PSO Adaptive Fading Memory Kalman Filter Based State Estimation of Indoor Thermal Model with Unknown Inputs

Bed Prakash Das
Department of Applied Physics
University of Calcutta
Kolkata, India
bpdaphy_rs@caluniv.ac.in

Kaushik Das Sharma
Department of Applied Physics
University of Calcutta
Kolkata, India
kdsaphy@caluniv.ac.in

Amitava Chatterjee
Department of Electrical Engineering
Jadavpur University
Kolkata, India
cha_ami@yahoo.co.in

Jitendranath Bera
Department of Applied Physics
University of Calcutta
Kolkata, India
jnbaphy@caluniv.ac.in

***Abstract*—An adaptive filtering approach is proposed in this paper to address the thermal state estimation methodology along with the model parameters jointly for an indoor thermodynamic resistance capacitance model with uncertain stochastic heating inputs. The adaptive dynamics of the state of the model is combined with a particle swarm optimization (PSO) based metaheuristic approach to feed the knowledge of measurement noise statistics and the initial estimation error covariance along with forgetting factor for implementation of fading memory Kalman filter (FMKF). This study has been carried out with the variation of uncertain influential input information to enhance the estimation efficiency with the proposed PSO adaptive FMKF (PSO-AdFMKF) strategy for a real life the test thermodynamic environment scenario inside the building space. Potential observations demonstrate that the proposed estimation algorithm performs encouragingly, with a satisfactory improvement of estimation performance in terms of evaluating error metrics.**

Keywords—Indoor building model, Adaptive fading memory Kalman filter, RC network thermal model, HVAC model

I. Introduction

Around 30% of the world's energy use and greenhouse gas emissions [1] are pertaining to buildings. This percentage is anticipated to climb as people spend more time inside. HVAC (heating, ventilation, and air conditioning) systems, which are in charge of delivering thermal comfort and acceptable air quality, are the major energy consumers in buildings. When adjusting the supply air flow and temperature entering a thermal zone, heating, ventilation and cooling (HVAC) systems frequently employ an energy-efficient predictive control logic based on the temperature of the inside air. Improved HVAC power input prediction, which is correlated with occupant thermal comfort, is a logical strategy to lower the energy cost of HVAC systems. Moreover, considering indoor air quality (IAQ) [2] is so directly linked to one's health and productivity, occupants are likewise concerned about it.

Modeling the dynamic behaviour of the energy distribution for an indoor building space is consistently regarded as a challenging subject to comprehend due to the presence of numerous built-architecture analysis-related uncertainties. These constraints are time-varying in nature, alter with the environment, and are influenced by various occupants' actions [3]-[4]. Contemporary study in this field has focused on creating intelligent indoor environmental conditions for smart homes by integrating machine intelligence [5]-[6], wireless sensor networks (WSN) [7] with IoT-enabled equipment [8]. As sensor-based intelligent buildings are developed, environmental parameter optimization [9]-[11] has also become a significant research challenge.

Estimation of unknown stochastic inputs belonging to various thermodynamic indoor test conditions employing a range of recursive filtering algorithm for linear and nonlinear systems includes variation of Kalman filters (*KF*) like fading memory Kalman filter (*FMKF*) [10], extended Kalman filter (*EKF*) [12], unscented Kalman filter (*UKF*) [11] etc.

However, in order to develop and implement such a recursive filtering algorithm, detailed knowledge of the target system's dynamic properties and process noise is required, which is used to create process and observation models. It is difficult to predict the initial guess, measurement noise covariance (R), and initial state estimation error covariance ($\tilde{P}_0$) under the demanding circumstance of the unknown dynamic system behaviour of the time-varying distribution in real - life conditions. As a result of most of these, the observation and process equations do not match the real system, leading to filter divergence [13] and emphasizing the importance of the R and $\tilde{P}_0$ values.

In this paper, a particle swarm optimization (*PSO*) based adaptive fading memory Kalman filter (*PSO-AdFMKF*) has been proposed and implemented, considering an adaptive forgetting factor in view of accommodating the convergent feature of filtering method. Adequate adaptation method for an unknown input augmented joint state and parameters estimation process with PSO based metaheuristic approach has been proposed in this research as conceptualize in Fig.1. The study of this paper has revealed a dominating estimation performance of 20% and 4.9% superior to conventional *KF* and *FMKF* based approach respectively. On the other hand, 49% improved estimation has been obtained with the variation of measurement knowledge.

The remaining portion of the paper is structured as follows. The mathematical foundations of the proposed are presented in Section II. The materials and methods used for the proposed work are depicted in Section III. The recommended model's case study and results evaluation are included in Section IV. A conclusion has been reached with a

978-1-6654-9291-1/22/$31.00 ©2022 IEEE

comparative study and a focus on future development in section V.

