frac{\partial(\rho U)}{\partial t}+\nabla\bullet(\rho U\otimes U)=-\nabla p+\nabla\bullet\tau+S_M$$

$$\frac{\partial(\rho e)}{\partial t}+\nabla\bullet(\rho U e)=\nabla\bullet(\lambda T)+p\nabla\bullet U+\tau:\nabla U+S_E$$

3.1.2.2 Turbulence Model

The turbulence model used for our fluid domain is $k-\varepsilon$ ($k-$epsilon) model. It is considered as the industry standard model and offers a good compromise in terms of accuracy and robustness. In CFX, $k-\varepsilon$ model is used combined with scalable wall function which improves robustness and accuracy when the near-wall mesh is very fine. It has been proven to provide good prediction capability for many flows. The two equations $k-\varepsilon$ model can be written as:

$$\frac{\partial(\rho k)}{\partial t}+\nabla\bullet(\rho U k)=\nabla\bullet[(\mu+\frac{\mu_t}{\sigma_k})\nabla k]+P_k\text{-}\rho\varepsilon$$

$$\frac{\partial(\rho\varepsilon)}{\partial t}+\nabla\bullet(\rho U\varepsilon)=\nabla\bullet[(\mu+\frac{\mu_t}{\sigma_\varepsilon})\nabla\varepsilon]+\frac{\varepsilon}{k}(C_{\varepsilon1}P_k-C_{\varepsilon2}\rho\varepsilon)$$

In addition, since gravity is a very important factor in the flows domain, a buoyancy source terms are included in our simulation.

3.1.2.3 the Cooling System

The cooling system is simplified and modelled by the CFX Expression Language (CEL). A User CEL function is used to simulate the behaviour of controller to turn on/off the condensing unit based on the sensed temperature of the monitoring sensor. The function can be expressed into the following pseudo code:

```
if (T_sensor > T_max)
CU = 1.0 // turn on condensing unit
else if (T_sensor < T_min)
CU = 0.0; // turn off condensing unit
```

Where T_{sensor} presents the sensed temperature of the monitoring sensor;

T_{max} presents the upper limit of the temperature allowed in the cold room;

T_{min} presents the lower limit of the temperature allowed in the cold room;

CU presents the on and off status of the condensing unit. 1 refers to its on status and 0 refers to its off status.

3.1.2.4 Boundary Conditions and Initial Conditions

There are three boundary conditions in the model. They are inlet, outlet and wall respectively. Inlet is a boundary condition where the fluid flows into the computational domain. Due to the fact that the two jets of the heat exchanger circulate the airflow into the cold room, they are modelled as the inlet. Outlet is a boundary condition where the fluid of flow is predominantly out of the computational domain. Taking into account the fact that the two intakes of the heat exchanger draw the airflow out of the cold room, they are modelled as an outlet. In terms of the wall, it is the sold boundary that allows the permeation of the heat and other variables into and out of the domain by setting the heat flux or fixed temperature values. There are four different choices of heat transfer models of wall provided in CFX code: adiabatic, fixed temperature, heat flux and heat transfer coefficient. To maintain the purpose of a simplified model, the walls in our case are modelled at a fixed temperature of 6°C.

As we mentioned in section 3.1.1, the upper and lower limit of the temperature value allowed in the cold room is 5.9°C and 3.8°C respectively. In order to evaluate the effectiveness of the User CEL function that simulates the behaviour of the controller to turn on/off the condensing unit, we set the initial temperature of the cold room is at 5°C.

3.2 Collection of Sample Dataset from Temperature Sensors

In order to ignore the fluctuation of temperature caused by opening the door, we prevent people to access the cold room so that we can model the door as a solid wall. In addition, since the small volume of the cold room we consider to partition the cold room into 48 thermal zones as a reasonable high resolution (the temperature in each zone is considered to be well mixed). As a result, the entire empty cold room can be considered as a symmetric structure and only half of the cold room (24 zones) is necessary to be sampled by the temperature sensors (each temperature sensor for each zone). The 24 sample dataset will be mapped to the other 24 symmetric zones as well.

