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ESTIMATION OF EFFECTIVE THERMAL PARAMETERS OF HEATING SOURCES BASED ON DYNAMIC MEASUREMENTS IN SMART HOME

This work is devoted to the method of determining the effective thermal parameters of heating sources in a smart home, which involves a combination of algorithms for data analysis and the equation of the physical process of heat transfer. The use of such parameters allows one to create software and hardware solutions for modeling the thermal map of the house, as well as to analyze energy consumption using the machine learning models. Since, for the most part, the total consumption of heating energy is known, it is of interest to determine the part of the energy that corresponds to the individual heating sources. To this end, the article proposes a mathematical model and algorithm for estimating the effective thermal characteristics of heating sources based on the heat transfer equation and data analysis approaches that can be used to obtain information about individual heating sources. The task of determining such parameters is reduced to two stages. At the first stage, using the finite-difference approach to the heat transfer equation, the effective thermal parameter of the heating sources is determined. Further, according to the data of energy consumption and distributions of room temperatures and temperatures on the surface of heating elements, by applying data analysis methods, an algorithm for estimating individual effective thermal characteristics of heating elements installed in rooms is proposed.

Key words: smart home, energy optimization, heat transfer.

Introduction

A smart home as a significant part of smart grid systems is recognized as being widely developed by many companies and government energy institutions. The fact that it has received much attention over the last few years is substantiated by the statistics which claims that revenue in the smart home market amounts to the US $73.719 million in 2019 and it is expected to show an annual growth rate (CAGR 2019-2023) of 17.6 %, resulting in a market volume of US $141.220 millions by 2023 [1]. Within the smart home technology, and optimization of building heating strategy is the leading target in the emission reduction and the minimization of load on energy sources.

Generally, the use of heating energy is related to the building's thermal properties, the heating system parameters, and the behavior of residents (which may be described by the observed behavioral patterns). To investigate the first factor, several studies, for instance, [2] and [3] have been performed on the impact of thermal properties on the heating process. Results obtained in these works tie together thermophysical characteristics, in particular, heat transfer coefficient, heat conductivity/loss, etc., nevertheless it can be improved by taking into account more precise models.

Extracted occupant behavioral patterns have been studied in an increasing number of studies, for example, [4], [5], and [6]. Conducted experiments highlighted the possibility of using learnable models of occupant behavioral patterns to minimize heating energy consumption.

The investigation of heating system parameters via indirect modern approaches like machine learning based on collected data lays beyond the scope of many smart home technologies because the majority of heat sources are old-style gas/electric boiler-radiator systems (especially in Europe and Asia) and it is difficult to get their settings measured over time. Also, new intelligent heating systems are being intensively developed.

This work aims to broaden the knowledge of heating sources installed in a typical smart home using the indirect approach, however, based on the heat transfer model. We propose an approach to utilize the historical indoor temperature, the surface radiator temperatures, and the aggregated energy values as the input parameters for the designed model, which describes the behavior of each heating source.

Problem statement

To start with, let's consider a single-family smart home fully integrated with indoor/outdoor temperature sensors, a smart thermostat, and temperature sensors installed on the radiator surfaces. The latter may contain TRVs (thermostatic radiator valves). In this paper, the investigation of the effective thermal parameters of heating sources is based on the data taken from those spaces, where radiators are equipped with surface temperature sensors.

The heat transfer in the chosen space (Fig. 1) can be outlined in terms of the following differential equation [7]:

$$c(\mathbf{r})\rho(\mathbf{r})\frac{\partial T(\mathbf{r},t)}{\partial t} = div\left(\kappa(\mathbf{r})\nabla T(\mathbf{r},t)\right) + g(\mathbf{r},t), \tag{1}$$

where $c(\mathbf{r})$ denotes the heat capacity coefficient, $\kappa(\mathbf{r})$ is the heat conductivity coefficient, $\rho(\mathbf{r})$ denotes the substance density, $g(\mathbf{r},t)$ is the healing power, $T(\mathbf{r},t)$ stands for the space temperature, t is the time variable, $\mathbf{r}$ is the vector of spatial coordinates.

