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Splitting measurements of the total heat demand in a hotel into domestic hot water and space heating heat use

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ABSTRACT

To achieve more efficient energy use in buildings, space heating (SH) and domestic hot water (DHW) heat use should be analysed separately. Unfortunately, in many buildings, the heat meters measure the total heat use only, typically not divided into SH and DHW. This article presented a method for splitting the total heat use into the SH and the DHW. The splitting follows the assumption that the outdoor temperature is the main parameter explaining the hourly SH heat use, while the hourly DHW heat use is not influenced by this parameter. In the article, the modelled SH heat use was extracted from the total heat use based on the energy signature curve and the singular spectrum analysis. Thereafter, from the residuals between the modelled SH heat use and the total heat use, the DHW heat use was identified. The application of the method for the hotel in Norway showed that restored values represented the trends of the measured SH and DHW heat use well. The coefficient of determination (R2) for the modelled SH heat use was 0.97, and 0.76 for DHW. The methodology is useful for obtaining valuable information for monitoring and improving the energy performance of SH and DHW systems.

1. Introduction

For the European Union (EU) power system, energy savings in buildings is a vital topic. This topic is important from both an economic and environmental perspective [1]. The amount of energy use in buildings is currently reaching 40% of the total energy use [2]. For this reason, achieving a highly energy-efficient building stock is one of the main targets of the current energy policies in EU [2]. Out of all the technical systems in buildings in the EU, space heating (SH) and domestic hot water (DHW) are often the most significant consumers of energy. According to Ref. [3], SH and DHW heat use together accounts for more than 20% of the total EU energy utilisation. SH consumes approximately 85% of the heat demand in the EU. The remaining 15% is related to DHW use [3]. Thus, increasing energy efficiency in SH and DHW systems is essential for attaining the EU energy targets [4].

The European Directive 2018/844 [5] claims that analysis of the energy performance for buildings should be conducted based on calculated or measured energy use. The estimations shall reflect the typical energy use for SH, DHW, and other technical systems in a building [5]. This approach to analysis is important for the development of energy-saving solutions in all technical components of the building. The proper implementation of this approach requires that energy meters are installed for the main energy-consuming systems in the buildings. As a part of the smart meter promotion strategy, at least 80% of the EU electricity meters should be replaced by smart meters until 2020 [6]. Smart heat meters, on the other hand, are usually not available in buildings [7]. However, a significant share of buildings uses only one heat meter for the total heat use. In such systems, this single meter cannot measure the SH and DHW heat use separately. SH and DHW systems have different regimes of work and influencing factors on their performance. Accordingly, the analysis of heat use in these two systems should be performed independently [8]. Separate statistical data for the DHW and the SH heat use are essential for improving a number of issues, such as SH and DHW systems sizing, designing of energy management and control systems, as well as improving the existing standards, the prediction models and the energy use profiles. Thus, the separation of the total heat demand into the components associated with the SH and DHW heat use is an important task.

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Nomenclature

$f(x)$	piecewise regression model for the ESC
x	independent variable in a piecewise regression, which is the outdoor temperature for the considered case (°C)
β_i	ith coefficient of the piecewise model
ε	residual error
E_{SH}	ESC model of space heating heat use
E_{DHW}	ESC model of domestic hot water heat use
E_{TH}	measured total heat use (kW)
E_{Loss}	heat losses in the DHW system (kW)
E_{TH}	time series of the total hourly heat use in the building
N	number of the elements in the data sample
L	window length
X	Hankel matrix
X_i	i-th elementary matrix of X
σ_i	i-th singular value of the matrix X
U_i	left singular vectors of the matrix X
V_i	right singular vectors of the matrix X
d	intrinsic dimensionality of the time series trajectory space
$\tilde{e}_n$	elementary time series components
$\tilde{e}_i$	ith elementary time series component
$\sum \tilde{e}_k$	sum of the components selected from $\tilde{e}_i$
E'_{SH}	SSA model of space heating heat use
E'_{DHW}	SSA model of domestic hot water heat use

2. Literature review

Several research groups investigate the problem of extracting the SH and the DWH heat use from the total heat use measurements [9,10]. However, since the problem is not trivial, and the researchers set different requirements for the results, there is no unique methodology for performing such data analysis. Some of the existing solutions are discussed in the text below.

A method for separating the total heat demand in the building into SH and DHW heat use is presented in Ref. [9]. In this research, 10-min resolution data from a single-family house in Denmark is used. The method assumes that the DHW heat use generates short-lived spikes in the time series. Opposite, the SH heat use changes slowly during the day due to climate and user behaviour. For this reason, the authors in Ref. [9] propose to estimate the SH heat use by a non-parametric kernel smoother. All the values significantly above the kernel smoother are considered as the DHW heat use spikes. Currently, this method is not yet verified by the SH and the DHW heat use data which are measured separately. Therefore, it is challenging to estimate its accuracy and reliability.

Splitting weekly heat use from 1 m into DHW and SH is considered in Ref. [10]. The authors in Ref. [10] assume that the period when the outdoor temperature is higher than the base temperature [11] is only the DHW heat use period. In this way, they found DHW heat use for several warm weeks during the year. Afterwards, the same authors proposed to use the DHW monthly variation factors to extrapolate the DHW heat use from warm months to other months of the year [10]. For dwellings in the United Kingdom, these factors are given in “The government's standard assessment procedure for energy rating of dwellings” [12]. Further, the research work in Ref. [13] considers the related problem in Belgium. Based on actual measurements in dwellings, the monthly variation factors for DHW heat use are calculated [13]. For other types of buildings, except dwellings, these factors are not presented in the literature. In some buildings, SH heat use can be observed even in the warm months. Therefore, for an individual building, application of monthly variation factors for DHW heat use can lead to inaccurate results.

The research work in Ref. [14] shows a method that estimates the hourly space heating and the daily DHW heat use profile. The mentioned study uses the hourly values of the total heat demand in the building. The method includes the following steps: 1) the daily total heat use profile for an average summer day is calculated; 2) the non-DHW use is calculated as a minimum of total heat use profile for an average summer day or average for hours from 0:00–04:00 o'clock; 3) the DHW profiles are calculated by deducting the non-DHW heat use from the value of the heat use at each hour of the day. This study in Ref. [14] shows that the method gives satisfactory results when the DHW use during summer is at least at the same level as the space heating. The method does not consider the DHW heat use in other periods, except for the warm season.