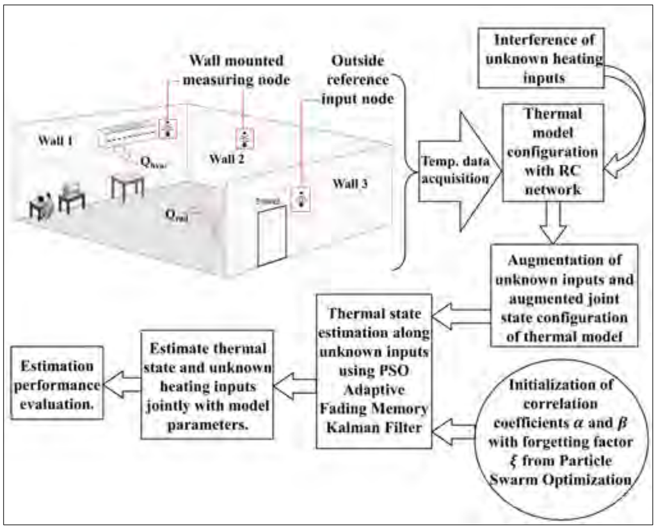

Fig. 1. Schematic diagram for proposed PSO-AdFMKF based indoor thermal state estimation with unknown inputs

II. Mathematical Preliminaries

A. Modelling of Building Thermal Dynamics

The dynamic behavior of the thermal energy distribution inside a building space has been formulated in this section using three resistance one capacitance (3R-1C) model associated with unknown heating inputs include thermal heat gain due to occupants and HVAC supply. The RC network modelling has been carried out according to [10] employing ordinary differential equations as:

$$C_{w1}\frac{dT_{w1}}{dt} = \frac{T_{w2}-T_{w1}}{R_{w12}} + \frac{T_{w4}-T_{w1}}{R_{w41}} + \frac{T_o-T_{w1}}{R_{w1}} + Q_{hvac} \tag{1}$$

$$C_{w2}\frac{dT_{w2}}{dt} = \frac{T_{w3}-T_{w2}}{R_{w23}} + \frac{T_{w1}-T_{w2}}{R_{w12}} + \frac{T_o-T_{w2}}{R_{w2}} \tag{2}$$

$$C_{w3}\frac{dT_{w3}}{dt} = \frac{T_{w4}-T_{w3}}{R_{w34}} + \frac{T_{w2}-T_{w3}}{R_{w23}} + \frac{T_o-T_{w3}}{R_{w3}} + Q_{rad} \tag{3}$$

$$C_{w4}\frac{dT_{w4}}{dt} = \frac{T_{w1}-T_{w4}}{R_{w41}} + \frac{T_{w3}-T_{w4}}{R_{w34}} + \frac{T_o-T_{w4}}{R_{w4}} \tag{4}$$

where, T_{w1}, T_{w2}, T_{w3}, and T_{w4} indicate the temperatures measured at the four nodes installed on the indoor wall and T_o denotes the reference input temperature measured at the outside wall in °*C*. R_{w1}, R_{w2}, R_{w3}, R_{w4}, R_{w12}, R_{w23}, R_{w34}, R_{w41} are the thermal resistances in *K*/*kW* and C_{w1}, C_{w2}, C_{w3}, C_{w4} are the thermal capacities in *kJ*/*K*. Two unknown heating inputs are Q_{hvac} and Q_{rad} designated for thermal heat gain due to occupants and HVAC supply respectively in *kW*.

The linear state space characterization of the inside building thermodynamic events may be structured as follows:

$$T = [T_{w1} \quad T_{w2} \quad T_{w3} \quad T_{w4}]^T \tag{5}$$

The input vector may be modelled as a combination of the known and unknown inputs., as:

$$U = [u \quad u^*]^T \; ; \; u = [T_o]^T, \; u^* = [Q_{hvac} \quad Q_{rad}]^T$$

This leads to form the dynamic model for this uncertain indoor thermal distribution as:

$$\dot{T} = A \cdot T + B \cdot u + E \cdot u^* \tag{6}$$

$$y = C \cdot T + D \cdot u \tag{7}$$

The corresponding A, B, C, D and E can be derived from (1) to (4).

The unknown heating inputs Q_{hvac} and Q_{rad} associated with the model have been estimated simultaneously employing augmented state space representation, as described in [10]. Hence the dynamic response of the model is further reconfigured portraying the concept of augmented state space realization in the following manner:

$$\begin{aligned}\dot{T}_{ag} &= A_{ag} \cdot T_{ag} + B_{ag} \cdot u \\ y_{ag} &= C_{ag} \cdot T_{ag} + D_{ag} \cdot u\end{aligned} \tag{8}$$

where, the augmented state vector is

$$T_{ag} = [T_{w1} \quad T_{w2} \quad T_{w3} \quad T_{w4} \quad Q_{hvac} \quad Q_{rad}]^T$$

As the state estimation procedure is dependent on the unknown the time invariant RC model parameters, a parallel estimation of these parameters has been performed simultaneously. The proposed estimation technique in this paper has been put into action to estimate building thermal dynamics jointly with the thermal resistances and capacitances employing this augmented linear system adapting with its dynamic behavior.