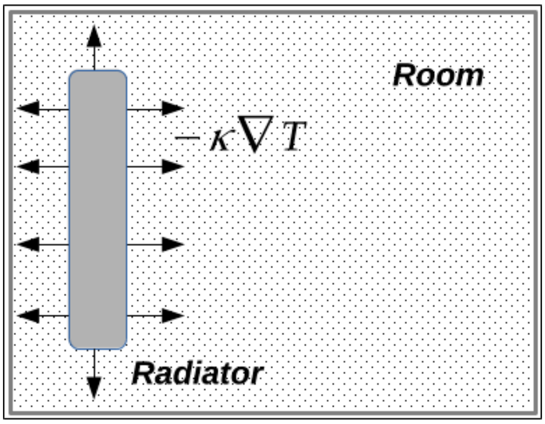

Fig. 1. Schema of heat fluxes in a room

Here, caution must be taken in the understanding of parameter $g(\mathbf{r},t)$, i.e., $g(\mathbf{r},t)$ is a part of aggregated heating power consumption in the entire building, which stands for the part related to the particular heating source, $g(\mathbf{r},t) \in Q(\mathbf{r},t)$, where $Q(\mathbf{r},t)$ is the total heating power.

Integrating equation (1) over the radiator volume V_r results in

$$c_r^* V_r \frac{\partial \bar{T}_r(t)}{\partial t} = \kappa S\left(\nabla T \cdot \mathbf{n}\right) + G(t), \tag{2}$$

where $G(t) = g(t)V_r$, $c_r^* = c\rho$ is the effective radiator heat capacity, r is the notation corresponding to the radiator entity, c is the radiator heat capacity, which is determined by the used material, ρ is the density of radiator material, $\bar{T}_r(t)$ is the averaged surface radiator temperature, $\kappa S\left(\nabla T \cdot \mathbf{n}\right) \approx \kappa S\left(\bar{T} - \bar{T}_r\right)$, $\mathbf{n}$ is the normal vector, $\bar{T}$ is the average temperature in the room, S is the surface radiator area.

It is straightforward to verify that for each space

$$\left(\bar{T}_r(t) - \bar{T}(t)\right)\kappa S = G(t) - c_r \frac{\partial \bar{T}_r(t)}{\partial t}, \tag{3}$$

where $c_r = c_r^* V_r$. Equation (3) describes the temperature dynamics in a space caused by the installed heating source.

By generalizing equation (3) to the whole set of spaces and by taking into account the fact that only the aggregated heating power is available, i.e., $G(t)$ is unknown for each room, we can customize our problem via the following representation:

$$\sum_j \left(\bar{T}_r^{(j)} - \bar{T}^{(j)}\right)\omega_j = \sum_j \left(G^{(j)} - \frac{c_r}{\Delta t}\left(\bar{T}_r^{(j+1)} - \bar{T}_r^{(j)}\right)\right), \tag{4}$$

where $\omega_j \sim \kappa S$ (ω_j is equivalent to κS) is the effective thermal parameter of heating source $\frac{\mathrm{W}}{\mathrm{K}}$, calculated at each time step j, $\bar{T}^{(j)}$ and $G^{(j)}$ are the average room temperature and the aggregated heating power correspondingly, Δt is the duration of a time interval $[j, j+1]$. Estimation of the parameter ω_i for each space (room) i can be expressed as $\omega_i = \frac{1}{N}\sum_j \omega^{(j)} \cdot S_i / S_{total}$, S_i in the area of radiator surface, S_{total} is the total area of all radiator surfaces presented in a building, N is the total number of time intervals, $j = 1, \ldots, N$.

In case, if a term $\frac{c_r}{\Delta t}\left(\bar{T}_r^{(j+1)} - \bar{T}_r^{(j)}\right)$ of the right side in (4) is insignificant, equation (4) can be written in the simplified form

$$\sum_j \left(\bar{T}_r^{(j)} - \bar{T}^{(j)}\right)\omega_j = \sum_j G^{(j)}. \tag{5}$$

Using the model (4), the problem of identification of the effective thermal parameter of heating source is formulated as follows: given the indoor temperature data measured in each space with radiator, the total heating energy consumed in the building, the surface radiator temperatures, and the radiator surface areas, one has to calculate parameter ω_i over the time interval of the provided data measurements.

