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Optimal State Estimation of Air Handling Unit System without Humidity Sensor using Unscented Kalman Filter

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***Abstract*—One of the main Heating, Ventilating and Air Conditioning (HVAC) devices which is located on the path of coolers or boilers is the air handling unit (AHU). AHU is a device which provides healthy and clean air by providing proper temperature and humidity. There are a lot of nonlinearities and couplings among variables of this system which makes design of the control system and state estimation, an attractive and challenging problem. In this paper, purpose is to design an unscented Kalman filter (UKF) based on scaled unscented transformation (UT) for state estimation of the AHU system controlled via a linear quadratic regulator (LQR). This filter employs UT and statistical characteristics to calculate more terms of the Taylor extension and increase estimation accuracy. Using UT preserving nonlinear characteristics of the AHU without linearization, offers an optimal estimation with proper speed and accuracy which can be used for any kind of state feedback controller. Simulation results demonstrate proper performance of the proposed method compared to extended kalman filter (EKF).**

***Index Terms*--Air handling unit, extended kalman filter, linear quadratic regulator, scaled unscented transformation, unscented kalman filter.**

I. Introduction

Purpose of each HVAC system and its control is to create a proper and desired environment for human life. One part of each HVAC is AHU. AHUs are one of the main components of the annealing cycle which can be used on the path of water and air chillers, boilers or alone. This system changes temperature condition considering air flow and a proper control system and the environment of interest reaches the desired temperature and humidity. Nonlinear and complicated nature and high coupling of the variables is one of the challenges of the AHUs. Therefore, presenting an effective control method which can operate acceptably considering all practical constraints, has always been one of the important and open areas in the control of AHUs [1-3]. In [4], various methods have been proposed for modelling AHUs and the performance of the AHU has been analyzed in [5].

In [6], performance of the AHU in tracking the desired temperature and humidity in the presence of disturbances controlled by feedback linearization and pole placement has been compared. In [7], adaptive fuzzy controller has been presented for controlling the AHU. In [8], PID controllers with variable coefficients monitored by the fuzzy system have been used to control AHU in the presence of uncertainty. Model predictive control (MPC) method has been proposed in [9] for tracking and optimizing energy consumption in a multi-area AHU. In addition, predictive controller is used to minimize energy in HVACs [10]. In [11], an MPC has been proposed for controlling HVACs. Predicting weather and price of the consumed electric energy are considered.

A robust controller based on full order and reduced order observer has been designed for AHU [12]. In [13], sliding mode controller has been designed for AHU despite reducing open frequency and closing the valves which are considered as disturbance. In [14], H_∞ controller and decoupled sliding mode controller designed for controlling the AHU in the presence of uncertainty have been compared. In [15], state dependent Riccati equation controller based on pseudo linearization and extended Kalman filter has been presented for the AHU. LQR controller has been designed in [16] for optimal control and tracking the reference trajectories.

As mentioned before, in the air handling system, observers like full order and reduced order Luenberger observers and extended Kalman filter have been used. Luenberger observer estimates the states based on linearized model of the air handling system. Since equations of this system are severely nonlinear, linearization cannot present an accurate estimation of the states. Extended Kalman filter employs linearization around the previous estimated point in its equations which

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suffers from the aforementioned problem. UKF is a nonlinear distribution sampling method which uses a limited number of Sigma points to create probability of a state distribution through nonlinear dynamic of the system. These sigma points are selected to obtain real covariance and mean to increase second order Taylor sets for a nonlinear system. Thus, UKF employs statistical characteristics of the sigma points instead of linearization to offer an optimal estimation of the states, preserving nonlinear characteristics of the system. Therefore, compared to extended kalman filter, unscented filter gives a more accurate estimation with smaller error [17]. Parameters of the UT can be determined via trial and error or based on different algorithms. In [18], standard model based optimization has been used to determine two parameters of the UKF, offline. In [19], extended and unscented kalman filters have been compared for harmonic analysis of nonstationary signals indicating superiority of the UKF. In order to identify the model using Takagi-Sugeno fuzzy method, UKF has been used which has shown better performance compared to EKF in terms of estimation accuracy [20]. In order to control manipulators in unmanned aerial vehicles (UAVs) which requires an accurate estimation of all existing variables, UKF and a novel model of this filter called Event-triggered cooperative UKF have been used [21-22]. In [23], a new type of this filter has been presented for detecting dynamic of nonlinear systems in the presence of unknown input and external excitations through data fusion of the system measurements. Furthermore, in [24], a new formulation of this filter called Iterated maximum correntropy UKF has been proposed for systems with non-Gaussian noises. UKF is used to estimate speed in PMSMs [25]. In [26], the augmented EKF is utilized for identification of vehicle dynamics.