B. Conventional Kalman Filter Based State Estimation

In conventional KF approach, the linear time invariant augmented joint state system, as in (8), can be described in discrete time equations as:

$$T_{ag\_Jt_k} = \Phi \cdot T_{ag\_Jt_{k-1}} + \Gamma \cdot u_{k-1} + w_{k-1} \tag{9}$$

where, the discretized system dynamics has been represented through the matrices Φ, Γ and H implementing Euler's method. In this equation (9), the augmented joint state has been constituted as $T_{ag\_Jt} = [T_{ag} \quad \theta_p]^T$ with the parameter vector $\theta_p = [R_T \quad C_T]^T$. Here, the thermal resistance and capacitance vector $R_T = [R_{w1} \quad R_{w2} \quad R_{w3} \quad R_{w4} \quad R_{w12} \quad R_{w23} \quad R_{w34} \quad R_{w41}]^T$ and $C_T = [C_{w1} \quad C_{w2} \quad C_{w3} \quad C_{w4}]^T$. The stochastic process noise w_{k-1} is assumed to be uncorrelated zero mean Gaussian white noise at time step $k-1$ with a nonnegative definite covariance matrix $Q_{k-1} = E[w_{k-1}{w_{k-1}}^T]$.

In the measurement model, the measurement equation for observation vector $y_{ag\_Jt_k}$ can be formulated as:

$$y_{ag\_Jt_k} = H \cdot T_{ag\_Jt_k} + v_k \tag{10}$$

where, the measurement matrix H accepts the measurement from augmented joint state $T_{ag\_Jt_k}$ to produce the observation vector $y_{ag\_Jt_k}$. The stochastic measurement noise v_k is assumed to be zero mean Gaussian white noise and uncorrelated with covariance matrix $R_k = E[v_k {v_k}^T]$, which is a nonnegative definite matrix. In this study Q and R are considered as constant.

The *a posteriori* state estimation $\hat{T}_{ag\_Jt_{k|k}}$ at time step k can be obtained from the *a priori* state estimation $\hat{T}_{ag\_Jt_{k|k-1}}$ at time step *k*-1, according to the measurement and process information $y_{ag\_Jt_k}$ in the following manner:

$$\hat{T}_{ag\_Jt_{k|k-1}} = \Phi \cdot \hat{T}_{ag\_Jt_{k-1|k-1}} + \Gamma \cdot u_{k-1} \tag{11.a}$$

$$\tilde{P}_{k|k-1} = \Phi \cdot \tilde{P}_{k|k-1} \cdot \Phi^T + Q \tag{11.b}$$

$$G_k = \tilde{P}_{k|k-1} \cdot H^T \cdot (H \cdot \tilde{P}_{k|k-1} \cdot H^T + R)^{-1} \tag{11.c}$$

$$\hat{T}_{ag\_Jt_{k|k}} = \hat{T}_{ag\_Jt_{k|k-1}} + G_k \cdot (y_{ag\_Jt_k} - H \cdot \hat{T}_{ag\_Jt_{k|k-1}}) \tag{11.d}$$

$$\tilde{P}_{k|k} = \tilde{P}_{k|k-1} - G_k \cdot H \cdot \tilde{P}_{k|k-1} \quad (11.e)$$

The state estimation update along with measurement update has taken place taking the state estimation error covariance $\tilde{P}_{k|k}$ into account. The Kalman gain G_k is enforced to adjust the weight of the residual $(y_{ag\_Jt_k} - H \cdot \hat{T}_{ag\_Jt_{k|k-1}})$.

C. Fading Memory Kalman Filter Based State Estimation

The discrete time augmented system of (9) and (10) can be intuitively perceived for better performance with the modification of the memory feature in Kalman filter's innovation term as fading memory Kalman filter. In [14], the augmented system has been realised through minimizing the cost function ψ_N, which can be formulated as:

$$\psi_N = \sum_{k=1}^{N} \left[\left(y_{ag\_Jt_k} - H \cdot \hat{T}_{ag\_Jt_{k|k-1}} \right)^T \xi^{2k} R^{-1} \left(y_{ag\_Jt_k} - H \cdot \hat{T}_{ag\_Jt_{k|k-1}} \right) + \widehat{w}_k^T \xi^{2k+2} Q^{-1} \widehat{w}_k \right] \quad (12)$$

The forgetting factor ξ induces to reconstruct the state and measurement update formulation in conventional *KF* modifying the *a priori* state estimation error covariance (11.b) as:

$$\tilde{P}_{k|k-1} = \xi^{2k} \cdot \Phi \cdot \tilde{P}_{k|k-1} \cdot \Phi^T + Q \quad (13)$$

This *FMKF* implementation has been put into action to instigate the influential role of measurement data in contrast to the system dynamics. The choice of forgetting factor ξ has a key role to produce the estimated $\hat{T}_{ag\_Jt_{k|k}}$.