Some approaches propose the alternative way of the SH and DHW heat use identification. They rely on the application of buildings simulation tools [15]. For example, a methodology which uses occupant focused approach and time-of-use survey (TUS) is considered in Ref. [16]. To develop activity-specific profiles for occupancy and domestic equipment use, the Markov Chain Monte Carlo techniques is applied for TUS activity data. The authors assume that the heat demand is dependent on the household size, type of the day, and the season. The DHW heat use profiles combine the probability distributions for particular TUS activities with average daily DHW heat demand.

Several stochastic multi-energy simulation models are developed for the UK residential building stock [17–19]. Among the models presented in these articles, the CREST Heat and Power (CHAP) model is of particular interest. CHAP model uses a four-state occupancy model and existing activity profiles for DHW modelling. At the same time, the SH model applies a two-node RC approach to determine the required heat input to maintain a specific setpoint temperature. The model shows good results for energy system analyses of UK residential buildings in general. However, it produces less accurate results for a single building with specific configurations.

The DHW heat use profiles are integrated within a set of building performance simulation archetype models. Such simulation also provides the possibility of estimating SH heat use. The research in Ref. [20] describes an approach where volumetric flow rates and water temperatures are measured to characterise the DHW use in 20 buildings of different sizes. The authors execute several stochastic simulations for the measured data to get representative DHW use profiles. They propose to use these profiles as an input to simulation tools [20]. A number of building simulation tools could be also used for estimation of the SH and the DHW heat in the building. Among the popular tools for building simulation are IDA ICE, EnergyPlus, and TRNSYS [21]. However, usually, these tools require the development of a complex model for all the components in a building. Usually, such a model is suitable only for a particular building. In addition, practice shows that such models are less accurate than the analysis based on actual measurements [22].

The application of a test rig for testing heating equipment in the thermo-technical laboratory is discussed in Ref. [23]. In this laboratory, for different heating conditions, the heat demand profiles for SH and DHW heat use is emulated.

Some authors propose to use the models and profiles of the SH and DHW heat use created based on statistical data from the buildings stock databases [24,25]. For instance, the Neural Networks model of the SH and DHW heat use in typical Canadian households is considered in Ref. [24]. The model uses data from the 1993 Survey of Household Energy Use (SHEU) database, which represents information from the Canadian housing stock. Similar models may serve as a basis for the separation of the SH and DHW heat use in typical buildings. However, their development requires the availability of the appropriate database. Moreover, the accuracy of the splitting for individual buildings will be questionable.

Linear regression models may be used to predict heat demand in buildings, e.g. as done in Ref. [26]. Pedersen in Ref. [27] and Sørensen et al. in Ref. [28] use linear regression models to separate DHW from total heat delivery. In Ref. [28], a linear regression model for total heat delivery is developed, taking the outdoor temperature, hour of the day, weekdays and holidays into account. When estimating DHW, the outdoor temperature is set to the approximate break-point temperature of the model, resulting in a DHW daily load profile with hourly mean values [28].

The separated SH and DHW heat use profiles are also modelled in Ref. [25]. The modelling approach is the coupling of the behavioural, stochastic, and energy balance models. The synthetic load profile captures the typical hourly, daily, and annual characteristics of the DHW heat use. The SH model is a combination of a simplified physical method with a behavioural model for standardised buildings. The approach requires knowledge about the activity categories, such as occupant's presence at home, sleeping, hygiene, and cooking activities. Such modelling approach may give good results, but the data required for new studies on a bigger scale (hotels, nursing homes etc.) requires much effort and usually not feasible.

SH and DHW hourly energy loads in buildings are also studied in Ref. [29]. The authors estimate the hourly DHW heat use depending on the water volume use, the building activity, and type of DHW system. Meanwhile, hourly SH loads are modelled, taking into account the outdoor temperatures, the building setpoint temperatures, the night setbacks, and weekends.

The literature review shows that the problem of dividing the total heat use into the parts related to the SH and DHW is not solved yet, especially for larger buildings with limited knowledge about the users. Most of the existing methods are simplified and focused only on restoring average daily profiles for a considered year. Some of the above-mentioned methods allow us to obtain general models of SH and DHW heat use for particular buildings category, but not for an individual building [24]. The other methods solve the considered problem only for several warm months based on the assumption that SH is not working in the summertime [14]. The number of methods requires extensive knowledge about users behaviour, physical properties of the building and parameters of the systems, which limits their application [25]. Moreover, the major part of the existing articles analyses heat use in apartment buildings. For non-residential buildings, including hotels, the problem is less studied.

In this article, we present a method for splitting hourly measurements of the total heat use into the SH and the DHW heat use. The first step of the method was to develop SH heat use model based on the total heat use data. This step relied on the energy signature curve (ESC) and singular spectrum analysis (SSA). The DHW heat use model was extracted from the residuals between the SH heat use model and the total heat use. The methodology was tested on one-year hourly measurements in a hotel, located in Eastern Norway. The investigation was performed in such a way that the results of the total heat use splitting could be compared with the measured SH and DHW heat use, which were measured separately at the hotel. The methodology is useful for obtaining valuable information about DHW and SH heat use in the building where only one heat meter is available. The models obtained by the total heat use splitting for DHW and SH heat use can be used for improving the energy performance in the building and energy efficiency.

The paper has six sections. Section 3 introduces the methodology for splitting the total heat use into the SH and the DHW heat use. Section 4 represents the description of the hotel, where the methodology was tested. In Section 5, the main results of the methodology application are discussed. The values resulting from the splitting are compared with the measured SH and DHW use. Finally, the most important conclusions of the investigation are presented in Section 6.

3. Method

The methodology consists of two subsections. Section 3.1 dedicated to the application of the ESC to extract the models of the SH and the DHW heat use from the total heat use in the building. Section 3.2 proposes the method which is based on the SSA for the decomposition of the SH and the DHW heat use in Section 3.1.