In this paper, optimal linear regulator is used to control temperature and humidity of the AHU. This method is based on state feedback but all states of the systems are not accessible because measuring all states of the AHU and increasing number of sensors increases costs. Therefore, an observer is required to estimate the states. In this paper, UKF is used to estimate states of the AHU. As mentioned, one of the main advantages of this filter is the linearization around the equilibrium point. Linearization methods cannot preserve nonlinear nature of the system. In this filter, estimation is performed with higher accuracy through certain selection of the Sigma points from the Gaussian distribution accurately and broadcasting them through a nonlinear function. By employing UT, distribution of these points can be selected and higher order errors can be controlled using the design parameters. Using UKF, preserving nonlinear characteristics of the AHU without linearization, an optimal estimation of the system is obtained with proper speed and accuracy which can be used for LQR state feedback controller. Simulation results show proper performance of the proposed method compared to EKF.

The rest of this paper is organized as follows. Section 2 presents nonlinear model of the AHU. UT, UKF and state estimation using this filter are presented in section 3. Section 4 presents simulation results of LQR controller based on state estimation using UKF, and EKF and UKF are compared. Finally, the paper is concluded in section 5.

II. DYNAMIC OF THE AHU

Schematic of a single-area AHU under variable air volume is shown in Fig. 1.

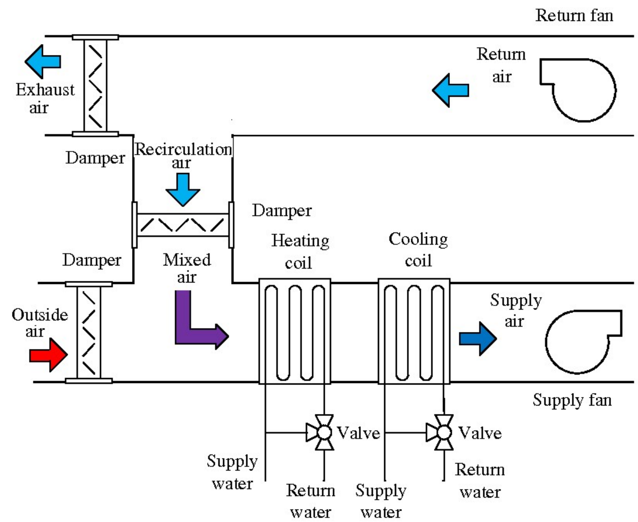

Figure 1. Schematic of a single zone AHU

In order to present dynamic model of the AHU, some assumptions are considered: 1) the AHU is designed for cooling in summer in which there exist cold water and air loops. 2) gases are ideal and are fully combined. 3) effect of air velocity changes on pressure of the area is negligible and the air does not leak (except at exhaust valves of the area). 4) air flow is homogeneous. Considering these assumptions and using thermodynamic, heat and mass transmission laws, equations of the AHU would be as follows:

$$\begin{cases} \dot{T}_t = \dfrac{\dot{Q}_o - h_{fg}\dot{M}_o}{\rho_t C_{pa} V_t} + \dfrac{\dot{f}_a h_{fg}}{C_{pa} V_t}(w_t - w_s) - \dfrac{\dot{f}_a}{C_{pa} V_t}(T_t - T_s) \\ \dot{w}_t = \dfrac{\dot{M}_o}{\rho_a V_t} - \dfrac{\dot{f}_a}{V_t}(w_t - w_s) \\ \dot{T}_s = \dfrac{\dot{f}_a}{V_c}(T_t - T_s) - \dfrac{\dot{f}_a h_w}{C_{pa} V_c}(0.25 w_o + 0.75 w_t - w_s) \\ \quad + \dfrac{0.25 \dot{f}_a}{V_c}(T_o - T_t) - \dot{f}_w \left(\dfrac{\rho_w C_{pw} \Delta T_c}{\rho_a C_{pa} V_c} \right) \end{cases} \tag{1}$$

