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Development of DMC controllers for temperature control of a room deploying the displacement ventilation HVAC system

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Abstract
In this paper, by developing a new Dynamic Matrix Control (DMC) method, we develop a controller for temperature control of a room cooled by a displacement ventilation HVAC system. The fluid flow and heat transfer inside the room are calculated by solving the Reynolds-Averaged Navier-Stokes (RANS) equations including the effects of buoyancy in conjunction with a two-equation realizable k - epsilon turbulence model. Thus the physical environment is represented by a nonlinear system of partial differential equations. The system also has a large time delay because of the slowness of the heat exchange. The goal of the paper is to develop a controller that will maintain the temperature at three points near three different walls in a room within the specified upper and lower bounds. In order to solve this temperature control problem at three different points in the room, we develop a special DMC method. The results show that the newly developed DMC controller is an effective controller to maintain temperature within desired bounds at multiple points in the room and also saves energy when compared to other controllers. This DMC method can also be employed to develop controllers for other HVAC systems such as the overhead VAV (Variable Air Volume) system and the radiant cooling hydronic system.

Keywords: Computational fluid dynamics; Dynamic matrix control method; Energy efficiency of buildings; Temperature control in enclosures.

1. Introduction
Effective energy management for facilities such as hospitals, factories, malls, or schools is becoming increasingly important due to rising energy costs and increase in the associated greenhouse gas (GHG) emissions. One of the major users of energy is buildings. Most modern buildings employ a heating and cooling system depending upon the climate and time of the year. The focus of this paper is on control of HVAC units in buildings deployed for cooling during summer months to maintain temperature inside the building for human comfort and other operational requirements. In many climates around the world, the air-conditioning requirements for cooling the buildings can be very high during the summer months, and it turns out that the major portion of energy consumption of a building is from HVAC units. For example, it has been reported that the energy consumption of HVAC units in general accounts for 40%

of total energy use by a building [18] and on an extremely hot day it could be as high as 65% [19]. Improvement in the control of HVAC systems can therefore result in significant savings (e.g. 25% in energy use, see [20]).

To control HVAC systems, the traditional method is the on/off control at the level of HVAC components, for example an air-conditioning unit. This kind of control is a very low-level control. In recent years, some advanced control strategies have been developed that can be implemented in operating the HVAC systems in an integrated fashion for commercial buildings to improve their energy efficiency. There have been some results reported in the literature to investigate the energy requirements of buildings using different HVAC systems, see [14-16] and the references there in. Our goal is to control the temperature inside the building as well as well as save energy. There are many types of methods, which can be employed to control the operation of HVAC systems. To mention a few from the literature, an immune PID adaptive controller has been presented in Reference [9], which is quite different from the traditional PID controller [8]. References [2, 4-6, 10-12] introduce Model Predictive Control (MPC) method for building cooling systems. In particular, the DMC method, as one of MPC methods has been widely employed in the study of HVAC control systems involving large time delays, see for instance [11-12] and the references therein. In another study [7], the authors have used Artificial Neural Network (ANN) based models to control the temperature of a building and have obtained impressive results. The fuzzy control method of Zadeh [17] has also been widely used for control of many nonlinear systems; a fuzzy control method is given in Reference [3] which shows promise for temperature control in buildings using different HVAC systems. However, all these studies have limitations with respect to the nature of the disturbance and the time delay; they are limited to small disturbance in temperature as well as small time delay in heat exchange. Thus, it remains an important and challenging problem to design good controllers, which can keep the temperature stable in a smaller time interval as well as result in more savings in energy.

In this paper, we develop a controller for temperature control inside a room within a desired band of temperatures for comfort. The details of the geometry of the room and the HVAC system based on displacement ventilation for cooling the room are taken from Reference [1]. The control of this system is difficult since the HVAC system has no heater, which means that we can only cool the room, but not heat it. In addition, the time delay in heat exchange also exists in the system. All of these factors make it difficult in achieving the temperature control objective using the methods described in the references listed above. After many computational experiments, we have determined and developed an effective method to solve this control problem. The DMC controller is developed based on the traditional one for controlling a one-input three-output system. We employ two groups of model systems to illustrate the effectiveness and disadvantages of this method, and finally show the effectiveness of the controller for not only temperature control but also in energy savings for the HVAC system under consideration.

2. Fluid flow simulation in the room

The flow field inside the room with and without displacement ventilation was simulated by the CFD software FLUENT, which solves the Unsteady Reynolds-Averaged Navier-Stokes (URANS) equations employing the finite-volume method on a collocated grid. In Fluent, URANS equations are solved using the second-order upwind scheme and the pressure is calculated using the PRESTO scheme. The SIMPLE algorithm is employed for the coupling of the velocity and pressure. In our calculations, both the one-equation Spalart Allmaras (S-A) turbulence model and the two-equation k-ε realizable turbulence model were employed. The S-A model is a simpler turbulence model, which only uses one equation to describe the turbulent eddy viscosity, compared to the k-ε realizable model, which uses two equations to calculate the eddy viscosity. We computed the flow field using both the S-A and k-ε realizable models on the same grid and found little difference in the results. The geometry of the room and other details of displacement ventilation are taken from Reference [1]. Figure 1 shows the schematic of the room with the two outlet vents in the ceiling and six inlet vents on the floor. The dimensions of the room are 12 ft x 12 ft x 9.5 ft with a surface are of 804 ft^2 and volume of 1368 ft^3.The inlet vents on floor of the room are 6"×9" in cross-section, which gives an area of 2.25ft^2 for the six vents. The air flow in the room meets the ASHRAE guidelines of air movement. The six inlet vents are placed on the floor near the adiabatic walls. This is done in order to keep the installation of the vents on the floor practical, so that the vents may not be blocked by the furniture in the room. The two outlet vents in the ceiling are 1′-6"×1′-6" in size, giving an area of 4.5ft^2 (0.418m^2)) for the 2 outlet vents. We set three sensors in the room to monitor the temperature at three points close to three walls, whose locations are shown in Figure 1. The temperature