3.3 Result Validation and Discussion

Figure 2 illustrates the partial comparative results from the CFD simulation (blue line) and the dataset from the temperature sensors (red line) at certain sample points. From figure 2 we can see that the overall accuracy of the model is reasonable. The maximum absolute difference between the simulation result and real result occurs at sample sensor 24 with a value of 1.29114°C. The minimum absolute difference between the simulation result and real result occurs at sample sensor 1 with a value of 0.069°C. Other absolute differences of temperature vary between 0.069°C and 1.29114°C based on different positions.

3.4 Trade-off between Minimum Number of Sensors and the Accuracy of Temperature Profile

Figure 3 shows the trade-off between the minimum number of sensors and the accuracy of the temperature profile in the empty cold room. From figure 3 we can see that given 48 sensors for 48 zones in the empty cold room, the accuracy of the temperature profile is 100%. Without given any sensors to evaluate the temperature profile, our model can predict it at an approximate accuracy of 0.62°C. By inspecting the figure 3, users can get to know that with a target accuracy of temperature profile and a known CFD model, what is the minimum number of sensors needed to achieve such a target.

4 Conclusion and Future Work

In this paper, we propose a model-based framework which combines the wireless sensors technique with CFD modelling technique together to achieve a satisfactory trade-off between minimum number of wireless sensors and the accuracy of temperature profile in cold rooms. A case study is presented to demonstrate the usability of the framework. As a result, an optimization to use less wireless sensors while obtaining desired accuracy of the temperature profile achieves.

In order to answer the optimization question comprehensively, two future works have been identified. Firstly, in our case only the temperature distribution in an empty cold room is considered. But in a real-world cold room where the situation can be extremely complex and the temperature distribution can be affected by more factors such as shelves, position of products stored, activities of people, door opens and closes, etc. Therefore it is necessary to take these factors into account to obtain a comprehensive evaluation of our framework. Secondly, the framework tolerates from the inherent flaws of the CFD modelling technique. It is difficult to implement a real-time online monitoring of temperature distribution in cold rooms. Faster while accurate model is necessary to be developed.

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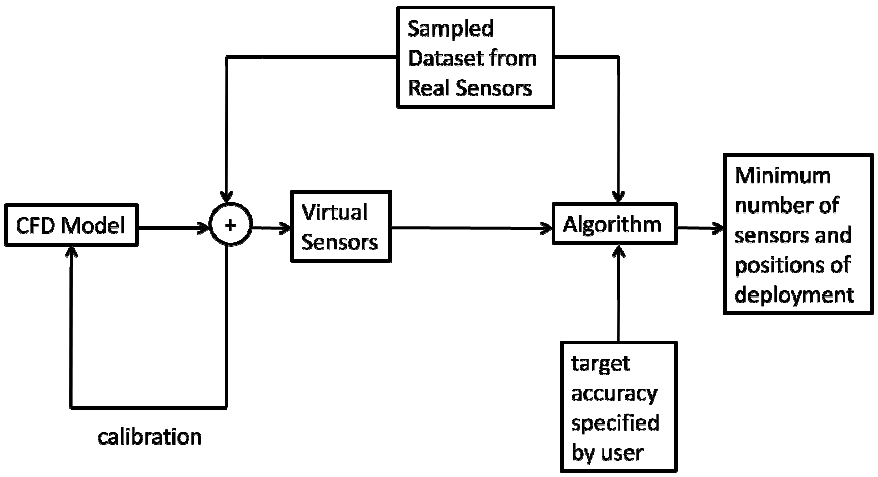

Figure 1: the model-based framework.