where the state variables T_t, w_t and T_s are temperature of indoor air, humidity ratio of indoor air and supply temperature, respectively, and input variables $\dot{f}_a$ and $\dot{f}_w$ are air flow rate and cold water flow rate, respectively. It is considered that only temperature of indoor air is measured as the output signal of AHU. The physical parameters of AHU are defined as follows: w_s and w_0 are the humidity ratios of the outdoor and supply air, T_o is outdoor temperature, ΔT_c is the temperature difference in the cooling unit, $\dot{M}_o$ and $\dot{Q}_o$ are the strength of humidity and heat loads, V_t and V_c are the volume of the indoor zone and cold unit, h_w and h_{fg} are the enthalpy of saturated water and vaporization, ρ_a and ρ_w are the mass density heat of the air and cold water, and C_{pa} and C_{pw} are the mass specific heat of the air and cold water.

TABLE I. THE VALUE OF PHYSICAL PARAMETERS OF AHU

Param.	Value	Unit	Param.	Value	Unit
w_o	0.0082	kg H_2O/(kg dry air)	C_{pw}	4180	J/(kgC)
w_s	0.0080	kg H_2O/(kg dry air)	h_w	80000	kJ/kg
T_o	32	C	h_{fg}	2500	kJ/kg
ΔT_c	6	C	ρ_a	1.18	kg/m^3
$\dot{M}_o$	0.000122	kg/s	ρ_w	1000	kg/m^3
$\dot{Q}_o$	21500	kW	V_c	1	m^3
C_{pa}	1000	J/(kgC)	V_t	400	m^3

Table 1 represents nominal values of these parameters. Nonlinear state space representation of the AHU can be described as in (2).

$$\dot{x}(t) = f\left(x(t), u(t)\right) \tag{2}$$

where $x = \left[T_t, w_t, T_s\right]^T$ and $u = \left[\dot{f}_a, \dot{f}_w\right]^T$ are the state and input vectors and f is a continuous nonlinear function-vector as follows:

$$f = \begin{bmatrix} -\alpha_1 u_1 (x_1 - x_3) + \beta_1 u_1 (x_2 - w_s) + \gamma_1 \left(\dot{Q}_o - h_{fg} \dot{M}_o\right) \\ \alpha_2 \dot{M}_o - \alpha_1 u_1 (x_2 - w_s) \\ \begin{Bmatrix} \alpha_3 u_1 (x_1 - x_3) + 0.25 \alpha_3 u_1 (T_o - x_1) \\ \quad - \gamma_2 u_1 (0.25 w_o + 0.75 x_2 - w_s) - \beta_2 u_2 \end{Bmatrix} \end{bmatrix} \tag{3}$$

where, the following definitions are considered in the above equations:

$$\begin{aligned} &\alpha_1 = \frac{1}{V_t},\ \alpha_2 = \frac{1}{\rho_a V_t},\ \alpha_3 = \frac{1}{V_c},\ \beta_1 = \frac{h_{fg}}{C_{pa} V_t} \\ &\beta_2 = \frac{\rho_w C_{pw} \Delta T_c}{\rho_a C_{pa} V_c},\ \gamma_1 = \frac{1}{\rho_t C_{pa} V_t},\ \gamma_2 = \frac{h_w}{C_{pa} V_c} \end{aligned} \tag{4}$$

Equilibrium point of the AHU equations described using (1) and the values given in Table 1 is obtained as $x_e = \left[24 \quad 0.008126 \quad 14.5\right]^{\mathrm{T}}$ and $u_e = \left[2.5983 \quad 0.001362\right]^{\mathrm{T}}$. Therefore, the variable changes, $\tilde{x} = x - x_e$ and $\tilde{u} = u - u_e$ should be applied to the obtained state space equations in (2). Using these variable changes, the equilibrium points of the new state space would be zero.