of the exterior wall of the room was kept at a constant temperature while the other five walls were considered adiabatic. Figure 2 show the 3-D Cartesian mesh inside the room.
A Fluent UDF (User Defined Function) was created to simulate the temperature of the exterior wall of the room. This temperature curve simulated the exterior surface and was assumed to be at a constant value of 320K. A 3-D Cartesian mesh inside room was generated by GAMBIT with a uniform grid spacing of 3".
In the following sections, we develop the DMC method to control the temperature of this room with three temperature sensors.
Remark 1: The temperature sensors are not real. We assume that there are three sensors, which can give us temperature data, which is obtained from CFD simulations using FLUENT. We only use these three points' temperature as reference temperature for the present control method.

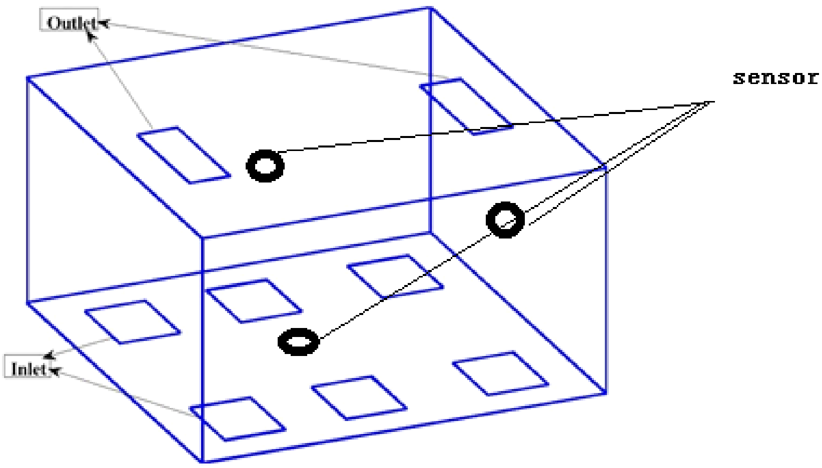

Figure 1. 3D view of the room with three sensors, two outlet vents and six inlet vents employed in displacement ventilation

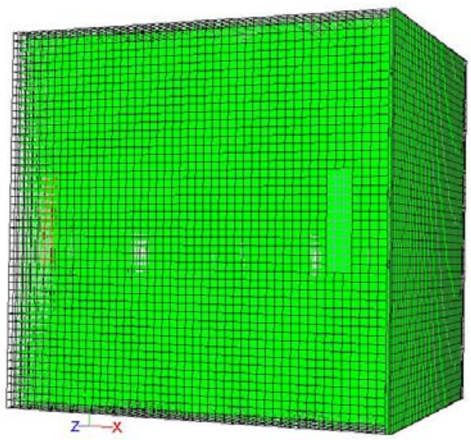

Figure 2. The 3-D Cartesian mesh inside the room

3. Dynamic matrix control (DMC) method

Dynamic Matrix Control (DMC) has been shown to be an effective advanced control technique in many industrial process control applications and has recently been extended to the procedure control systems which often have large time delay and uncertainty. Our HVAC system has these characteristics. We consider designing a DMC controller, which is a model-based control method [11-12]. Traditional DMC method can be used in single-input-single-output (SISO) systems, and there are some theories about the DMC controllers for multi-input-multi-output (MIMO) systems, for example in Reference [21]. However the DMC controllers for MIMO systems have only been discussed from a theoretical point of view. In this paper it is developed for a single-input-multiple-output (SIMO) system and is applied to an application governed by a set of highly nonlinear partial differential equations governing fluid flow.

3.1 Model foundation

In DMC based controller, we first need to determine a system model. The model in DMC is determined by the step response, which is similar to the traditional model composed of the difference equation. From the change of exterior wall temperature in Figure 3, we know that the average exterior wall temperature is 320K. Thus, we set the exterior wall temperature equal to 320K without control, and when the room temperature is near 320K, we give a step signal to mass-flux (0.1) to make the HVAC system cool the room. At this time we can obtain three temperatures from three sensors that can be used in the model as the step response data, which is shown in Figure 3.

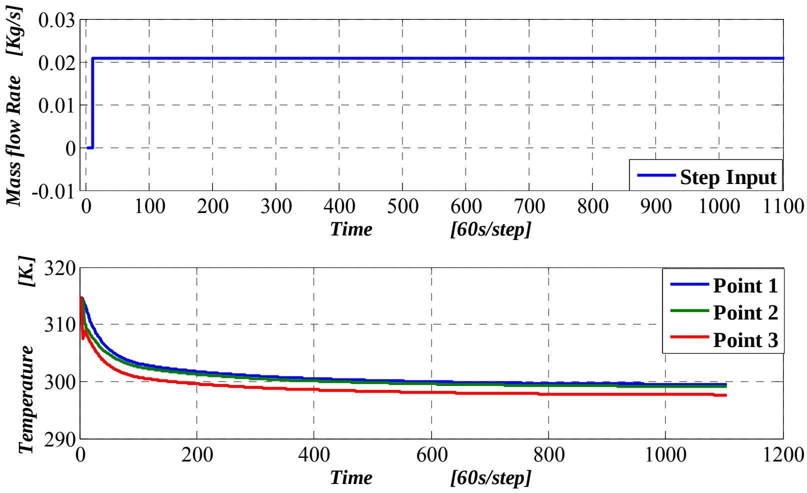

Figure 3. The input signal and the step responses

According to the superimposition principle of the linear system, suppose the original output value of the system at k is $y_0\,(k)$, the control value $u(k)$ (here it is the mass flow rate) has an increment $\Delta u(k)$ at k. The output predictive values $Y_n\,(k)$ with $n = 1, 2, 3$ (here they are temperature) at future time steps are:

