Poster Abstract: Applying Extended Kalman Filters to Adaptive Thermal Modelling in Homes

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Abstract

A key challenge for intelligent domestic heating systems is to obtain sufficient knowledge of the thermal dynamics of the home to build an adaptive thermal model. We present a study where stochastic grey-box modelling is used to develop thermal models and an extended Kalman filter is used for parameter estimation for a room in a family home.

1 Introduction

A key challenge for *intelligent* domestic heating systems (IDHS) is to obtain sufficient knowledge of the thermal dynamics of the home to build an adaptive thermal model that can reliably predict the spatial and temporal effects of its actions. This challenge has been studied extensively for large buildings where thermal models are maintained via the *off-line* or *on-line* learning. In the former, the thermal model is learned either once or at infrequent intervals and assumed to be fixed over an arbitrary horizon. For example, Gao et al. applies linear regression to historical data to learn a fixed thermal model of a room in an office [1]. Likewise, Rogers et al. conducted a field-study of 750 UK homes and used non-linear regression to infer the thermal model of each home [3]. However, the assumption of a fixed model is inadequate in highly dynamic environments, and instead the on-line (or *adaptive*) learning where models are updated continuously has been shown to be more effective. In particular, variants of the extended Kalman filter (EKF) have been used for adaptive thermal modelling in buildings [2]. Although, such techniques are equally applicable to modern homes, one must consider the challenges peculiar to homes (e.g., more diverse heating systems, less reliable occupancy patterns, lack of structural data) for their effective use.

Against this background, we propose an adaptive modelling approach based on stochastic grey-box modelling and the EKF to infer thermal properties of homes. We apply it to a room in a family home and show that our thermal model predicts the room temperature where the 95th percentile of the absolute prediction error is 0.95°C and 1.37°C for 2 and 4 hours predictions, respectively; in contrast to the corresponding 2.09°C and 3.11°C errors of the existing historical-average based thermal model (called *PreHeat*, see [4]).

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2 Case Study

We consider the living room of a family house in Cambridge, UK, that is equipped with the per-room based underfloor heating which is controlled via a *room unit*. The room unit has temperature and occupancy detection sensors, and a radio module to communicate with a PC (see [4]). The use of underfloor heating involves multiple heat transfers processes whereby heat is transferred from the source to an intermediate thermal mass (floor) that slowly leaks to its surroundings - introducing thermal lags and additional leakages, thus making this room interesting from a control perspective.

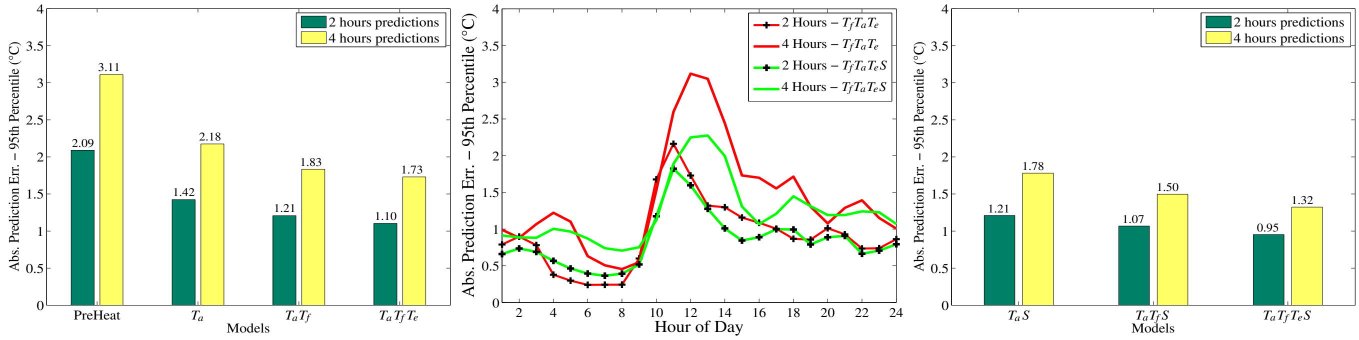
3 Thermal Modelling

We adapt the grey-box modelling approach which uses the prior physical knowledge of the system and observed data to derive a thermal model. In our case, the prior knowledge of the room includes the (i) use of underfloor heating (ii) binary status of heating (iii) indoor air temperature and (iv) presence of considerable process noise. We note that there is no knowledge of the (i) heater output (ii) floor and house *envelope* temperature (iii) thermal capacities and resistance of the walls and (iv) the room layout (e.g., dimension of the walls). These *system states* are considered *hidden* and therefore must be inferred indirectly. We now outline a number of increasingly complex thermal models.