III. UNSCENTED KALMAN FILTER

Usually, in control problems, all states of the system are not accessible and it is unavoidable to use estimated values instead of the main values. Therefore, importance of estimation in control is obvious for everyone. Among model-based error detection and identification methods, observer-based methods are more important. Among observer-based methods, kalman filter is highly accepted. Indeed, it should be noted that kalman filter algorithm is only used for linear systems; thus, extended kalman filter has been proposed for nonlinear systems. Although efficiency of the algorithms based on EKF is widely known, but its practical application in complex systems is restricted. Thus, when EKF is applied to a complex system, implementation and numerical computation (calculating Jacobin matrix) issues arise. Therefore, EKF estimation might have bias error. On the other hand, linearization at each step might create large errors in convergence of the filter. These problems appear more in complex industrial systems. EKF employs the first terms of the Taylor series to linearize the nonlinear system. Thus, in cases, where the system is severely nonlinear and upper terms of the Taylor series are important, the model which is linearized using this method, is not a good approximation of the real system as a result of which state estimation of these systems would be inaccurate. In addition, it has been shown that approximating a Gaussian distribution using a constant number of parameters is simpler than approximating an arbitrary nonlinear function and a new extension of the kalman filter called unscented filter has been presented in which mean and covariance are directly calculated via nonlinear equations of the system. Unlike EKF, UKF does not approximate a nonlinear system with a linear system but it employs the same nonlinear system to calculate statistical characteristics of the system. In this method, it is not required to calculate Jacobin matrix of the system [17]. In the following, UT which is the basis of UKF is investigated.

A. Unscented Transformation

This transformation is a method for calculating statistical characteristics of the random variables which are mapped via a nonlinear function. The main idea of this method is that approximating a probability density function is simpler than approximating a nonlinear function [17]. In this method, a set of points called Sigma points are selected such that mean and covariance are predetermined. A nonlinear function is applied to these points so that an image of the transformed points is developed. Then, statistical characteristics of the transformed points can be calculated to obtain an estimation of mean and covariance of the nonlinear function [18]. Assume x is a random vector of dimension n_x, g is a nonlinear function and y is the map of x obtained using this function, in other words:

$$y = g(x) \tag{5}$$

In addition, x is its mean and P_x is its covariance. In order to calculate statistical characteristics (mean and covariance) of y, unscented transformation can be used. To this end, $2n_x + 1$ weighted samples or Sigma points $S_i = \{W_i, X_i\}$ are selected from PDF of x such that they cover mean and covariance of the random vector x. This is the minimum number of samples with this characteristic. This selection is made as follows.

$$\begin{aligned} &\chi_0 = \hat{x} && W_0 = \lambda / (n_x + \kappa) && i = 0 \\ &\chi_i = \hat{x} + \left(\sqrt{(n_x + \kappa) P_x}\right)_i && W_i = 1 / \left(2(n_x + \kappa)\right) && i = 1, \ldots, n_x \\ &\chi_i = \hat{x} - \left(\sqrt{(n_x + \kappa) P_x}\right)_i && W_i = 1 / \left(2(n_x + \kappa)\right) && i = n_x + 1, \ldots, 2n_x \end{aligned} \tag{6}$$

where κ is a weighting parameter and $(\sqrt{(n_x + \kappa) P_x})_i$ is the ith row or column of the matrix $(n_x + \kappa) P_x$. After sampling the Sigma points, they are all inserted in a nonlinear function.

$$y_i = g(\chi_i), \qquad i = 0,...,2n_x \tag{7}$$

Finally, output mean ($\bar{y}$) and covariance (P_y) are calculated as follows.

$$\bar{y} \approx \sum_{i=0}^{2n_x} W_i^{(m)} y_i \tag{8}$$

$$P_y \approx \sum_{i=0}^{2n_x} W_i \left(y_i - \bar{y}\right)\left(y_i - \bar{y}\right)^T \tag{9}$$

It is proved that using UT, mean and covariance are approximated up to the second term of the Taylor series of the nonlinear function and the approximation error only includes third and upper terms which are adjusted by the parameter κ, while EKF with linearization only uses the first term of the Taylor series for approximation. By optimal selection of the parameter κ, estimation accuracy can be increased. Specially, when the function is severely nonlinear. This parameter adjusts the distance between the Sigma points and the mean. Distance of the ith Sigma point from mean ($|\chi_i - \hat{x}|$) is proportional to $\sqrt{(n_x + \kappa)}$ and the larger is κ, the Sigma points are more scattered with respect to the mean. In a specific case, $\kappa = 3 - n_x$ is suggested for κ. But, if $n_x > 3$, then $W_0 < 0$ and covariance might not be positive semi-definite resulting in problems for the numerical solution. In order to solve this problem, scaled UT can be used.