$$\begin{cases} Y_1(k) = Y_0^1(k) + \Gamma_1 \Delta u(k), \\ Y_2(k) = Y_0^2(k) + \Gamma_2 \Delta u(k), \\ Y_3(k) = Y_0^3(k) + \Gamma_3 \Delta u(k), \end{cases} \tag{1}$$

where

$Y_n(k) = \left[y_n^T(k+1) \quad y_n^T(k+2) \quad \ldots \quad y_n^T(k+N) \right]^T$, $Y_0^n(k) = \left[y_{n,0}^T(k+1) \quad y_{n,0}^T(k+2) \quad \ldots \quad y_{n,0}^T(k+N) \right]^T$,

$\Gamma_n = \left[a_{n,1} \quad a_{n,2} \quad \ldots \quad a_{n,N} \right]^T$, $n = 1, 2, 3$.

Γ_n is the dynamic coefficient vector of the point n's step response. $Y_n(k)$ expresses the predictive system output of the future N moments. The equation (1) has been obtained assuming that $\Delta u(k)$ doesn't change any more. If the added control quantity changes at M sample intervals: $\Delta u(k)$, $\Delta u(k+1)$,…, $\Delta u(k+M+1)$, then the model output value would be

$$\begin{cases} y_{1,M}(k+i) = y_{1,0}(k+i) + \sum_{j=1}^{i} a_{1,i-j+1} \Delta u(k+j-1)\ ,\ (i = 1,2,...,M) \\ y_{2,M}(k+i) = y_{2,0}(k+i) + \sum_{j=1}^{i} a_{2,i-j+1} \Delta u(k+j-1)\ ,\ (i = 1,2,...,M) \\ y_{3,M}(k+i) = y_{3,0}(k+i) + \sum_{j=1}^{i} a_{3,i-j+1} \Delta u(k+j-1)\ ,\ (i = 1,2,...,M) \end{cases} \tag{2}$$

Thus we obtain the three points' predictive model described above. Note that the subscript M of $y_{n,M}$ (n = 1 ,2 ,3) symbolizes change with time of the control value $\Delta u(k)$ ($M<N$), which means that to calculate $\Delta u(k)$, we need to know $\Delta u(k\text{-}i)$,(i=1,2,…M).

3.2 Rolling optimization

The DMC controller has the ability to adapt if we use certain optimal criterion to calculate the control value. Our goal is to make the predictive output value $y_{n,M}(k+i)$ (i =1,2,…N, n = 1,2,3) track the expected orbit $y_{n,r}(k+i)$ (i =1,2,…N, n = 1,2,3). To ensure that $\Delta u(k+i-1)$ does not change significantly, we employ the following quadratic optimization objective function:

$$\min J(k)=\min\left(\sum_{n=1}^{3}\left(\sum_{i=1}^{N}q_{n,i}\left[y_{n,r}(k+i)-y_{n,M}(k+i)\right]^2\right)+\sum_{i=1}^{M}r_i\Delta u^2(k+i)\right), \tag{3}$$

where $y_{n,r}(k)$ is the expected output, $y_{n,M}(k)$ is the predictive output, and $\Delta u(k)$ is the increment of input. We can rewrite the function in a vector form as follows:

$$\min J(k)=\min\left(\left\|Y_{1,r}(k)-Y_{1,M}(k)\right\|_{Q_1}^2+\left\|Y_{2,r}(k)-Y_{2,M}(k)\right\|_{Q_2}^2+\left\|Y_{3,r}(k)-Y_{3,M}(k)\right\|_{Q_3}^2+\left\|\Delta U(k)\right\|_{R}^2\right), \tag{4}$$

where

$$Y_{n,r}(k)=\left[y_{n,r}(k+1)\quad y_{n,r}(k+2)\quad \ldots\quad y_{n,r}(k+N)\right]^T,$$

$$Y_{n,M}(k)=\left[y_{n,M}(k+1)\quad y_{n,M}(k+2)\quad \ldots\quad y_{n,M}(k+N)\right]^T,$$

$$\Delta U(k)=\left[\Delta u(k)\quad \Delta u(k+1)\quad \ldots\quad \Delta u(k+M-1)\right]^T,$$

$$Q_n=\left[q_{n,1}\quad q_{n,2}\quad \ldots\quad q_{n,N}\right],\ n=1,2,3,\ R=\left[r_1\quad r_2\quad \ldots\quad r_M\right].$$

Q_n is the error weight matrix and R is the control weight matrix.
From the formula in equation (2), we obtain:

$$Y_{n,M}(k)=Y_{n,0}(k)+A_n\Delta U(k)$$

$$Y_{n,0}(k)=\left[y_{n,0}(k+1)\quad y_{n,0}(k+2)\quad \ldots\quad y_{n,0}(k+N)\right]^T$$

$$A_n=\begin{bmatrix} a_{n,1} & 0 & \cdots & 0 & 0 & 0 \\ a_{n,2} & a_{n,1} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n,M} & \cdots & \cdots & a_{n,1} & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n,N} & \cdots & \cdots & \cdots & \cdots & a_{n,N-M+1} \end{bmatrix},\ n=1,2,3. \tag{5}$$