D. Particle Swarm Optimization fundamentals

Particle swarm optimization (PSO) is a popular population-based search technique to address non-convex optimization problems [15]. Swarm intelligence has been put into practice to identify the most suitable adapted solutions for the desired forgetting factor (ξ) along the initialization coefficients for state estimation error covariance $(\tilde{P}_0)$ and measurement noise covariance (R)in the proposed PSO based adaptive FMKF to make the adaptive indoor thermal model effectively operational. These three parameters are used to define the particle vector, expressed as a candidate solution for the optimization problem. The multidimensional objective space has been continuously explored and exploited with convenient update of the candidate solution to optimize the cost function with its corresponding global best position.

Let, a swarm of $\mathcal{Z}_p$ size has been considered to be resided in a $\mathcal{D}$-dimensional search space. Individual particle$i$ contains a position vector as $X_i = (x_{i1}, x_{i2} \dots, x_{i\mathcal{D}})$ and a velocity

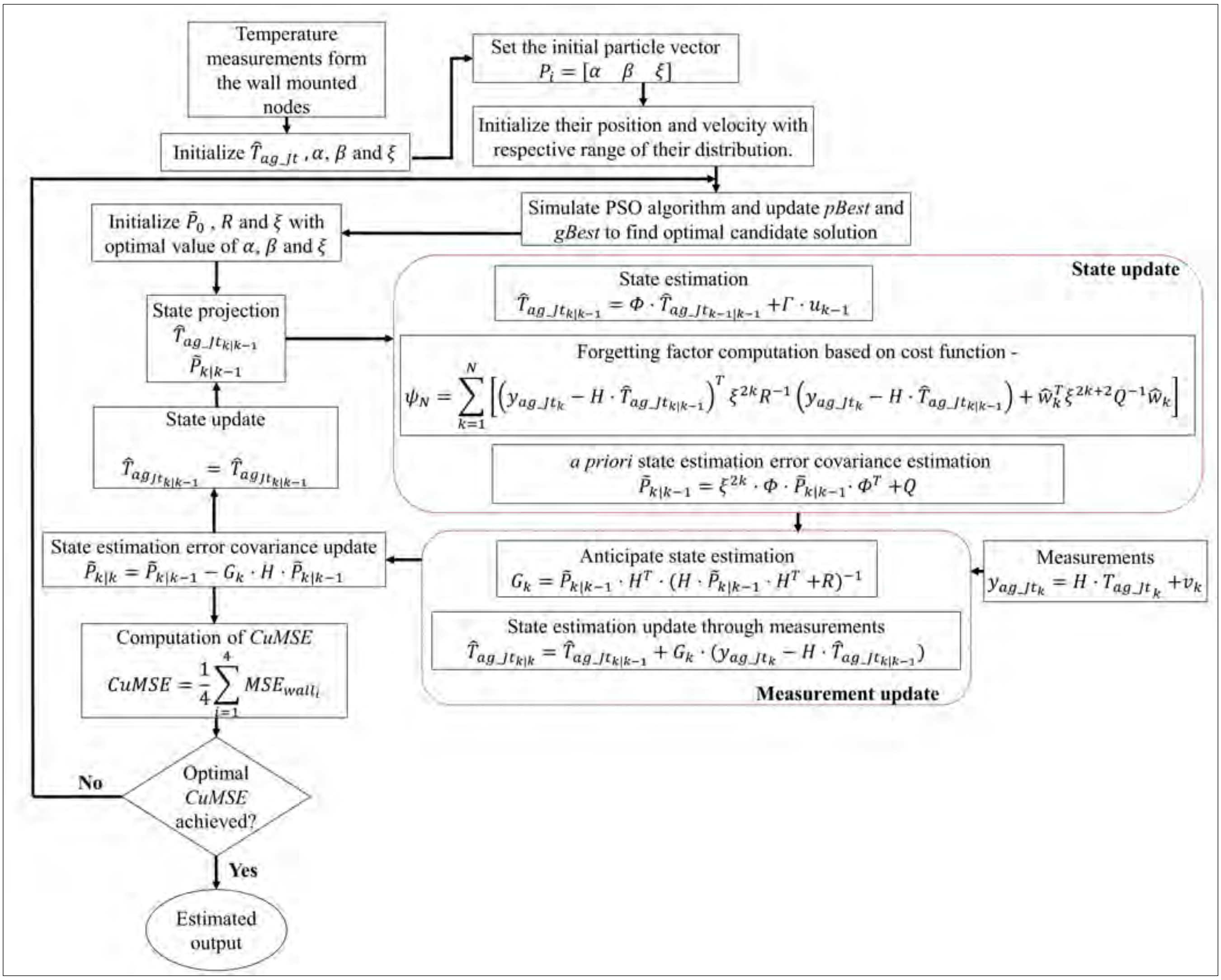

Fig. 2. Flowchart of proposed *PSO-AdFMKF* method

vector as $V_i = (v_{i1}, v_{i2} \ldots, v_{iD})$ for particle propagation through the search space. The search process of finding personal best position ($pBest$) and exploiting the neighborhood particle to explore the overall best position as ($gBest$) has been performed with the advancement of particle in each iteration. At time-step 'n', the particle updates its velocity and position to propagate to the next candidate solution as [15]:

$$V_i(n+1) = wV_i(n) + C_1 r_1[pBest(n) - X_i(n)] + C_2 r_2[gBest(n) - X_i(n)] \quad (14)$$

$$X_i(n+1) = X_i(n) + V_i(n+1) \quad (15)$$

where, w is an inertia weight, the random variables $r_1, r_2 \in [0, 1]$ with positive acceleration coefficients C_1 and C_2, that have balancing impact on the cognitive and social component respectively.

III. Materials and Method

The PSO based adaptive FMKF (*PSO-AdFMKF*) has been proposed here to estimate the indoor temperature profile along with the unknown inputs associated with the thermodynamic environment inside the building.

A. Optimization of Influencial paramter for PSO-AdFMKF