Data processing and calculations

For the numerical experiments to verify and investigate the proposed approach, we have chosen a well-documented open-access REFIT Smart Home database [4]. It consists of temperature, energy, and building parameters collected from twenty dwellings in the UK from a period of three years and it is considered as the state-of-art database for smart home prototyping and research. In the current study, the natural gas used to heat a sample dwelling, hence the gas readings collected m^3 are extracted from REFIT. To simplify the current study, the SQLite engine has been used to store REFIT data along with Python 3 and Jupyter Notebook as the main programming environment.

A. *Data preparation*

To understand the samples – space and radiator temperatures as well as energy data (represented as natural gas), firstly we visualize these readings obtained from the arbitrarily chosen winter day when heating was on.

As it is seen from Fig. 2, the space temperatures do not significantly deviate in comparison with the corresponding radiator temperatures. This fact explains low heat relaxation in the building. Aggregated gas usage shows a clear correlation with the surface radiator temperatures which allows us to use these data in equation (4). Also, a delay between the rise of the surface radiator and the space temperatures can be considered as the determiner of the heat conductivity coefficient k .

During the analysis of the provided dataset, we figured out that the aggregated gas $G(t)$ is usually contributed by many consumers like heating elements, cookers, washer, etc. Therefore, before the substitution of $G(t)$ into the equation (4), it should be cleared of the non-heating contributors.

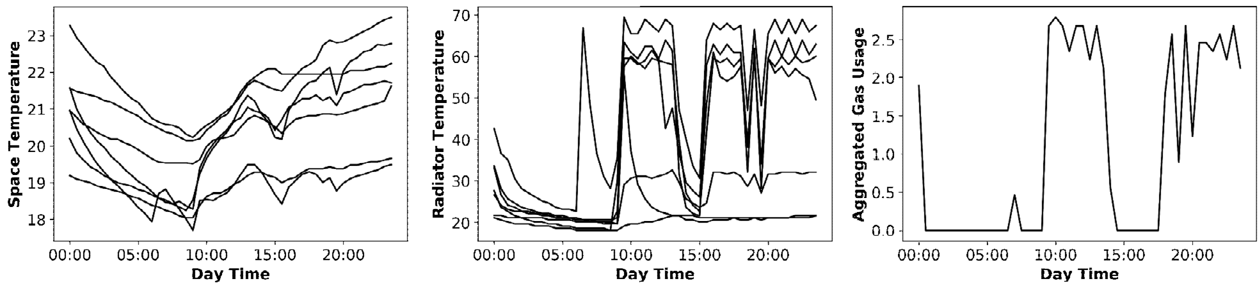

Fig. 2. Space (room), radiator temperatures, and aggregated gas consumption

To do that, we have developed the simple algorithm: a) summer gas usage $G(t)$, $t \in [summer]$, when heating process is off, is analyzed day-by-day to identify some typical time-based pattern; b) if the pattern in a) is detected, then mean values corresponding to that pattern $\tilde{G}_{typical}(t)$ have to be subtracted from the full-time series: $G(t) := G(t) - \tilde{G}_{typical}(t)$. Time-based pattern identification can be done via cluster analysis [8]. For example, the typical daily clusters can be determined using simple k-means clustering. Since they are identified, the average value of the gas usage from each of the clusters should be subtracted time-dependently from the original time series $G(t)$. The results of the mentioned in [8] algorithm are shown in Fig. 3.