Then we obtain another form of $J(k)$:

$$\begin{aligned} J(k)&=\sum_{j=1}^{3}\left[Y_{j,r}(k)-Y_{j,M}(k)\right]^T Q_j\left[Y_{j,r}(k)-Y_{j,M}(k)\right]+\Delta U(k)^T R\Delta U(k) \\ &=\sum_{j=1}^{3}\left[Y_{j,r}(k)-Y_{j,0}(k)-A_j\Delta U(k)\right]^T Q_j\left[Y_{j,r}(k)-Y_{j,0}(k)-A_j\Delta U(k)\right]+\Delta U(k)^T R\Delta U(k). \end{aligned} \tag{6}$$

We employ the formula in equation (6) to get the optimal increment $\Delta U^*(k)$ by the following operation:

$$\frac{\partial J(k)}{\partial \Delta U(k)}=-\sum_{j=1}^{3}\left(\left[Y_{j,r}(k)-Y_{j,0}(k)\right]^T Q_jA_j+A_j^TQ_j\left[Y_{j,r}(k)-Y_{j,0}(k)\right]+2A_j^TQ_jA_j\Delta U^*(k)\right)+2R\Delta U^*(k)=0. \tag{7}$$

We obtain:

$$\Delta U^*(k)=\left[\sum_{j=1}^{3}\left(A_j^TQ_jA_j\right)+R\right]^{-1}\sum_{j=1}^{3}A_j^TQ_j\left[Y_{j,r}(k)-Y_{j,0}(k)\right]. \tag{8}$$

The formula in equation (8) can be used for calculating the input increments $\Delta U^*(k)$ for all M steps. However, we only need to use the first $\Delta u(k)$ to get the next step's inputs and thus we get:

$$\Delta u(k) = C^T \left[\sum_{j=1}^{3} \left(A_j^T Q_j A_j \right) + R \right]^{-1} \sum_{j=1}^{3} A_j^T Q_j \left[Y_{j,r}(k) - Y_{j,0}(k) \right], \tag{9}$$

where C=[1, 0, …, 0]. In equation (9), C, A, Q_j, and R can be determined a-priori by off-line calculations. Thus if we can keep $\Delta u(k)$ updated at all instances, then the system can be very well controlled.
There are many sources, which influence the output of the system. Thus, if the output $y_n(k+1)$ (n = 1,2,3) is not corrected, the error will be larger, and it will not assure that actual output gets close or tracks the expected value. The dynamic correction is used to correct the error. Then we can get the error:

$$e_n(k+1) = y_n(k+1) - y_{n,M}(k+1),\ n = 1,2,3, \tag{10}$$

where $y_n(k+1)$ is the output and $y_{n,M}(k+1)$ is the predictive output. We have the predictive value:

$$\mathrm{y}_{n,c}\left(k+1\right) = y_{n,M}(k+1) + h_n e_n(k+1),\ n = 1,2,3. \tag{11}$$

In equation (11), h_n is correction parameter. Thus, the predictive value after correction is as follows:
$\mathrm{y}_{n,0}\left(k+i\right) = y_{n,c}(k+i+1),\ i = 1,\ldots,N-1,\ n = 1,2,3.$
Then, we get:

$$\Delta u(k) = C^T \left[\sum_{j=1}^{3} \left(A_j^T Q_j A_j \right) + R \right]^{-1} \sum_{j=1}^{3} A_j^T Q_j \left[Y_{j,r}(k) - A_0 U(k-1) - h_j e_j(k) \right], \tag{12}$$

where
$U\left(k-1\right) = \left[u(k-N+1) \quad u(k-N+2) \quad \ldots \quad u(k-1) \right],$
and $Y_{n,r}(k)$ and $e_n(k)$ are defined by eqns. (4) and (10) respectively.

Remark 2: The DMC method introduced in this article is different from traditional one. First, traditional DMC method can only be used in SISO systems; however our method can be used in SIMO systems. Second, there are still errors when the systems are stable in our method, while in the traditional method one can get a zero-error result. That is because we only use one input to control three outputs. Third, for SIMO system, the three outputs' performances must be similar otherwise the errors will be too large.

4. Results

In this section, we first employ a model example to discuss the effectiveness of the new DMC controller. This simple example is used to illustrate the method's limitations. Next we show the effectiveness of the DMC controller in controlling the temperature in the room using the displacement ventilation HVAC system.

4.1 Model example

We employ two groups of systems:

$$Group\ 1:\ \begin{cases} G_1(z) = \dfrac{z^{-35}\left(-0.035 - 0.0307z^{-1}\right)}{1 - 1.638z^{-1} + 0.6703z^{-2}} \\ G_2(z) = \dfrac{z^{-35}\left(-0.135 - 0.0307z^{-1}\right)}{1 - 1.7z^{-1} + 0.8z^{-2}} \\ G_3(z) = \dfrac{z^{-35}\left(-0.1 - 0.05z^{-1}\right)}{1 - 1.5z^{-1} + 0.6z^{-2}} \end{cases} \tag{13}$$

$$Group\ 2:\ \begin{cases} G_1(z) = \dfrac{z^{-35}\left(-0.035-0.0307z^{-1}\right)}{1-1.638z^{-1}+0.6703z^{-2}} \\ G_2(z) = \dfrac{z^{-35}\left(-0.135-0.0307z^{-1}\right)}{1-1.7z^{-1}+0.8z^{-2}} \\ G_3(z) = \dfrac{z^{-35}\left(-0.1-0.25z^{-1}\right)}{1-1.6z^{-1}+0.7z^{-2}} \end{cases} \tag{14}$$