Single-Box Model (*Ta*) is the simplest model where the transfer of heat is assumed to be direct between the heater and the indoor air which then leaks to the outside. Here, no thermal delay for the heat transfer exists, enabling us to measure the effect of thermal delays in other models.

$$\hat{T}_a = T_a + r_h \lambda_h + \phi_{ao}(T_o - T_a) \quad (1)$$

Underfloor Heating Model ($T_a T_f$) models the transfer of heat from the heater to the indoor air via an intermediary



(a) Comparative analysis of models (b) Effect of solar radiance on pred. error (c) Thermal models with solar irradiance

thermal mass (floor), thus introducing a thermal lag. The indoor air then leaks heat to the outside.

$$\hat{T}_f = T_f + r_h\lambda_h + \phi_{fa}(T_a - T_f) \quad (2)$$

$$\hat{T}_a = T_a + \phi_{fa}(T_f - T_a) + \phi_{ao}(T_o - T_a) \quad (3)$$

Underfloor and Envelope Model ($T_aT_fT_e$) extends T_fT_a such that the heat escapes to outside via the house envelope.

$$\hat{T}_f = T_f + r_h\lambda_h + \phi_{fa}(T_a - T_f) \quad (4)$$

$$\hat{T}_a = T_a + \phi_{fa}(T_f - T_a) + \phi_{ae}(T_e - T_a) \quad (5)$$

$$\hat{T}_e = T_e + \phi_{ae}(T_a - T_e) + \phi_{eo}(T_o - T_e) \quad (6)$$

Complete Model ($T_aT_fT_eS$) extends $T_fT_aT_e$to include the effect solar irradiation on $\hat{T}_a$ and $\hat{T}_e$.

$$\hat{T}_f = T_f + r_h\lambda_h + \phi_{fa}(T_a - T_f) \quad (7)$$

$$\hat{T}_a = T_a + r_a\lambda_s + \phi_{fa}(T_f - T_a) + \phi_{ae}(T_e - T_a) \quad (8)$$

$$\hat{T}_e = T_e + r_e\lambda_s + \phi_{ae}(T_a - T_e) + \phi_{eo}(T_o - T_e) \quad (9)$$

4 Empirical Evaluation

We use data from November, 2011 to March, 2012 (150 days) which is sufficient to evaluate our models for infrequent events (e.g., turning off the heating for holidays) and the effect of seasonal changes. We use publicly available data for the external temperature and solar irradiance[1]. While the time and accuracy requirements of prediction vary based on the system and its objectives, we find that in our case, predicting 2 and 4 hours ahead with the accuracy of ±1°C and ±1.5°C, is sufficient for the effective heating control. Thus, we analyse the absolute errors for 2 and 4 hours predictions within 95th percentile (roughly corresponding to the confidence interval of ±2 SD) of all models, as in Figure 1(a). We note that as modelling increasingly captures the physical properties of the building, the prediction accuracy increases further. To drive our model selection further, we analyse the nature of the prediction error with $T_fT_eT_f$. Figure 1(b) shows the absolute prediction errors (95th percentile) of $T_fT_eT_f$ against the hour of day. The error is relatively large during the daytime hours, hinting on the importance of solar irradiance. This is indeed the case (Figure 1(b)) where the prediction accuracy improves when the solar irradiance is factored in $T_fT_eT_fS$, however, it is not completely eliminated in $T_fT_eT_fS$ as our solar irradiance data

[1] https://www.cl.cam.ac.uk/research/dtg/weather/ http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php

	Time		
	k	k+1	Units
Floor temperature	T_f	$\hat{T}_f$	°C
Room air temperature	T_a	$\hat{T}_a$	°C
Envelope temperature	T_e	$\hat{T}_e$	°C
External temperature	T_o	-	°C
Heater output	λ_h	$\hat{\lambda}_h$	°C/hr
Global Solar Irradiance	λ_s	-	J/m^2/hr
Solar Irradiance (Air)	λ_a	-	J/m^2/hr
Solar Irradiance (Envelope)	λ_e	-	J/m^2/hr
Heating time ratio	r_h	-	$\in[0,1]$
Irradiance ratio (Air)	r_a	$\hat{r}_a$	°C.m^2/J
Irradiance ratio (Envelope)	r_e	$\hat{r}_e$	°C.m^2/J
Leakage rate (Floor, Air)	ϕ_{fa}	$\hat{\phi}_{fa}$	1/hr
Leakage rate (Air, Outside)	ϕ_{ao}	$\hat{\phi}_{ao}$	1/hr
Leakage rate (Air, Envelope)	ϕ_{ae}	$\hat{\phi}_{ae}$	1/hr
Leakage rate (Envelope, Outside)	ϕ_{eo}	$\hat{\phi}_{eo}$	1/hr

Table 1. Notation used for thermal modelling.

consists of monthly averages and thus, can only be used as an approximation to the actual irradiance. Figure 1(b) confirms that solar irradiance can make predictions more accurate but it does not indicate which of our models will benefit the most by it. Therefore, we include solar irradiance in all models and calculate the 95th percentiles of prediction error for every model, as in Figure 1(c). It is evident that the prediction errors of $T_fT_eT_fS$ meet our requirements and hence, no further model extension is required.

5 Conclusions and Future Work

Adaptive thermal modelling techniques such as EKFs that previously has been used in large buildings can also be used in homes with necessary modification to tackle the challenges unique to homes. We demonstrated this technique for a room and showed that the EKF-based models can be useful for the efficient control of heating. Our future work is to extend our model to selected homes.

6 References

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