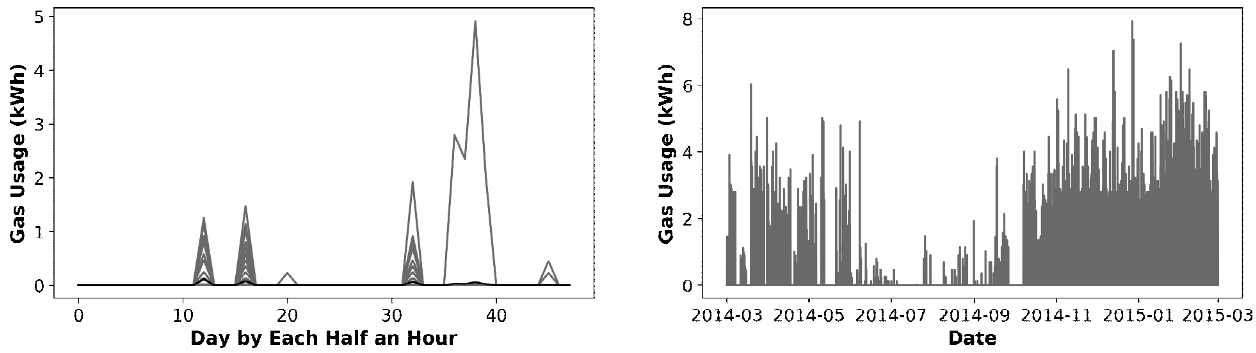

Fig. 3. Summer day-by-day gas usage (left) and annual heating gas usage after data cleansing (right)

A process of dealing with missing values, outliers, and general data cleansing is beyond this study, nevertheless, these steps have been applied and discussed in [9].

To end up with this sub-section, the last step of data preparation should be made: due to different length of available time series and dissimilar date-time intervals one must take into consideration the only respective joint sub-series, i.e., the resulted joint array $GRT(t)$ has been presented as follows:

$$GRT(t) = \left[G(t), \bar{T}(t), \bar{T}_r(t) \right], \tag{6}$$

where each of the time series $G(t)$, $\bar{T}(t)$ and $\bar{T}_r(t)$ is time-synchronized to each other.

B. Calculation of the effective thermal parameters

In this sub-section, the main steps for the calculation of the effective thermal parameters ω_j are discussed. After the preparation of joint arrays consisting of gas and temperature time series, one has to select the proper time intervals for the next calculations. In our numerical experiments, only data from the one arbitrary chosen building are used.

Firstly, we are interested in time intervals during the cold and transitive seasons (autumn and spring). Summer periods are not important in this study, because the heating process is off and we can only investigate the influence of the second term on the right side of the equation (4). Secondly, we consider only those intervals, where the strong similarity between gas usage and surface radiator temperature vectors are detected as for their direction. This allows us to omit the anomalies in data and ensure that only the valid intervals have been selected.

To deal with the second step, we propose the next scheme: similarity calculation followed by data normalization, which is required, because each time series has different value ranges.

Data normalization can be done via the well-known min-max feature scaling technique [10]:

$$y_k = b_1 + \frac{\left(y_k - \min(\mathbf{Y})\right)\left(b_2 - b_1\right)}{\max(\mathbf{Y}) - \min(\mathbf{Y})}, \tag{7}$$

where $y_k \in \mathbf{Y}$ is the feature value, b_1 and b_2 are the bound ranges?

With the completion of this step, we are now ready to apply the similarity validation step. As soon as the condition $x \cdot y > 0$, $x = G^{(j+1)} - G^{(j)}$, $y = T_r^{(j+1)} - T_r^{(j)}$, is satisfied, the cosine similarity measure [11] is used to validate the given intervals:

$$val\_score = (\mathbf{x} \cdot \mathbf{y}) / \|\mathbf{x}\| \|\mathbf{y}\| \ge thresh, \tag{8}$$

where $\mathbf{x}$ $\mathbf{y}$ are the vectors of data on each interval, $thresh$ is the threshold value.

Here we are working only with a one-step interval defined by two consecutive points, but in the general case, this approach can be expanded to deal with the intervals of different lengths using mean data vectors.