3.1. Energy signature curve for the SH and the DHW heat use analysis

The method proposed in this article uses the assumption that the SH and the DHW have different factors affecting them. It is well known that the main influencing factor on the SH heat use is the outdoor temperature [30,31]. In addition, for the DHW use, a seasonal variation is found related to the outdoor temperature [13]. However, on an hourly basis, the research in Ref. [32] has shown that the correlation between the DHW use and the outdoor temperature is insignificant. Thus, the regression model between the total heat use in buildings and the outdoor temperature is caused by the SH only. Meanwhile, the DHW heat use can be found in the residuals of this model.

The ESC shows the relationship between the heat use in an observed building and the outdoor temperature [27,33]. The ESC is a powerful instrument for the heat use analysis in buildings [34]. Fig. 1 shows an example of the ESC.

For a building with a heating season and no cooling taking into consideration, the ESC often consists of two parts. These parts are divided by the change point temperature (CPT), see Fig. 1. The CPT is a critical outdoor temperature that sets the boundary between the start and the end of the heating season. After the CPT, the SH use in

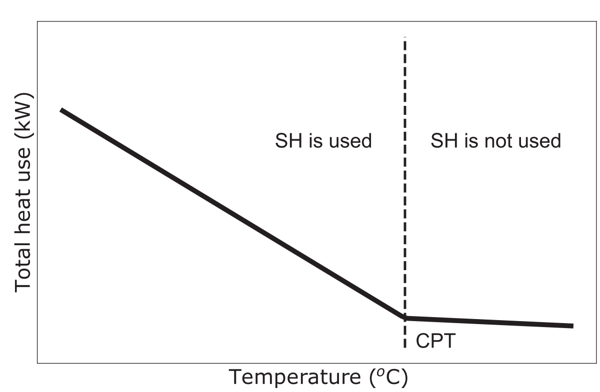

Fig. 1. An example of the energy signature curve.

the building is limited. The part of the curve before the CPT shows the SH season. Usually, in this period, the SH heat use is significantly higher than the DHW heat use. The function after the CPT shows the warm season when SH is not required. During this time, the main share of heat use is related to the DHW system. Nevertheless, depending on the system type, a small amount of heat use associated with the operation of the SH system may occur.

For some buildings, the last day of the heating season or the CPT are known. If the CPT is known, the ESC can be built by using the least square method for two parts of the model, See Fig. 1. Otherwise, the CPT can be identified by using the piecewise regression method. This method allowed us to find the CPT and construct separate models for the two parts of the ESC as shown in Equation (1):

$$f(x) = \begin{cases} \beta_0 + \beta_1(x - CPT) + \varepsilon & \text{If } x < CPT \\ \beta_0 + \beta_2(x - CPT) + \varepsilon & \text{If } x > CPT \end{cases} \tag{1}$$

where $f(x)$ is a model for the ESC, x is the outdoor temperature, β_0, β_1, β_2 are the coefficients of the piecewise model, and ε is the residual error.

Our investigation showed that the ESC model explains well the behaviour of the SH heat use. However, since the total heat use also includes DHW, the model was shifted relative to SH heat use by a certain constant value. In this article, we call this value the shifting coefficient. The shifting coefficient can be revealed from the behaviour of the SH system in the warm season, when the outdoor temperature is above the CPT. During the warm season, there were hours when the SH heat use in the building was equal to zero. The research [11] showed that the minimum value of the ESC coincides with these hours. The study in two other buildings except for the hotel also shows a similar result [32]. Thus, in this study, the coefficient of shifting was accepted to be equal to the minimum value of the total heat use ESC. Extracting this coefficient from the ESC allows us to obtain the SH heat use model. Finally, the following equation was suggested for the SH heat use model:

$$E_{SH} = f(x) - \min(f(x)) \tag{2}$$

The values of the total heat use, which lies above the modelled SH heat use give information about the trend of DHW heat use [9]. Therefore, initially, it was assumed that the positive residuals, obtained as the difference between the total heat use and the modelled SH heat use, represented the DHW heat use. When the negative values appeared in the residuals, the DHW heat use was supposed to be equal to zero. In a DHW system with continuous circulation, the DHW system operates continuously to deliver hot water. Accordingly, the system losses should be added to the DHW heat use obtained from the residuals. These losses can be found as an average value of the heat use at the night time, as proposed in Ref. [14]. Then the model of the DHW heat use can be identified by the following:

$$E_{DHW} = \begin{cases} E_{TH} - E_{SH} + E_{Loss} & \text{If } E_{TH} > E_{SH} \\ E_{Loss} & \text{If } E_{TH} \le E_{SH} \end{cases} \tag{3}$$

where $E_{TH}$is the measured total heat use and E_{Loss} presents the heat losses in the DHW system.

Finally, the SH heat use was balanced according to the DHW heat use model. SH heat use model was recalculated as a difference between the measured total heat use and DHW heat use obtained by Equation (3). In addition, it was introduced a condition that both DHW and SH heat use should be positive. In a case, if one of the parameters (DHW or SH heat use) becomes negative, the negative value was compensated from the remaining parameter. For example, if for a certain point, the modelled DHW heat use was negative, it was compensated from SH heat use, and vice versa. In such a way, all values of restored DHW and SH heat use were positive, and their sum was balanced to be equal to the total heat use.

The flowchart of the above-introduced algorithm for splitting SH and DHW heat use based on the ESC is shown in Fig. 2.

The proposed method might give a reasonable estimation for the trend of SH heat use. However, ESC is based on linear functions. For this reason, it cannot capture particular spikes and rapid fluctuations of the SH heat use. The residuals of the ESC model also contained some noise from the SH. This noise reduced the accuracy of the DHW model. To capture the spikes in the SH heat use in a better way and to improve both the SH and the DHW heat use models, we suggested performing additional analysis. Particularly, after the application of Equation (2), a time series decomposition was applied. For this purpose, the SSA was used. This step is further explained in Section 3.2.