Now, if we give the three systems in group 1 a step input, then we can get the open-loop systems' performance shown in Figure 4. We obtain

$$\left[\sum_{j=1}^{3}\left(A_j^T Q_j A_j\right)+R\right]^{-1} = \begin{bmatrix} 0.0714 & -0.1380 & 0.0669 \\ -0.1380 & 0.2789 & -0.1418 \\ 0.0669 & -0.1418 & 0.0756 \end{bmatrix}. \tag{15}$$

After using the DMC method, we can obtain the closed-loop systems' performance shown in Figure 5. When all of the systems are stable, there are still errors compared to the input shown in Figure 5, since it is one-input-three-output system. If we only consider one of the system's performances, for example G_3 (z) and employ the traditional DMC method, we can get the systems' performance in group 2. From Figure 6, we know that the error of G_1 (z) is very large. Thus, if we only consider one output to employ DMC method, other outputs' errors may unacceptable. At the same time, if the three systems are quite similar, the controller design method is very effective. To show this, we use the DMC method for the systems in group 2, and we get an open-loop systems' step input performance shown in Figure 6. Using our method, we obtain

$$\left[\sum_{j=1}^{3}\left(A_j^T Q_j A_j\right)+R\right]^{-1} = \begin{bmatrix} 0.0155 & -0.0303 & 0.0149 \\ -0.0303 & 0.0611 & -0.0310 \\ 0.0149 & -0.0310 & 0.0162 \end{bmatrix}. \tag{16}$$

From Figure 7, we know that G_3 (z)'s performance is different from the other two systems. As Figure 8 shows, the closed-loop systems' errors are still very large with our method. One way to solve this problem is to introduce some other inputs. Only one input cannot satisfy all the requirement of these three outputs.

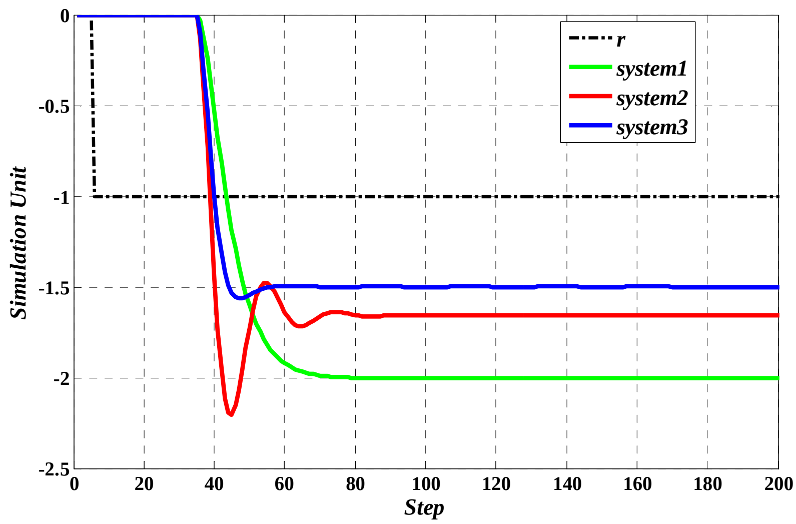

Figure 4. The three systems' open-loop step responses in group 1

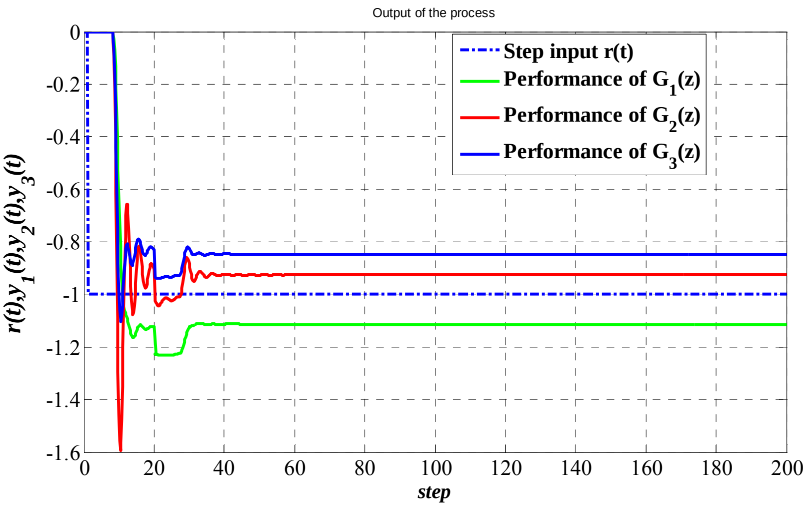

Figure 5. The three systems' closed-loop step responses considering three points' performance in group 1

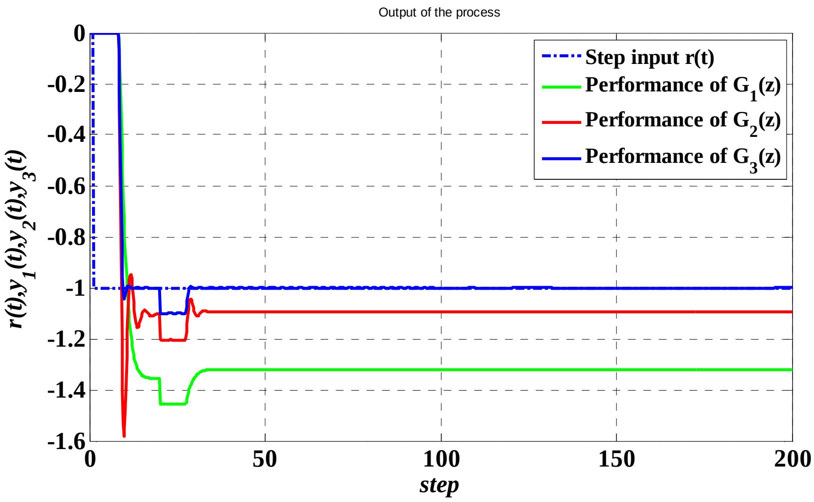

Figure 6. The three systems' closed-loop step responses only considering $G_3(z)$'s performance in group 1