Applying equations (7) and (8) to $G(t)$ and $T_r(t)$ time series from joint array $GRT(t)$ results in a new array consisting of the selected data ranges. The latter ones are used to calculate parameter ω_j over each of the obtained intervals:

$$\omega_j = \int_j^{j+1} \left(G(x) - (c_r/\Delta t)\left(\bar{T}_r(y) - \bar{T}_r(x)\right)\right)dx \Big/ \int_j^{j+1} \bar{T}_r(x) - \bar{T}(x)\,dx \approx \frac{\Delta G - c_r(1/\Delta t)\Delta\bar{T}_r}{\Delta T}, \tag{9}$$

where $y \in [j+1, j+2]$, $\Delta G = 0.5\left(G^{(j+1)} + G^{(j)}\right)$, $\Delta T = 0.5\left(\left(\bar{T}_r - \bar{T}\right)^{(j+1)} + \left(\bar{T}_r - \bar{T}\right)^{(j)}\right)$, $\Delta\bar{T}_r = \bar{T}_r^{(j+1)} - \bar{T}_r^{(j)}$.

In equation (4), the right side includes, for the exception of the main term ΔG, the term associated with the dynamics of the temperature $\Delta\bar{T}_r$. The comparison of results obtained for the cases of taking into account both terms and only the first one will be discussed in the next section.

Based on the above-mentioned equation (4) we have performed such steps: 1) for winter, spring and autumn seasons a set of values ω_j has been calculated; 2) based on those values the average value $\bar{\omega} = \frac{1}{n}\sum_j \omega_j$, where $j = 1, \ldots, n$ has been chosen for each of the season and; 3) the seasonally averaged value $\bar{\omega}_{full}$ has been utilized to find the specific values of ω_i for each room in the studied building via S_i / S_{total} the multiplier. A short scheme (fig. 4) illustrates this algorithm.

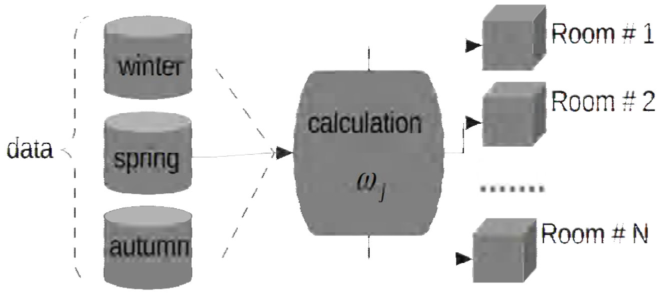

Fig. 4. Scheme of the proposed algorithm

Results and discussions

In this section, the calculation results of the effective thermal parameter w_j are discussed. According to the reported algorithm in the previous section, the calculations w_j have been carried out for the three seasons. From Fig. 5, 6, and 7 we can see the pairs of distribution w_j during winter, autumn, and spring, respectively.

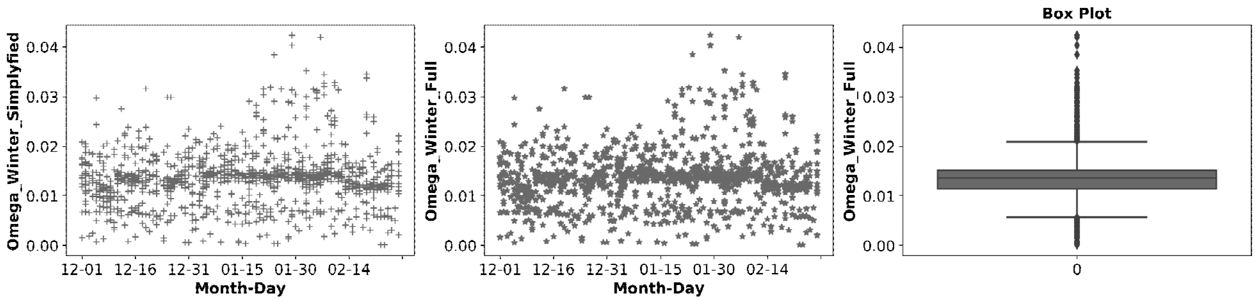

Fig. 5. Results for w_j during winter period

Each of the depicted pairs stands for calculation using the (4) and (5) equations. Here, we set the heat capacity coefficient $c_r \approx 10^{-3}\,\frac{\text{kWh}}{\text{K}}$. Required volumes V_r have been approximately calculated based on provided radiator sizes $V_r \approx 0.05\,\text{m}^3$. The third item in each figure is the box plot which indicates those w_j which may be abnormal.