B. Scaled Unscented Transformation

In this method, a set of auxiliary Sigma points are calculated according to the following equation:

$$\chi_i' = \chi_0 + \alpha\left(\chi_i - \chi_0\right), \qquad i = 0,...,2n_x \tag{10}$$

α is an arbitrary parameter and it is selected as a degree of freedom in the design such that it minimizes effect of upper terms in the nonlinear Taylor series. Selection of the Sigma points and scaling can be combined in the following step.

$$\lambda = \alpha^2\left(n_x + \kappa\right) - n_x \tag{11}$$

Thus, computation volume is reduced and the Sigma points are selected as follows.

$$\begin{aligned}
&\chi_0 = \hat{x} \\
&\chi_i = \hat{x} + \left(\sqrt{(n_x + \lambda)P_x}\right)_i \quad i = 1,...,n_x \\
&\chi_i = \hat{x} - \left(\sqrt{(n_x + \lambda)P_x}\right)_i \quad i = n_x + 1,...,2n_x \\
&W_0^{(m)} = \lambda / (n_x + \lambda) \\
&W_0^{(c)} = \lambda / (n_x + \lambda) + \left(1 - \alpha^2 + \beta\right) \\
&W_i^{(m)} = W_i^{(c)} = 1 / \left(2(n_x + \kappa)\right) \quad i = 1,...,2n_x
\end{aligned} \tag{12}$$

Weight of the Sigma points directly affects the errors caused by fourth and upper terms in the symmetric density functions. The parameter β also affects selection of the Sigma points which affects calculation of the covariance. Mean and covariance of y are calculated as follows [19].

$$\bar{y} = \sum_{i=0}^{2n_x} W_i^{(m)} y_i$$
$$P_y = \sum_{i=0}^{2n_x} W_i^{(c)} \left(y_i - \bar{y}\right)\left(y_i - \bar{y}\right)^T \tag{13}$$

C. Unscented Kalman Filter Algorithm

UKF is a recursive method in which scaled UT is used in an algorithm similar to the kalman filter including time and measurement updating for state estimation of a nonlinear system. In this algorithm, initial conditions are assigned first and after selecting the Sigma points, time updating is performed. Finally, after calculating measurement for employing the obtained information in order to increase the estimation accuracy, measurement updating is performed [17-20]. Procedure of this algorithm is as follows:

1) assigning initial conditions:

$$\begin{aligned}
&\hat{x}_0 = E\left[x_0\right] \\
&P_0 = E\left[\left(x_0 - \hat{x}_0\right)\left(x_0 - \hat{x}_0\right)^T\right]
\end{aligned} \tag{14}$$

2) selecting the Sigma points:

$$\chi_k = \left[\hat{x}_k \quad \hat{x}_k \pm \sqrt{(n_x + \lambda)P_x}\right] \tag{15}$$

3) Time updating

$$\chi_{k+1|k}^x = g\left(\chi_k^x, u_k\right) \tag{16}$$

$$\hat{x}_{k+1|k} = \sum_{i=0}^{2n_x} W_i^{(m)} \chi_{i,k+1|k} \tag{17}$$

$$P_{k+1|k} = \sum_{i=0}^{2n_x} W_i^{(c)} \left[\chi_{i,k+1|k} - \hat{x}_{k+1|k}\right]\left[\chi_{i,k+1|k} - \hat{x}_{k+1|k}\right]^T + Q_{k+1} \tag{18}$$

$$\gamma_{k+1|k} = h\left(\chi_k^x\right) \tag{19}$$

$$\hat{y}_{k+1|k} = \sum_{i=0}^{2n_x} W_i^{(m)} \gamma_{i,k+1|k} \tag{20}$$

4) Measurement updating

$$P_{\tilde{y}_k \tilde{y}_k} = \sum_{i=0}^{2n_x} W_i^{(c)} \left[\gamma_{i,k+1|k} - \hat{y}_{k+1|k}\right]\left[\gamma_{i,k+1|k} - \hat{y}_{k+1|k}\right]^T + R_{k+1} \tag{21}$$

$$P_{x_k y_k} = \sum_{i=0}^{2n_x} W_i^{(c)} \left[\chi_{i,k+1|k} - \hat{x}_{k+1|k}\right]\left[\gamma_{i,k+1|k} - \hat{y}_{k+1|k}\right]^T \tag{22}$$

$$K_{k+1} = P_{x_k y_k} P_{\tilde{y}_k \tilde{y}_k}^{-1} \tag{23}$$

$$P_{k+1} = P_{k+1|k} - K_{k+1} P_{\tilde{y}_k \tilde{y}_k} K_{k+1}^T \tag{24}$$

$$\hat{x}_{k+1} = \hat{x}_{k+1|k} + K_{k+1}\left(y_{k+1} - \hat{y}_{k+1|k}\right) \tag{25}$$

In which, matrices Q_k and R_k are covariance of the process noise and measurement.