3.2. Application of singular spectrum analysis for identifying the SH and DHW heat use

SSA is a useful method for time series analysis and data mining [35]. This method allowed us to decompose the time series of the total heat use into a sum of components, $\tilde{e}_i$. The components may give an interpretation of the time series structure. There are several software tools in Python [36] and R [37] for the SSA. The two groups of the components, related to the SH and the DHW heat use, could be found. Summation of the components within each group made it possible to restore the SH and the DHW heat use from the total heat use.

In this article, the time series $E_{TH} = (E_1, E_2, \ldots, E_N)$ of the total hourly heat use in the building was analysed. Where E_i is the hourly heat use, and N is the number of the elements in the data sample. For one-year hourly data sample, N was equal to 8760.

The algorithm of SSA is well developed and presented in many articles and books [38,39]. For example, the book [38] gives detailed explanations of the SSA technique, as well as examples of its application. The main steps of the SSA algorithm were shown in Appendix A.

In order to separate the SH and the DHW heat use by the SSA

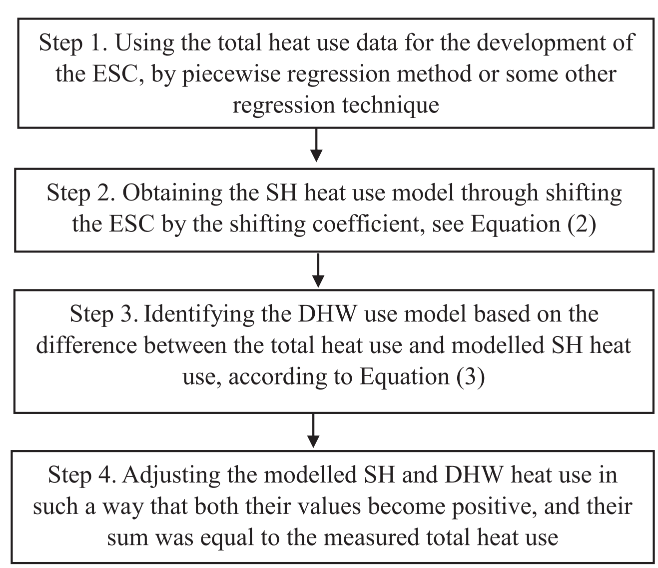

Fig. 2. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the ESC.

method, two main problems were solved. The first problem was the selection of an appropriate window length L for the SSA decomposition, see Appendix A. The SSA does not have strict recommendations for the selection of the optimal window length. Therefore, quite often, the trial and error method is applied. The second problem was identifying the groups of the components related to the SH and DHW. These two problems were attempted to be solved based on the SH heat use model obtained by the ESC method, as described in Section 3.1, see Equation (2). The SSA was iteratively applied for different windows length L (2, 3, …N/ 2). On each iteration for L_i the SSA components were calculated. Of all the components, only the components associated with the SH heat use were identified. These components were selected in such a way that their additive sum has a maximum correlation with the SH heat use model, see Equation (2):

$$corr\left(E_{SH}, \sum \tilde{e}_k\right) \rightarrow max \tag{4}$$

where $\sum \tilde{e}_k$ is the sum of the components selected from $\tilde{e}_i$.

From the considered window lengths, the one that gives the maximum value for Equation (3) was selected. For the best window length, the new SH heat use model as a sum of the components was identified. This SSA model was also shifted in a similar way as in Equation (2):

$$E'_{SH} = \sum \tilde{e}_k - \min\left(\sum \tilde{e}_k\right) \tag{5}$$

Using the E'_{SH} and E_{TH}, the new model for the DHW heat use (E'_{DHW}) was identified by Equation (3). Finally, the values for both the restored SH heat use and the DHW heat use were balanced in such a way that both of them became positive, and their sum was equal to the total heat use. The balancing was performed in a similar way to Chapter 3.1. First, the SH heat use model was adjusted as a difference between the measured total heat use and the DHW heat use, E'_{DHW}. After, all negative values of the DHW heat use and the SH heat use were compensated. Hence, if DHW heat use had negative values, they were compensated from the SH heat use, and vice versa.

The flowchart of the algorithm for splitting the SH and DHW heat use based on SSA is shown in Fig. 3.

The investigation in this article showed that the application of the SSA allowed us to capture the spikes of SH heat use better than when using the ESC alone and to improve both the SH and DHW heat models. In more detail, the application and comparison of both methods are shown in Section 5.

4. Building description

The one-year hourly SH and DHW heat use data were measured at a hotel located in Oslo, Norway. The hotel was built in 2000, with a total heated area of 10 571 m^2. It has 260 guest rooms, lobby, gym, and a conference room. The guest rooms are designed for families and solo travellers. The sizes of the rooms start from 23 m^2. All the private rooms have individual bathrooms with toilet facilities and a shower. Breakfast and supper are served in the hotel. According to hotel management, employees use hot water for cleaning, and guests use hot water for personal hygiene. In general, the considered hotel well represents the characteristics and regimes of typical hotels in Scandinavia.

The hotel uses district heating for both SH and DHW heat use. In the DHW system, the hot water circulates permanently to ensure fast delivery of hot water at the tapping points. Two energy meters measure the actual SH and DHW heat use separately. The sum of their readings characterises the measured total heat use in the building. The SH meter is less accurate than the DHW meter. DHW meter is collecting data with 1 kWh-steps, while the steps of SH metering is 10 kWh. The measured SH and DHW heat use include system heat losses. The measurements were carried out from April 1, 2018 to April 1, 2019. However, in January 2019 some data about SH and DHW heat use were missed in the data storage system.