The performance of the *PSO-AdFMKF* based thermodynamic estimation inside the building is influenced by a variety of design parameters. The precise choice of initial estimate of state, the initial state estimation error covariance ($\tilde{P}_0$) , the measurement noise covariance (R) and the forgetting factor (ξ) are crucial to achieve the optimal performance of the filtering algorithm. Accommodating the inadequate prior knowledge of these parameters, a PSO based metaheuristic approach has been employed to find out the suitable values of $\tilde{P}_0$, R , ξ for achieving an optimal/ suboptimal estimation efficiency of the proposed indoor thermal model with unknown inputs.

In this study, $\tilde{P}_0$ is assigned as αI with a range for α from 0.1 to 0.001, while R is allocated as βI with a range of β from 10^{-8} to 100 [16]. The operating range of ξ is set to 1.0001 to 1.01. In this combination I indicates the identity matrix of its corresponding associated dimension.

To evaluate the effectiveness of the proposed temperature estimation technique quantitatively the *mean squared error* (*MSE*) of the individual walls and *cumulative average mean squared error* (*CuMSE*) are calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_m(i) - x_e(i))^2 \quad (15)$$

$$CuMSE = \frac{1}{4}\sum_{i=1}^{4} MSE_{wall_i} \quad (16)$$

where, n is the number of sample points, x_e is the estimated output and x_m is the measured output.

B. Proposed PSO-AdFMKF Based Temperature Estimation

Essentially, the entire scheme of temperature estimation utilizing the proposed *PSO-AdFMKF* has been depicted in Fig. 2. The temperature measurements for the known walls have been recorded. The initial guess of the joint state as well as the augmented unknown inputs along with the correlation coefficients α, β and forgetting factor ξ are obtained from PSO to invoke the adaptiveness through the proposed method of *PSO-AdFMKF* in the relationship between estimated joint state of the augmented system under consideration. Every set of particles has been executed to obtain the best set minimizing the cost of *CuMSE*.

The *gBest* set of optimized α , β and ξ has been implemented to the estimation after exploiting and exploring the entire objective space. The proposed method of joint sate augmented particle swarm optimization enabled adaptive fading memory Kalman Filter (*Jt_State_Param_PSO-AdFMKF*) has been evaluated and compared with the performance of augmented joint state parameter based classical *KF* (*Jt_State_Param_KF*) and the *FMKF* (*Jt_State_Param_FMKF*) estimation process.