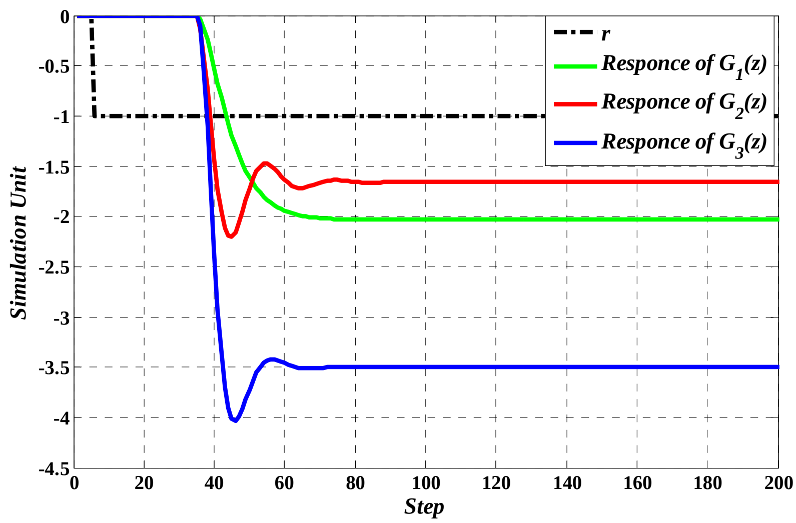

Figure 7. The three systems' open-loop step responses in group 2

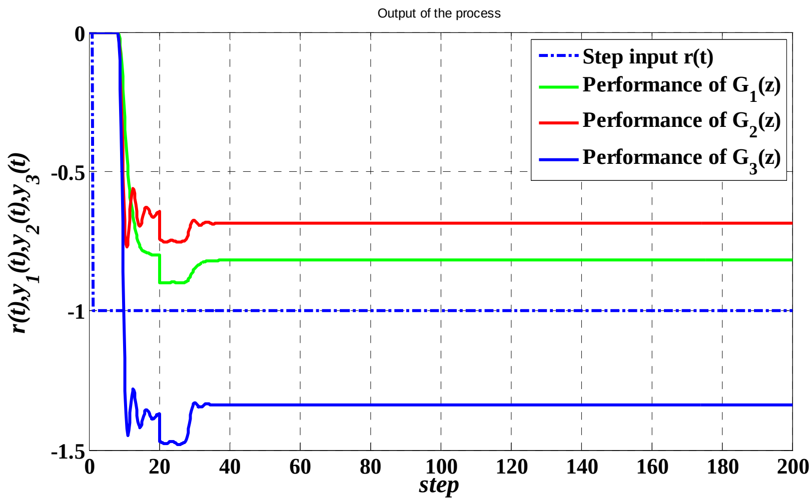

Figure 8. The three systems' closed-loop step responses considering three points' performance in group 2

4.2 HVAC application

We employ the DMC controller to control the temperature in the room deploying displacement ventilation HVAC system described before in section 2 titled "Flow Simulation in a Room." Using the DMC controller by UDF in FLUENT, we control the temperature in the room between 295.8K and 297.14K as shown in Figure 9; the error due to DMC controller is smaller than from the controller employed in Reference [1]. From Figure 10, it can be noted that the DMC controller saves more energy than the controller employed in Reference [1], since the DMC controller requires less input to get better performance. From Figure 11, it can be seen further that the DMC controller can save more energy.

The advantages of the DMC controller are as follows. First, it is an optimal controller using the minimal input to get better performance since the quadratic optimization objective function considers the input information. Second, it is a self-adapting controller which changes as the input changes. There are two disadvantages of the DMC controller. First, the DMC controller is a local controller which can only guarantee the stability of the system in a local area. Second, the DMC controller is a model-based controller whose model is linear. But our system is a highly nonlinear system and therefore there are errors if a linear model is employed to describe the nonlinear system. Furthermore, as the disturbance becomes bigger and bigger, we need to find another model and design a new controller. In the DMC controller, we set $N = 80$, $M = 5$, and Q_j and R are defined as the identity matrices with proper dimension. Then we obtain Γ_n defined in equation (1). Because Γ_n is a long vector, we don't give all the values here. Now, it is straightforward to get the following matrix:

$$\left[\sum_{j=1}^{3}\left(A_j^T Q_j A_j\right)+R\right]^{-1} = \begin{bmatrix} 0.461 & -0.519 & -0.201 & 0.068 & 0.192 \\ -0.413 & 0.848 & -0.324 & -0.176 & 0.064 \\ -0.206 & -0.206 & 0.943 & -0.325 & -0.207 \\ -0.034 & -0.083 & -0.209 & 0.846 & -0.520 \\ 0.191 & -0.039 & -0.210 & -0.412 & 0.471 \end{bmatrix}. \tag{17}$$

We want the temperature to stay at 296.6K, and therefore we set Y_r (k) = [296.6, 296.6, … 296.6]. Then we can obtain every control value in real time. It should be noted that the three temperature systems in room are similar, since temperatures of all three points are obtained from the same flow model for the room. Figure 12 shows the temperature distribution after control. In the systems, we assume that all six inlets' mass flow rates are controlled by the same $u(k)$ in the model. If we want to further promote the control performance, the six inlets' mass flow rates need to be controlled separately.