The investigation was performed in such a way that the results

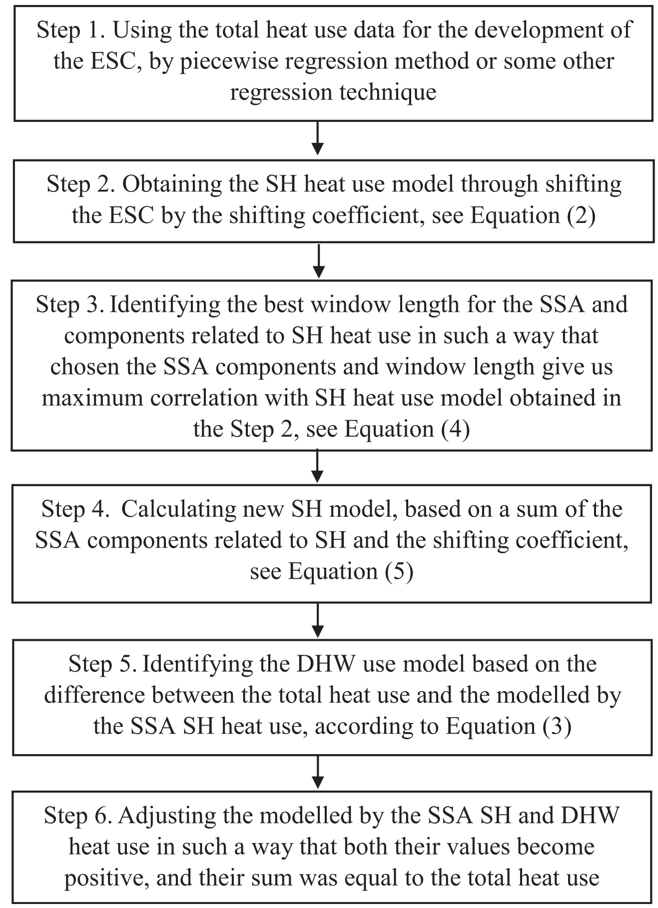

Fig. 3. Flowchart of the algorithm for splitting the total heat use into the SH and the DHW heat use by using the SSA.

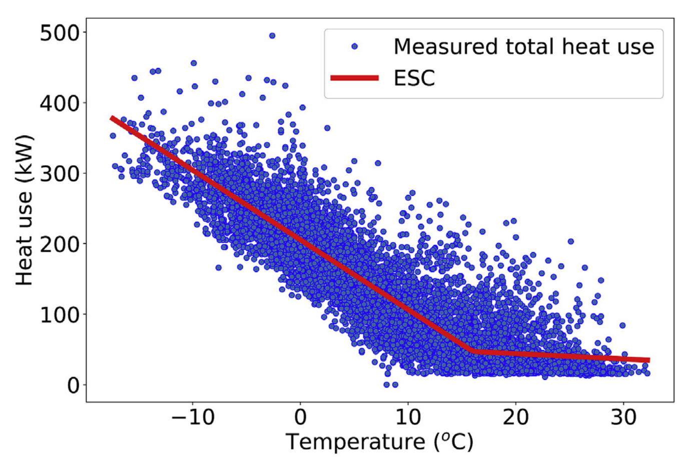

Fig. 4. ESC of the hourly total heat use in the hotel.

of the total heat use splitting could be compared and verified based on the actual measurements from two separate meters for DHW and SH. For this reason, the total heat use in the article represented the sum of the DHW and the SH heat use obtained from two heat meters installed at the hotel. To analyse the influence of the outdoor temperature on the heat use in the hotel, weather data from the closest weather station, Blindern in Oslo, were used [40].

5. Results

The section is separated into subsections that consider the steps of the methodology, see Section 3. Section 5.1 shows the analysis of the heat use by the ESC method. The results of the total heat use splitting into the SH and the DHW heat use based on the SSA method is discussed in Section 5.2. The profiles and validation of the modelled SH and DHW heat use are shown in Section 5.3.

5.1. Analysis of the SH and the DHW heat use based on the energy signature curve

One-year measured hourly data of the total heat use in the hotel and the outdoor temperature were used as input for the modelling and splitting of DHW and SH heat use. Based on this information, the ESC was developed, as shown in Fig. 4. ESC of the hourly total heat use in the hotel Fig. 4. The piecewise regression method was used to find the CPT.

From Fig. 4, we can see that the CPT was approximately 16 °C. Theoretically, there is no need for SH above the CPT. Therefore, above this outdoor temperature, heat use in the building was assumed to be fully dedicated to DHW. This condition makes CPT easily recognised by visual analysis and the regression methods. In the considered hotel, the SH heat use was different from the typical theoretical assumption. In order to explain this fact, the measured SH and DHW heat use after the CPT are presented in Fig. 5.

Fig. 5 shows the daily profiles of SH and DHW heat use in the warmest month of the year. As we can see from Fig. 5 that all the time in the warm months, even after the CPT, a certain amount of heat was consumed by SH. The SH heat use in the warm season might be explained by the fact that the control valve of the heat exchanger connecting the SH system to the district heating was wrongly sized or had faults. This meant that even this control valve was completely closed, it passed some amount of the water flow and gave SH use even above the outdoor temperature of 16 °C. This heat amount was not usefully used in the building, yet it was just heat loss circulating in the system [41].

The actual measurements showed that during the observed year, the SH contributed to 75% of the total heat use and 25% was related to DHW. Above the CPT, SH is responsible only for 7% of the heat use, while 93% was associated with DHW. For most buildings, the CPT is an approximate value. The value of the CPT indicated when SH was significantly reduced due to the warm weather, but not completely diminished. Since, to some extent, the CPT was an uncertain parameter, the only approximate value of the CPT could be found.

In general, the ESC might explain the trend of the measured SH heat use in the hotel as shown in Fig. 6. However, since the total heat use also included DHW heat use, the ESC of the total heat use was shifted according to the coefficient in Equation (2) to obtain the model of the SH heat use. This shifting coefficient corresponded to the minimum value in the ESC model. In our case, the ESC was shifted by 35 kW. Accordingly, the model of the SH heat use was obtained.

The DHW heat use was investigated within the residuals of the SH heat model. The circulation heat losses in the DHW system were estimated to 15 kW, based on the minimum heat use at the night

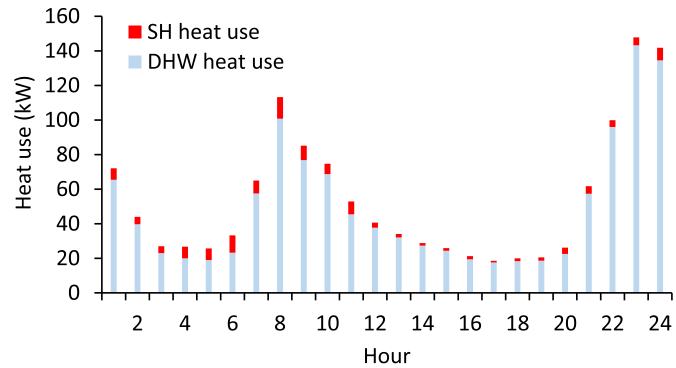

Fig. 5. Daily profiles of the measured SH and DHW heat use in July (heat use after the CPT).