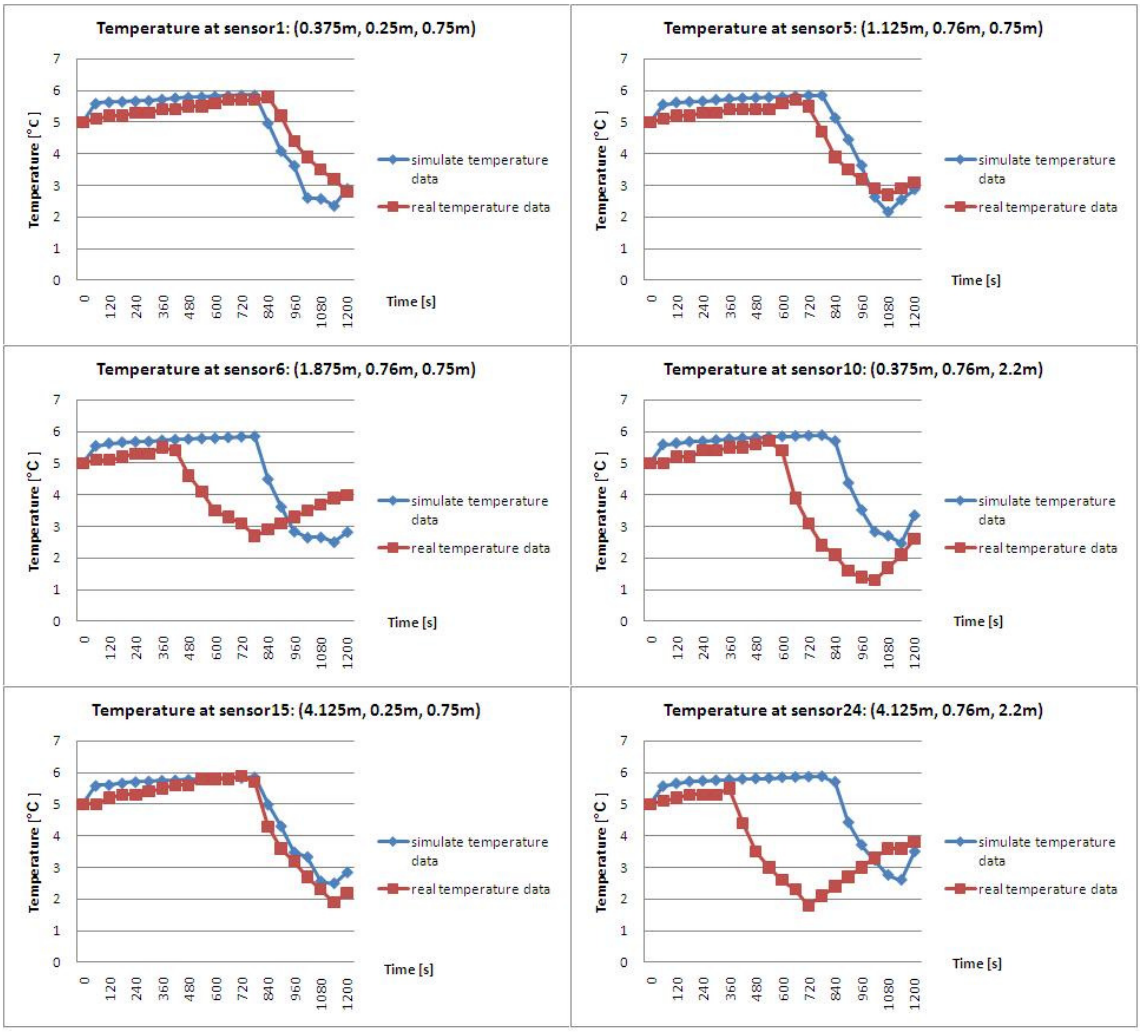

Figure 2: simulation results versus real temperature results.

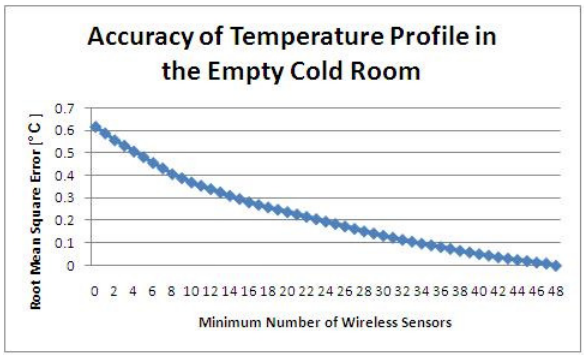

Figure 3: trade-off between minimum number of sensors versus accuracy of temperature profile.