IV. Simulation Results

In order to design the LQR controller, AHU equations are linearized around the equilibrium points and the linear state space is obtained as follows:

$$\dot{\tilde{x}} = A\tilde{x} + B\tilde{u}$$

$$A = \begin{bmatrix} -\alpha_1 & \beta_1 & \alpha_1 \\ 0 & -\alpha_1 & 0 \\ 0.75\alpha_3 & -0.75\gamma_2 & -\alpha_3 \end{bmatrix} \bar{u}_1$$

$$B = \begin{bmatrix} \beta_1\left(\bar{x}_2 - w_s\right) - \alpha_1\left(\bar{x}_1 - \bar{x}_3\right) & 0 \\ -\alpha_1\left(\bar{x}_2 - w_s\right) & 0 \\ \left\{ \begin{array}{c} \alpha_3\left(\bar{x}_1 - \bar{x}_3\right) + 0.25\alpha_3\left(T_o - \bar{x}_1\right) \\ -\gamma_2\left(0.75\bar{x}_2 + 0.25w_o - w_s\right) \end{array} \right\} & -\beta_2 \end{bmatrix} \quad (26)$$

Initial condition of the states and estimated states are also $x(0) = [24, 0.008126, 14.5]^T$ and $\hat{x}(0) = [19, 0.0081, 12.5]^T$. Weight coefficients of the cost function of the LQR controller are selected as $R_{lqr} = \text{diag}\left(10^2, 10^2\right)$ and $Q_{lqr} = \text{diag}\left(1, 10^5\right)$. Design parameters of the UKF are also considered as $\alpha = 0.001$, $\beta = 2$ and $\kappa = 0.1$. The reference temperature and humidity signals are considered as shown in Fig. 2 and 3. Real humidity and temperature and the humidity and the temperature estimated by UKF are shown in Fig. 4 and 5. In addition, estimation errors of these two variables are also shown in Fig. 6 and 7. According to the above figures, it can be seen that the proposed method has estimated system states with high accuracy and it has tracked the temperature and humidity reference trajectories despite their changes. Maximum convergence time is obtained for the humidity which is less than 0.5 s and the temperature has converged to its real value after about 5 ms which is equivalent to 5 samples. Control inputs are also shown in Fig. 8 and 9 which represent inputs with allowed amplitude and smooth changes which can be generated by the actuators.