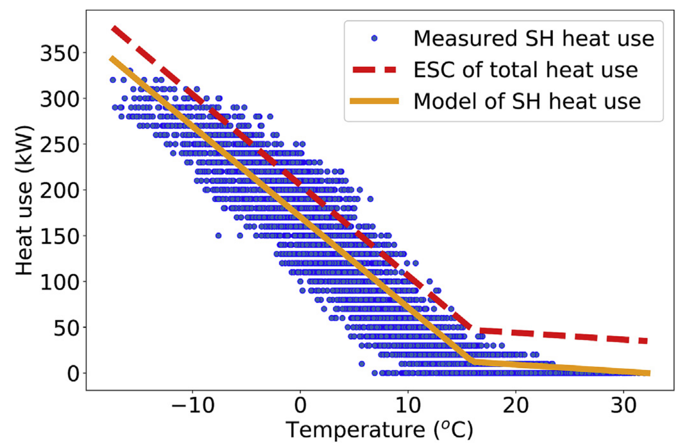

Fig. 6. Model of the SH heat use based on the ESC of the total heat use.

time during the summer, according to Ref. [14]. After, by using Equation (3), the model of the DHW heat use was obtained. Finally, all the values of the modelled SH and DHW use were adjusted in such a way that their sum was equal to the total heat use in the hotel.

Figs. 7 and 8 show the results of splitting total heat use into SH and DHW for February, one of the coldest month in Norway. Fig. 7 shows that the ESC model well explained the trend of the SH heat use in the hotel. For the yearly data sample, the coefficient of determination (R2) between the model and the measured SH heat use was 0.93, and Root Mean Square Error (RMSE) equals to 23. At the same time, the DHW heat use model (see Fig. 8) was affected by

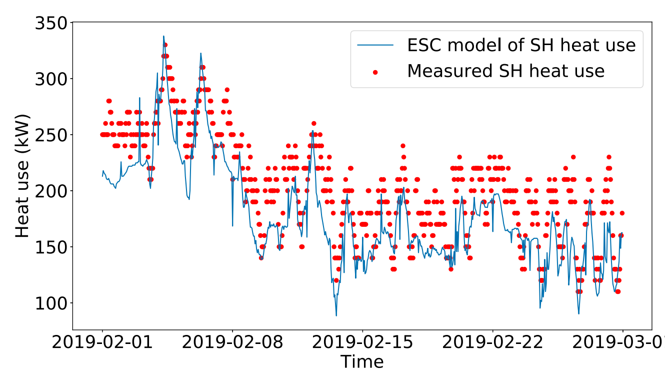

Fig. 7. Restored SH heat use based on the ESC.

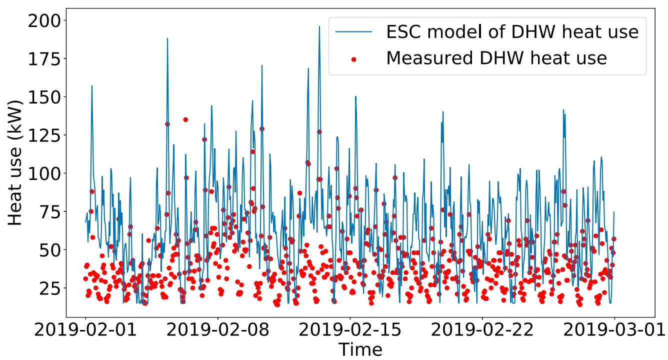

Fig. 8. Restored DHW heat use based on the ESC.

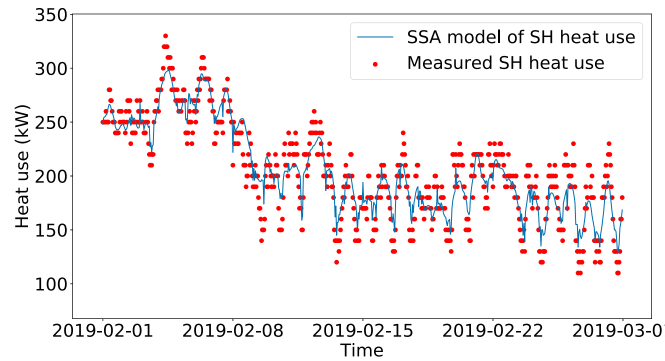

Fig. 9. Restored SH heat use based on the SSA.

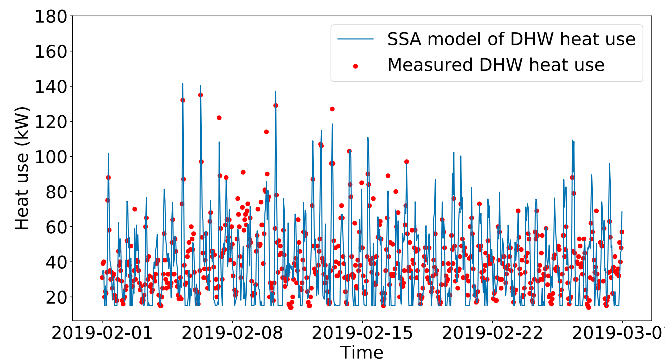

Fig. 10. Restored DHW heat use based on the SSA.

the SH noise in the residuals. For this reason, the R2 for the DHW heat use model was less accurate and equal to 0.57, and RMSE was 20.3. Therefore, the SSA method was used to further improve these models.