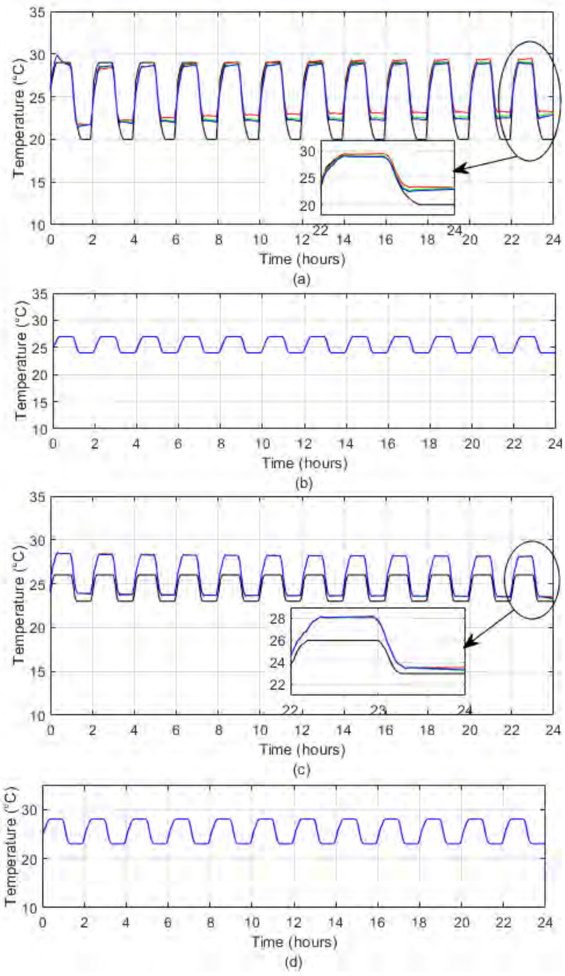

Fig. 3. Individual thermal zone estimation for Case Study-I: Scenario I. (a): Wall #1(T_{w1}), (b): Wall #2(T_{w2}), (c): Wall #3 (T_{w3}), (d): Wall #4 (T_{w4}).

—: Real observation; —: *Jt_State_Param_KF* estimation
—: *Jt_State_Param_FMKF* estimation; —: *Jt_State_Param_PSO-AdFMKF* estimation

C. Experimental Test Environment Scenarios

An interior experimental room of the building has been equipped with DHT-11 humidity and temperature sensors that are interfaced to a Raspberry Pi zero/W, a stand-alone microcontroller board with an ARM processing unit, to develop the remote sensing node.

Two independent scenarios with a test thermodynamic environmental case studies were used in the inside building space experimental evaluation. The measurements in Case Study-I were conducted over the span of 24 hours with the set point kept at 30 °C for one hour and 18 °C for the next hour alternately.

Wall #1 (T_{w1}) and wall #3 (T_{w3}) temperatures have been taken into account as the unknown states along with the unknown thermal model parameters to be estimated using the information of wall #2 (T_{w2}) and wall #4 (T_{w4}) temperatures for the test scenario-I. While taking T_{w2} and T_{w4} into account as unknown wall temperatures and T_{w1} and T_{w3} as known measured wall temperatures in scenario-II.

IV. Case Study Results and Discussion

The proposed methodology has been examined in contrast with existing estimation scheme for two self-reliant distinctive indoor thermodynamic conditions as mentioned in this paper. In this section the detailed study with analytical results has been represented.

A. *Investigation of Indoor Thermodynamic Scenarios*

The test thermodynamic scenarios have been investigated simultaneously with the *Jt_State_Param_PSO-AdFMKF*, *Jt_State_Param_FMKF* and *Jt_State_Param_KF* algorithm [11]. Initially, the temperatures of the unknown heating energy inputs associated walls i.e., wall #1 (T_{w1}) and wall #3 (T_{w3}) have been anticipated as the unknown states along with the unknown thermal resistance and capacitance parameters to be estimated, employing the known measurements of wall #2 (T_{w2}) and wall #4 (T_{w4}) temperatures. On the other hand, the modifications in response have been examined utilizing known measured temperatures of wall #1(T_{w1}) and wall #3 (T_{w3}) while keeping the other two walls T_{w2} and T_{w4} unknown states to be estimated.

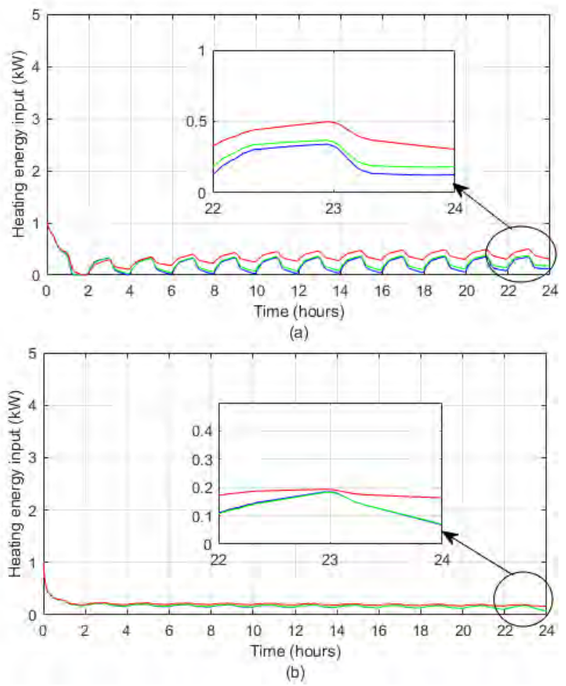

Fig. 4. Associated unknown heating inputs estimation results of Case Study-I: Scenario I. (a):Q_{hvac}, (b):Q_{rad}