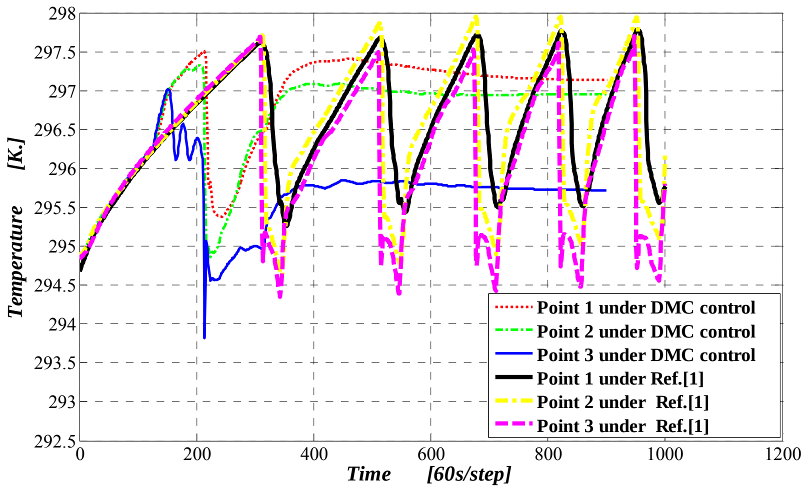

Figure 9. The comparison of temperature control results from Ref. [1] and the present fuzzy controller

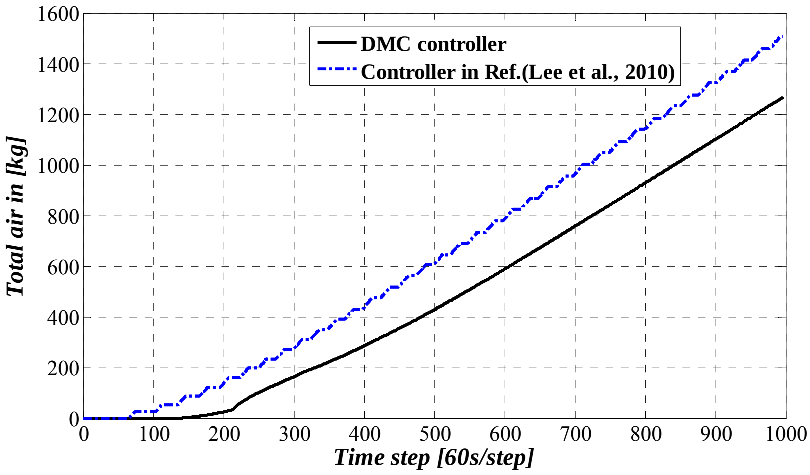

Figure 10. The cost of the cold air or energy saving using two different controllers

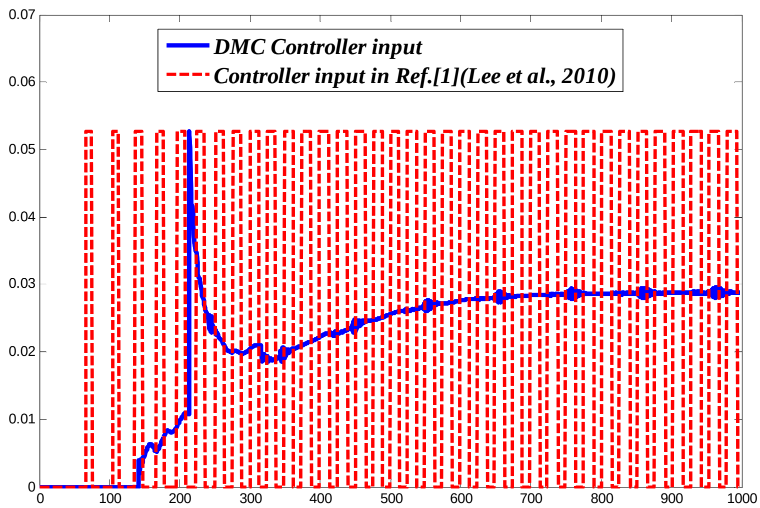

Figure 11. The control inputs of two different controllers

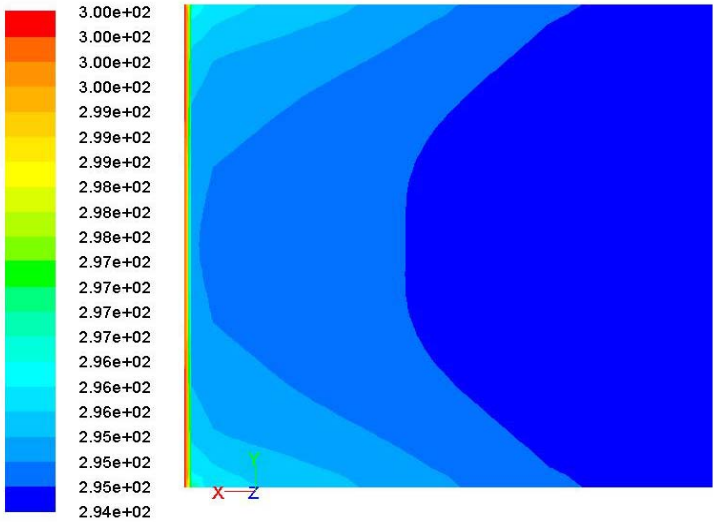

Figure 12. The temperature of room after control

5. Conclusion

This paper has developed a DMC controller for controlling the temperature in a room deploying a displacement ventilation HVAC system without heater. It is a nonlinear system with large disturbance, which has delay in the control variable and in the environment disturbance. By analyzing the temperature at three points in the room and a proper estimation of the environmental disturbance and the heat exchange delay, we have designed a DMC controller to control the displacement ventilation HVAC system. The control results using the DMC controller are analyzed and compared with those obtained from another controller. The DMC controller performs quite well and results in greater energy savings compared to those reported in Reference [1].