5.2. Using the singular spectrum analysis for the decomposition of the SH and DHW heat use in the hotel

The SSA decomposition for the time series of the total hourly heat use was carried out in order to split the SH and DHW heat use. The Python implementation of the SSA from Ref. [36] was used to perform the SSA decomposition. The SSA was iteratively applied for different windows length. For each step of the iteration, the components which corresponded to the SH were selected in such a way that their additive sum had the maximum correlation with the SH heat use modelled by the ESC (according to Equation (4)). The investigation showed that the same criterion could be applied to select the best window length for SSA modelling. Namely, the SSA models for windows lengths with a higher correlation between the SH heat use modelled by the ESC and the SSA demonstrated the higher accuracy of the SSA DHW heat use model. For this reason, the window length that allows us to receive the highest correlation between SH heat use obtained by the ESC and SSA can be considered as the best for the SSA modelling.

The SSA calculations for large window lengths require high computational power. Therefore, it was impossible to check all the windows lengths from 2 to $N/2$. Although some models were not considered due to computational limitations, the different windows lengths were examined. Based on the proposed criteria in Equation (4), the window length was chosen to 600 and the components related to SH were obtained. From all these components, the first component represented the trend for the SH heat use in the hotel. The other components explained the spikes and fluctuations of the SH heat use. The sum of the SSA components related to SH was shifted according to Equation (5).

The residuals of the SSA SH heat use model were used to develop the new DHW use model. The calculations were done according to Equation (3). Finally, the values for both the SH heat use and the DHW heat use were balanced in such a way that both of them become positive and their sum was equal to the total heat use. Figs. 9 and 10 show the results of splitting total heat use into SH and DHW based on SSA for February.

As we can see from Figs. 9 and 10, the models for both the SH and the DHW were improved compared to ESC model. For the yearly data sample, the R2 for the SSA SH heat use model was 0.97, and RMSE was 15.1. While for the DHW heat use R2 was 0.76, and RMSE 14.7. To recap, see the comment related to RMSE and R2 values for the ESC approach. The RMSE and R2 criteria, as well as Figs. 9 and 10 show that the SSA allowed us to better capture the spikes of the SH and DHW heat use.

5.3. Identifying profiles and validation of the modelled SH and DHW heat use

The restored DHW and SH heat use can be used for identifying the heat use profiles. Heat use profiles are a powerful instrument for estimating the DHW and SH heat use in the buildings. The profiles allow us to determine the hours of peak energy loads and other energy load characteristics of the building. In this article, the restored by SSA profiles for DHW and SH were compared and verified with profiles obtained from measured DHW and SH heat use.

Using the restored data from the model values for the SH and DHW heat use, the average monthly and daily load profiles were constructed. Figs. 11 and 12 compare the hourly and monthly profiles, respectively, with the measured heat use in the hotel.

Fig. 11 shows that the proposed method allows restoring well the average daily load profiles for the SH and the DHW heat use. The profiles obtained from the SSA model well captured the timing of the peak heat use during an average day. The profiles showed that the morning peak of the DHW use in the hotel occurs from 7:00 to 9:00 o'clock and the evening peak from 21:00 to 23:00 o'clock. Comparing to the DHW, the profile of the SH heat use was more uniform. However, it also showed a small increase in heat use in the morning and night-time.

The average monthly profile for the restored SH heat use was representative, compared to the measured SH heat use, see Fig. 12. a. This profile captured well the seasonal variation of the SH heat use. According to Fig. 12. a, the months with the coldest outdoor temperature (November, December, January, February and March)

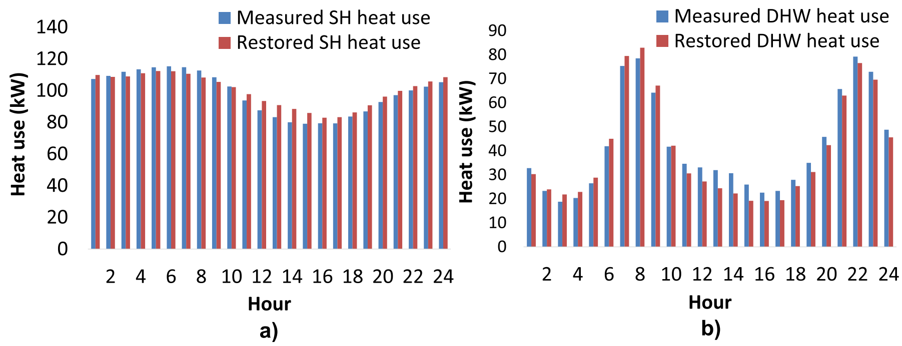

Fig. 11. Restored hourly SH and DHW heat use profiles: a) SH heat use and b) DHW heat use.

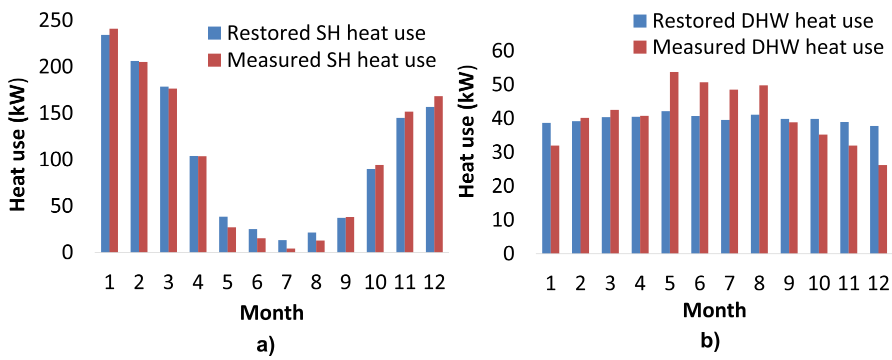

Fig. 12. Restored average monthly SH and DHW heat use profiles: a) SH heat use and b) DHW heat use.

has the highest SH use. At the same time, in the warm season (May, June, July, August and September) the SH heat use was small. The DHW heat use profile, see Fig. 12. b had particular inaccuracy for the months in the warm season. In these months, significant spikes of DHW heat use occurred, most likely related to an increased number of guests in the hotel in the warm season [32]. In addition, due to the SH heat use that occurred after the CPT in the hotel, it was difficult to capture precisely the DHW heat use from the ESC model for certain months. To recap, please see Fig. 5 and the comments related to the possible faults causing SH heat use in the warm period.