— : *Jt_State_Param_KF* estimation; — : *Jt_State_Param_FMKF* estimation; — : *Jt_State_Param_PSO-AdFMKF* estimation;

The potential efficiency of thermodynamic state estimation for scenario-I as well as scenario-II of this case study have been observed for T_{w1}, T_{w2}, T_{w3}, and T_{w4} along with the unknown inputs Q_{hvac} and Q_{rad} over a duration of 24 hours. The estimation results for scenario-I have been graphically presented, for each individual thermal zone, in Fig. 3 and the estimation of unknown heating inputs have been illustrated in Fig. 4.

Drawing a comparative analogy with the earlier case study, all the aforementioned algorithms are introduced to another test thermodynamic experimental setup as second scenario. Using two distinct variations of the preceding case study's settings, the unknown inputs and the performance of the thermal state estimation have been evaluated.

TABLE I
Estimation Performance Assessment – Case Study-I: Scenario-I

Method	Error Metrices	Wall 1	Wall 2	Wall 3	Wall 4	CuMSE
Jt_State _Param_ KF	MSE	3.0245	0.0123	2.5184	0.0243	1.3949
	RRMSE	5.3916	0.4317	6.6482	0.5965	
Jt_State _Param_ FMKF	MSE	2.2036	0.0123	2.4474	0.0243	1.1719
	RRMSE	4.6753	0.4317	6.5595	0.5965	
Jt_State _Param_ PSO-AdFMKF	MSE	**1.9449**	0.0123	2.4483	0.0243	**1.115**
	RRMSE	**4.4486**	0.4317	6.5678	0.5965	

B. *Comparative Study of Test Experimental Condition*

Individual test thermal environmental scenarios have been recorded and compared in terms of error metrices viz. mean squared error (*MSE*) and relative root mean squared error (*RRMSE*) in the tabulation to verify the supremacy of the proposed algorithm *Jt_State_Param_PSO-AdFMKF*. Here the comparative results are tabulated for both the test experimental thermodynamic environment along with the graphical results for the first test scenario.

The adaptive value for α and β are optimized as 1.0028 and 10^{-7} respectively while the forgetting factor ξ is evaluated as 1.0008 to achieve the optimal results of Table-I for test scenario-I. In the estimation for the second test scenario, the adaptive parameters are considered as α=0.8025, β=10^{-7} and ξ= 1.0007 for the competing performance as depicted in Table-II. A comprehensible amount of 49.47% of reduction in *CuMSE* can be observed in context of Table-I and II with the variation in knowledge of wall temperature measurement with existing unknown inputs. The perspective efficiency of the proposed method has been raised by 4.9% in compare to the *Jt_State_Param_FMKF* and 20% with respect to

TABLE II
Estimation Performance Assessment – Case Study-I: Scenario-II

Method	Error Metrices	Wall 1	Wall 2	Wall 3	Wall 4	CuMSE
Jt_State _Param_ KF	MSE	0.0938	1.1462	0.0123	1.1384	0.5976
	RRMSE	1.1752	3.9516	0.4453	4.2922	
Jt_State _Param_ FMKF	MSE	0.0937	1.1407	0.0123	1.0096	0.5641
	RRMSE	1.1750	3.9420	0.4453	4.0360	
Jt_State _Param_ PSO-AdFMKF	MSE	0.0937	**1.1406**	0.0123	**1.0076**	**0.5635**
	RRMSE	1.1750	**3.9418**	0.4453	**4.0318**	

Jt_State_Param_KF algorithm according to Table-I. With the alternative measurement condition, a similar superior performance of the recommended estimation procedure has been realized in Table-II.

Essentially, one may draw the observation that *Jt_State_Param_PSO-AdFMKF* regularly outperforms FMKF and KF based on all experimental results. Further evidence that *Jt_State_Param_PSO-AdFMKF* may regularly exceed *FMKF* and *KF* in terms of *MSE* and *CuMSE* values is provided by the numerical data shown in Tables I and Table II. A key contribution of this study is the demonstration of the effective adaptation of *FMKF* algorithm for such a challenging task with the presence of unknown inputs.