Regarding the use of box plots, it is seen that for each investigated season there are quite significant dispersions of values w_j. Not surprisingly, there are some inaccuracies in approximate calculations as well as incorrect data readings from sensors collected in the dataset. Therefore, we have applied a simple outlier detection method based on the Inter Quartile Range (IQR) [12] to eliminate undesired values. This method uses first and third statistical quartiles to highlight those values which lie beyond the mentioned intervals.

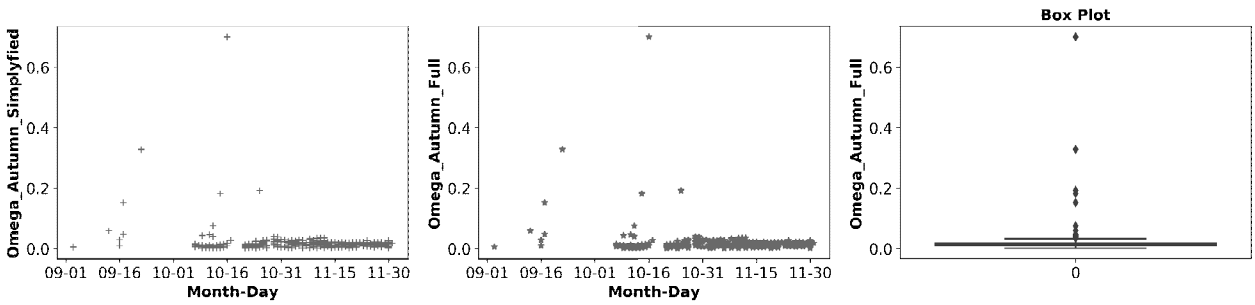

Fig. 6. Results for w_j during the autumn period

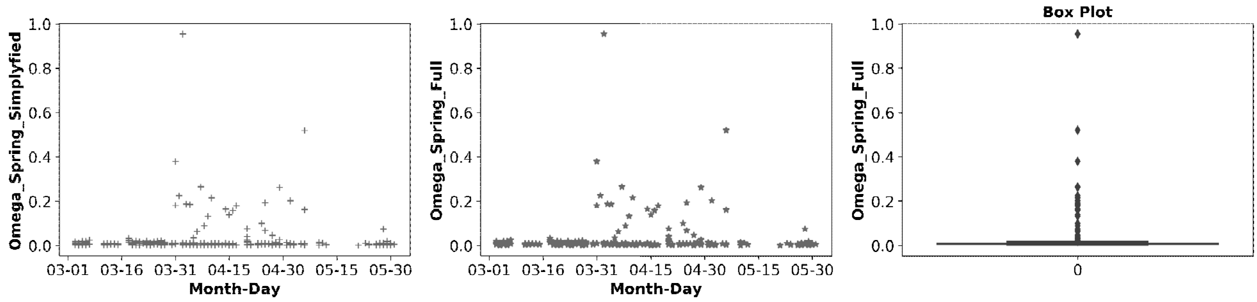

Fig. 7. Results for ω_j *during spring period*

In a view of the mentioned above, we have obtained the results for $\bar{\omega} = \frac{1}{N_s}\sum_{j=1}^{N_s}\omega_j$, calculated for each of seasons, where N_s is the number of time intervals during each of seasons (winter, autumn, and spring), s is the corresponding season. Table 1 details these results.

Table 1

Averaged $\bar{\omega}$ for winter, autumn, and spring

Season	Calculated using equation (4)	Calculated using equation (5)
Winter	≈ 13	≈ 12.9
Autumn	≈ 12	≈ 12
Spring	≈ 9	≈ 8

According to table 1, no noteworthy differences have been found while examining the values of parameter $\bar{\omega}$ calculated for each of three seasons. Also, these findings substantiate our proposal to neglect the second term of the right side in equation (4), because it does not cause any significant change of the final results. The dissimilarities ω_j during the investigated seasons are related to the incomplete rejection of outliers which appear in provided data.