The proposed method allowed us to split the SH and DHW heat use from the total heat use. Despite the fact that the obtained values of the SH and DHW heat use have particular inaccuracy, their application may be still useful. Both models for the SH and the DHW well represented the general trends of SH and DHW use. This is essential information for solving many energy saving issues in the hotels heating systems.

6. Conclusions

Statistical analysis and modelling are reliable tools for improving the energy performance of buildings and releasing the energy savings potential. In order to reach better results in this area, it is necessary to carry out data-driven analysis of energy use of the main technical systems in buildings, where SH and DHW systems often are the largest energy consumers. Despite this fact, quite often energy meters in buildings measure the total heat use only, not divided into the SH and the DHW heat use. However, the SH and the DHW have different regimes of work and influencing factors, and it is important to analyse the heat use in these two systems separately. Thus, the separation of the total heat use data into components associated with the SH and the DHW heat use become an essential task. The literature review shows that the problem of dividing the total heat use into the parts related to the SH and DHW for individual buildings is not solved yet.

In this article, the method for splitting the total heat use into the SH and the DHW heat use was proposed. For splitting, we used the assumption that hourly SH heat use is highly correlated with the outdoor temperature. At the same time, the DHW is not affected by this parameter on hourly basis. Using this assumption, the model of the SH heat use was extracted from the total heat use in the building. For this purpose, the method based on the ESC and the SSA was applied. Finally, the DHW use was found within the residuals of the SH heat use model.

The method was tested on the data for the heat use in the hotel in Norway. The hotel has two separate heat meters for the SH and DHW. Thus, it was possible to perform the comparison of the measured SH and DHW heat use with the results of the splitting. The analysis showed that the SH heat use model had the coefficient of determination R2 equal to 0.97, while for the DHW heat use R2 was equal to 0.76. In addition, the proposed method allowed us to restore well the daily load profiles for the SH and the DHW heat use. However, the monthly profiles for the DHW were less accurate than for the monthly SH profiles. The results of the analysis in the hotel showed that the obtained models for the SH and the DHW represented well the general trends of the heat use. The proposed method allows us to gain valuable information about the DHW and the SH heat use in buildings where only one heat meter is available. The models and profiles for DHW and SH heat use, obtained from total heat use splitting, may be used as an instrument for improving energy efficiency in buildings.

The investigation in this study has several limitations. First of all, the proposed approach was dedicated to the case when 1 m measured the total SH and DHW heat use. However, in some buildings, 1 m could be used not only for SH and DHW heat use, but also may include other heat needs. The further consideration for these conditions should be done. The restored DHW heat use was obtained based on the SH heat use model. This means that the DHW heat use model included also particular inaccuracy of the SH heat use model. Therefore, the restored DHW heat use might be less accurate than for the SH heat use, especially for several warm months. For this reason, the ways to modify the approach and improve the model for DHW heat use should be investigated in our future work. Furthermore, the research was done for the regular hotel located in Eastern Norway. SH and DHW heat use in other types of buildings (schools, apartments, offices etc) have their own specific features that may be used to improve the results of splitting. In addition, passive houses were out of the scope of this research. Passive houses consume less heat for SH compering to the regular one, which will influence the shape of the energy signature curve. Therefore, the study for other locations and types of buildings should be performed.

Author statement

Dmytro Ivanko: Conceptualization, Methodology, Formal analysis, Software, Investigation, Writing – original draft, Visualization, Writing – review & editing, Sørensen Åse Lekang: Data curation, Writing – review & editing, Natasa Nord: Conceptualization, Formal analysis, Writing – original draft, Supervision, Writing – review & editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

The main steps of the SSA algorithm are as following [38]:

1) Calculating the trajectory matrix for the time series

According to the SSA method, the one-dimensional time series E_{TH} should be transformed into a sequence of multi-dimensional vectors lagged with the window length L. The window length is a value that should be selected from 2 to $N/2$. In such a way, the series $X_1, X_2, \ldots, X_K$ with vectors $(E_i, E_{i+1}, \ldots, E_{i+L-1})$ will be obtained. Where $K = N - L + 1$, for $i = 1, \ldots, N - L$. These vectors will form the following trajectory matrix:

$$X = \begin{matrix} E_1 & E_2 & E_3 & \ldots & E_K \\ E_2 & E_3 & E_4 & \ldots & E_{K+1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ E_L & E_{L+1} & E_{L+2} & \ddots & E_N \end{matrix} \tag{A1}$$

The matrix X is called a Hankel matrix. The anti-diagonal elements of this matrix are equal.

2) Decomposition of the trajectory matrix

The singular-value decomposition (SVD) of the trajectory matrix can be written as:

$$X = \sum_{i=1}^{d} X_i = \sum_{i=1}^{d} \sigma_i U_i V_i^T \tag{A2}$$

where X_i is the i-th elementary matrix of X, σ_i is the i-th singular value of the matrix X, the vectors U_i are the left singular vectors of the matrix X, vectors V_i are the right singular vectors of the matrix X, d is the intrinsic dimensionality of the time series trajectory space (typically $d = L$)

3) Selection of eigen-vectors

At this step of the SSA, the splitting the elementary matrices X_i into separate groups and summing the matrices within these groups was performed. The grouping procedure partitions the set of indices$\{1 \ldots d\}$ into m disjoint subsets $\{I_1, I_2, \ldots, I_m\}$. These calculations led us to the following decomposition:

$$X = X_{I1} + \ldots + X_{Im} \tag{A3}$$

Selecting the subsets $\{I_1, I_2, \ldots, I_m\}$ is called eigentriple grouping. The choice of several leading eigentriples corresponds to the approximation of the time series in optimality property of the SVD. In this article, the simplified conditions when $m = d$, $I_j = \{j\}$, $j = 1, \ldots, d$, and $X_{Ij} = \sigma_i U_i V_i^T$ were used. In this case, the corresponding grouping is called elementary.

4) Reconstruction of the one-dimensional series

Based on X_{Ij}, a diagonal averaging was performed to form the elementary time series components $\tilde{e}_i$. In this way, the initial time series $E_{TH} = (E_1, E_2, \ldots, E_N)$ was decomposed into a sum of reconstructed components:

$$\tilde{e}_n = \sum_{1}^{d} \tilde{e}_i \tag{A4}$$

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