References

[1] Lee, C., Harris, A. and Agarwal, R. K. (2010), Reducing Energy Demand in Commercial Buildings: Balancing Convection and Radiant Cooling. In: Proceedings of the ASME 4th International Conference on Energy Sustainability, pp. 1047-1055.

[2] Cigler, J. and Privara, S. (2010), Subspace Identification and Model Predictive Control for Buildings. In: Proceedings of the11th International Conference on Control, Automation, Robotics & Vision, pp.750-755.

[3] Kajl, S., Malinowski, P., Czogala, E. and Balazinski, M. (1995), Prediction of Building Thermal Performance using Fuzzy Decision Support System. In: Proceedings of the 1995 IEEE International Conference on Fuzzy Systems, pp. 225-232.

[4] Li, Q. and Meng, Q. (2008), Development and Application of Hourly Building Cooling Load Prediction Model. In: Proceedings of the International Conference on Advances in Energy Engineering, pp. 392-395.

[5] Ma, Y., Borrelli, F., Hencey, B., Coffey, B., Bengea, S. and Haves, P. (2010), Model Predictive Control for the Operation of Building Cooling Systems. In: Proceedings of the American Control Conference, pp. 5106-5111.

[6] Ma, Y., Borrelli, F., Hencey, B., Packard, A. and Bortoff, S. (2009), Model Predictive Control of Thermal Energy Storage in Building Cooling Systems. In: Proceedings of the 48th IEEE Conference on Decision and Control held jointly with the 2009 28th Chinese Control Conference, pp. 392-397.

[7] Moon, J.W. and Kim, J. J. (2010), ANN Based Thermal Control Models for Residential Buildings. Building and Environment, vol. 45, pp. 1612-1625.

[8] Ang, K.H. and Chong, G. and Li, Y. (2005), PID Control System Analysis, Design, and Technology. Int. IEEE Transactions on Control Systems Technology, vol. 13, pp.559-576.

[9] Peng, D., Zhang, H., Yang, L. and Xu, L. (2007), Study of Immune PID Adaptive Controller and its Applications in Thermal Control System. In: International Conference on Computational Intelligence and Security, pp. 470-474.

[10] Gattu, G. and Zafiriou, E. (1992), Nonlinear Quadratic Dynamic Matrix Control with State Estimation. Industrial and Engineering Chemistry Research, vol. 31, pp. 1096-1104.
[11] Dwivedi, D. and Kaistha, N. (2009), Temperature Inferential Dynamic Matrix Control of Reactive Distillation Systems, vol. 7, pp. 435-440.
[12] Jiang, Z. and Huang, X. (2009), The Character Study of Dynamic Matrix Control. In: Proceedings of the Int. Conference on Intelligent Human-Machine Systems and Cybernetics, pp. 138-141.
[13] Donnelly, P., Becker, R., and Dedorko, D. (2008), PCM Membranes in Architectural Enclosures. In: Proceedings of the Washington University McDonnell Academy Global Energy and Environment Partnership (MAGEEP), P. Biswas ed., pp. 130-138.
[14] Thorsell, T. and Bomberg, M. (2011), Integrated Methodology for Evaluation of Energy Performance of the Building Enclosures: Part 3-Uncertainty in Thermal Measurements, Journal of Building Physics, vol. 35, pp. 83-96.
[15] Saber, H.H. Maref, W. and Swinton, M.C. (2011), Thermal Response of Basement Wall Systems with Low-Emissivity Material and Furred Airspace, Journal of Building Physics, vol. 35, pp. 83-96.
[16] Sailor, D.J., Elley, T.B. and Gibson, M. (2011), Exploring the Building Energy Impacts of Green Roof Design Decisions--a Modeling Study of Buildings in Four Distinct Climates, Journal of Building Physics, Vol. 35, pp. 372-391.
[17] Zadeh, L.A. (1972), A Rationale for Fuzzy Control, Journal of Dynamic Systems, Measurement, and Control, vol. 94, pp. 3-4.
[18] Cheng, H.M., C. Chen, C. Cheng, and C. Chiu. (1998), An Application of Distributed Air Conditioning Control Network. In: Proceedings of the 1998 American Control Conference, vol. 6, pp. 3420-3424.
[19] Hasnain, S.M., Alawaji, S.H., A1-Ibrahim, A. and Smiai, M.S. (1999), Application of Thermal Energy Storage in Saudi Arabia. International Journal of Energy Research, vol. 23, pp. 117-124.
[20] Zaheer-uddin, M. and Zheng, G.R. (2001), Multistage Optimal Operating Strategies for HVAC Systems, ASHRAE Transactions, vol. 107, pp.346-352.
[21] Nippert, C.R. (2002), Simple Models that Illustrate Dynamic Matrix Control. In: Proceedings of the American Society for Engineering Education Annual Conference & Exposition, pp.3513-3520.

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