To obtain ω_i for radiators following the available rooms we propose the following expressions:

$$\bar{\omega}_{full} = \frac{1}{3}\sum_{s=1}^{3}\bar{\omega}_s,\ \omega_i = \bar{\omega}_{full}\cdot S_i/S_{total}, \tag{9}$$

where $\bar{\omega}_s$ corresponds to $\bar{\omega}$ calculated for the season s (winter, spring, and autumn).

This equation gives allows us to determine a set for effective thermophysical parameters of radiators installed in different rooms. These results can be presented as follows:

Table 2

Calculated individual ω_i values

Room #	1	2	3	4	5	6	7	8	9
ω_i	0.1	0.06	0.19	0.12	0.12	0.1	0.12	0.12	0.08

The evidence from this study highlights the idea that the effective thermophysical parameters of heating sources can be estimated using the proposed model and data collected in a smart home via temperature and energy sensors. This study has gone some way towards enhancing our understanding of the heating behavior and heating source's efficiency either. One possible application based on these parameters is a smart home energy recommender system that enables residents to detect a malfunction or prepare an optimized heating/cooling scheduler. Another example is utilizing calculated parameters w_i for energy disaggregation problems, i.e., splitting aggregated energy data into meaningful classes correspond to time intervals and particular energy users. We hope that our research will help solve the discussed problems as an important step in the smart home energy management research.

Conclusions

This paper has underlined the approach of estimation of the effective thermophysical parameters of heating sources installed in smart homes which are equipped with temperature and energy meters. We have proposed a thermophysical model as well as an algorithm of using collected data for determination and investigation of required parameters. Within the model, the behavior of these parameters has been studied using available data collected during three seasons: winter, autumn, and spring, when the heating process is supposed to happen. The results of our modeling confirm the assumption that effective thermophysical parameters w_j are of the same range even regardless of the second term of the right side in equation (4) which stands for an impact of the thermal capacity of the heating source.

Also, a method of calculating the individual effective thermophysical parameter for each room with the installed radiator has been declared. To further our research we are planning to expand the idea of using explored parameters in developing a rule-based machine learning algorithm to get the different heating and energy-consuming scenarios for smart homes.

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ВИЗНАЧЕННЯ ЕФЕКТИВНИХ ТЕПЛОВИХ ПАРАМЕТРІВ ДЖЕРЕЛ ОБІГРІВУ РОЗУМНОГО БУДИНКУ НА ОСНОВІ ДИНАМІЧНИХ ВИМІРЮВАНЬ

Цю роботу присвячено методиці визначення ефективних теплових параметрів джерел опалення у розумному будинку, яка передбачає комбінацію застосування алгоритмів аналізу даних та рівняння фізичного процесу теплопереносу. Використання таких параметрів дозволяє створювати програмно-апаратні рішення для моделювання теплової карти будинку, а також здійснювати аналіз енергоспоживання у контексті моделей машинного навчання. Оскільки, здебільшого, відоме сумарне споживання енергії обігріву, інтерес представляє визначення тієї частини енергії, яка відповідає окремим джерелам обігріву. З цією метою у статті запропоновані математична модель та алгоритм для оцінки ефективних теплових характеристик джерел обігріву на базі рівняння теплопереносу та підходів статистичного аналізу даних, які можна використовувати для отримання інформації про індивідуальні джерела обігріву. Задача визначення таких параметрів зводиться до двох етапів. На першому етапі, з використанням скінченно-різницевого підходу до рівняння теплопереносу, визначено ефективний тепловий параметр джерел обігріву. Далі, за даними енергоспоживання та розподілами кімнатних температур і температур на поверхні обігрівальних елементів, шляхом застосування методів аналізу даних, запропонований алгоритм оцінки індивідуальних ефективних теплових характеристик встановлених в кімнатах обігрівальних елементів.

Ключові слова: інтелектуальний дім, оптимізація енерговитрат, теплообмін.