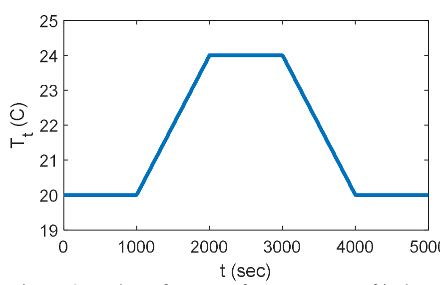

Figure 2. The reference of temperature of indoor air

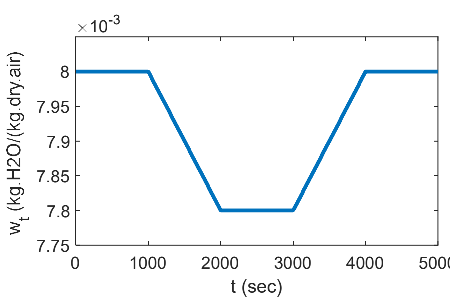

Figure 3. The reference of humidity ratio of indoor air

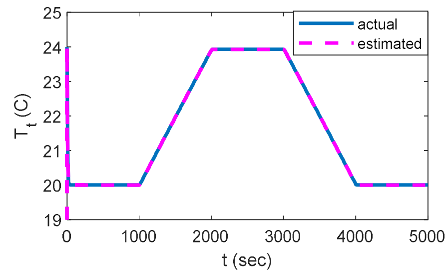

Figure 4. The actual and estimated of temperature of indoor air by UKF

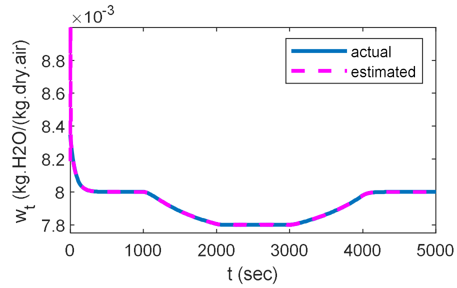

Figure 5. The actual and estimated of humidity ratio of indoor air by UKF

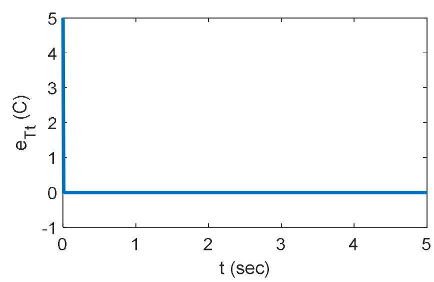

Figure 6. The estimation error of temperature of indoor air by UKF

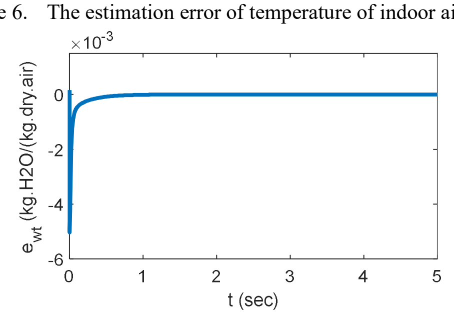

Figure 7. The estimation error of humidity ratio of indoor air by UKF

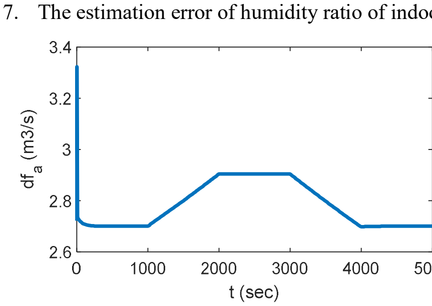

Figure 8. The air flow rate

In order to illustrate accuracy of UKF compared to EKF, the estimation error of humidity ratio of indoor air is shown in Fig. 10. Norm-II and norm-infinity of estimation errors of the two variables are given in Table 2. Both norms are smaller in UKF specially for humidity which requires more complicated control compared to temperature and converges to its real value, later.

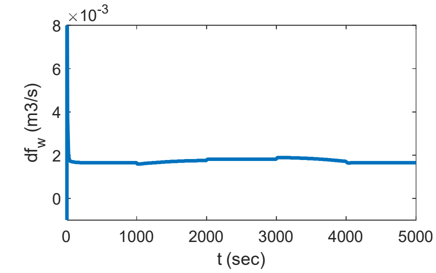

Figure 9. The cold water rate

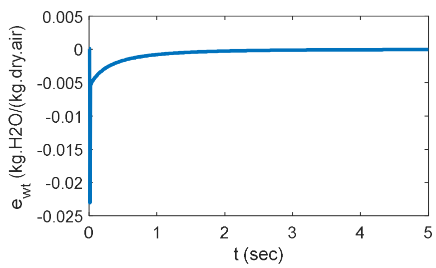

Figure 10. The estimation error of humidity ratio of indoor air by EKF

TABLE II. COMPARISON BETWEEN UKF AND EKF

	$L_2\left(T_t - \hat{T}_t\right)$	$L_2\left(w_t - \hat{w}_t\right)$	$L_\infty\left(T_t - \hat{T}_t\right)$	$L_\infty\left(w_t - \hat{w}_t\right)$
UKF	5	3.260×10^{-3}	5	8.178×10^{-4}
EKF	5.6189	0.4697	5.3842	0.4550

V. CONCLUSION

In this paper, design of the UKF based on scaled UT is proposed for estimating temperature and humidity of the AHU. In addition, LQR controller is used to control these two variables. Considering the complicated coupling between input variables and states and nonlinear nature of the AHU, UKF is a proper option for state estimation of this system because it employs UT and preserves nonlinear characteristics without linearization and offers a higher accuracy. Simulation results indicate speed and accuracy of the designed UKF for AHU. In addition, numerical results show superiority of this filter in estimating states of the AHU compared to EKF.

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