V. Conclusion

This is evident from the proposition of this paper that the superior performance for joint state estimation of indoor thermodynamic model with unknown inputs using metaheuristic approach based adaptive *FMKF* algorithm has been established with clarity. This stochastic state estimation technique has been successfully used in indoor spaces with realistic conditions to forecast the temperature distributions in multiple walls. In the more challenging circumstance of having several unknown input signals, such as heating energy inputs, this joint-state estimate has been carried out. In comparison to the *KF* and *FMKF* oriented estimation techniques, the findings show that the proposed strategy performs well ahead of approximately 4.9% and 20% across a variety of input circumstances and with considerable fluctuations in wall temperature. The proposed *Jt_State_Param_PSO-AdFMKF* algorithm can be improved further considering the modification in adaptation rule with more complex nonlinear thermal model taking into account of higher degree of uncertainty inside the building thermal environment. A future study will examine more difficult nonlinear scenarios with several internal uncertainties that may still be able to increase temperature estimation accuracy.

Acknowledgment

Bed Prakash Das would like to convey the gratitude towards the Department of Science and Technology, Govt. of West Bengal along with Council of Scientific and Industrial Research, Govt. of India for encouraging the research work.

References

[1] A. Ghahramani, S. A. Karvigh, and B. Becerik-Gerber, “HVAC system energy optimization using an adaptive hybrid metaheuristic,” *Energy and Buildings*, vol. 152, pp. 149–161, 2017.

[2] L. Yu, D. Xie, C. Huang, T. Jiang, and Y. Zou, “Energy optimization of HVAC systems in commercial buildings considering indoor air quality management,” *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5103–5113, 2019.

[3] A. Leventis, T. Antonakopoulos, C. Stavroulopoulos, T. Luckenbach, and V. Makios, “Intelligent devices for appliances control in Home Networks,” *IEEE Transactions on Consumer Electronics*, vol. 49, no. 2, pp. 328–336, 2003.

[4] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, “Sensor-based activity recognition,” *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 6, pp. 790–808, 2012.

[5] B. P. Das, K. D. Sharma and J. Bera, "Environment Dependent Neural Network Model For Occupancy Detection," *2019 IEEE Region 10 Symposium (TENSYMP)*, pp. 593-598, 2019, doi: 10.1109/TENSYMP46218.2019.8971248.

[6] C. Luppe and A. Shabani, "Towards reliable intelligent occupancy detection for smart building applications," *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp. 1-4, 2017, doi: 10.1109/CCECE.2017.7946831.

[7] Y. Zhang, G. Tian, S. Zhang, and C. Li, “A knowledge-based approach for Multiagent Collaboration in smart home: From activity recognition to guidance service,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 2, pp. 317–329, 2020.

[8] G. Mois, S. Folea, and T. Sanislav, “Analysis of three IOT-based wireless sensors for Environmental Monitoring,” *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 8, pp. 2056–2064, 2017.

[9] Y. Kono, Y. Susuki, M. Hayashida, I. Mezić, and T. Hikihara, “Multiscale modeling of in-room temperature distribution with human occupancy data: A practical case study,” *Journal of Building Performance Simulation*, vol. 11, no. 2, pp. 145–163, 2017.

[10] B. P. Das, K. Das Sharma, A. Chatterjee, and J. Bera, “Joint State estimation of indoor thermal dynamics with unknown inputs using augmented fading memory Kalman filter,” *Journal of Building Performance Simulation*, pp. 1–17, 2022. doi: 10.1080/19401493.2022.2111604

[11] Y. Li, J. Castiglione, R. Astroza, and Y. Chen, “Real-time thermal dynamic analysis of a house using RC models and joint state-parameter estimation,” *Building and Environment*, vol. 188, pp. 1–32, 2021.

[12] L. Liu, Y. Su, J. Zhu, and Y. Lei, “Data fusion based EKF-UI for real-time simultaneous identification of structural systems and unknown external inputs,” *Measurement*, vol. 88, pp. 456–467, 2016.

[13] A. A. Manin, S. V. Sokolov, A. I. Novikov, M. V. Polyakova, D. N. Demidov, and T. P. Novikova, “Kalman filter adaptation to disturbances of the observer’s parameters,” *Inventions*, vol. 6, no. 4, p. 80, 2021.

[14] M. S. Rahimi Mousavi and B. Boulet, “Estimation of the state variables and unknown input of a two-speed electric vehicle driveline using fading-memory Kalman filter,” *IEEE Transactions on Transportation Electrification*, vol. 2, no. 2, pp. 210–220, 2016.

[15] K. Das Sharma, A. Chatterjee and A. Rakshit “A Random Spatial lbest PSO Based Hybrid Strategy for Designing Adaptive Fuzzy Controllers for a Class of Nonlinear Systems” *IEEE Transactions on Instrumentation & Measurement*, vol-61, no.-6, pp-1605-1612, June, 2012.

[16] Y. Wang, S. Sun, Y. Tian, J. Sun, and L. Xu, “Image reconstruction based on fuzzy adaptive Kalman filter in electrical capacitance tomography,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.