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Validation of the Energy Demand Load Profile Estimator "PROFet" for Trondheim Non-residential Buildings

Abolfazl Mohammadabadi[1,*], *Igor* Sartori[2,**], and *Laurent* Georges[1,***]

[1]Norwegian University of Science and Technology, Trondheim, Norway
[2]SINTEF Community, Oslo, Norway

Abstract. Accurate long-term forecasts of aggregate energy load profiles are crucial for effective energy system planning at regional and national scales. This study aims to validate PROFet, a flexible load profile modeling tool. PROFet forecasts weather-dependent heating and electrical load profiles at an hourly resolution for both residential and non-residential buildings connected to district heating systems. Given that the tool's accuracy for residential buildings has been demonstrated in previous studies, further validation is needed for non-residential buildings. To achieve this, our study evaluates PROFet's extrapolation performance using an out-of-sample test dataset from Trondheim municipality. The results show that PROFet accurately forecasts the hourly heating load during the space-heating season but is less accurate during periods when domestic hot water needs dominate. The tool exhibits nearly identical performance across the three cases, except for efficient kindergartens, where the estimation accuracy is lower.

1 Introduction

Effective decision-making in the energy industry and grid investment demands a thorough understanding of future uncertainties. In the present competitive and dynamic environment, energy supply, demand, and prices are growing increasingly unpredictable [3]. Most studies in the field of load forecasting focus solely on the aggregated consumed load of the system, neglecting the consumption of individual customers. These studies indicate that electrical consumption varies based on key factors, including weather conditions (such as the outdoor temperature and climate changes in different seasons), as well as calendar and historical variables (like the day of the week, workdays, or holidays). However, it is noteworthy that not only does the electrical load vary on different days of the week and in different seasons of the year, but different customers also exhibit distinct electrical consumption patterns under the same weather conditions, date, and even time of day [4].

The input for nearly 90% of studies in the realm of electricity load forecasting primarily consists of weather parameters and historical electricity consumption [5]. Quilumba et al. [6], discusses the endeavors undertaken to enhance system-level intraday load forecasting. It employs clustering to identify customer groups with comparable load consumption patterns from smart meters before conducting load forecasting.

*e-mail: abolfazl.mohammadabadi@ntnu.no
**e-mail: igor.sartori@sintef.no
***e-mail: laurent.georges@ntnu.no

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PROFet, an energy demand load profile estimator, serves as a tool for estimating load profiles, generating aggregated forecasts for heating and electric loads separately within a specified area. The tool requires only outdoor air temperature, holidays, and floor areas as additional data inputs. Trained on the trEASURE database, which encompasses monitored energy data from various buildings in Norway, PROFet utilizes hourly resolution data from approximately 300 entries, representing around 2.4 million square meters of floor area. These entries cover 11 building categories, comprising both residential and predominantly non-residential buildings. The data entries have been split into three different efficiency categories: Very Efficient (E, buildings with typical heat demand profiles for Passive House and Low Energy Buildings), Efficient (T, buildings with typical heat demand profiles for buildings built according to the building regulations from 2010 or later) and Regular (R, the remaining buildings). The division of building entries into these three efficiency categories has been accomplished through a recently introduced method known as the "Self-inferred energy classification/categorization method." Further details about this method are elaborated in [1].

The prediction accuracy of PROFet has been successfully demonstrated for residential buildings in a previous communication, see Andersen et al. However, it needs to be further validated for non-residential buildings. Our paper complements the previous work by using an alternative classification method and by validating the tool on schools, kindergartens, and nursing homes using out-of-sample data from the Trondheim municipality.

2 Methodologies

2.1 The PROFet model

PROFet estimates energy-signature-curves-based load profiles for various building types categorized by different energy efficiencies. The energy signature curve for space-heating typically comprises two parts: an outdoor temperature-dependent segment referred to as the heating season, and an outdoor temperature-independent segment known as the non-heating season, separated by a base temperature. We will not delve into the cooling season, as it is irrelevant to our work.

The original classification method of buildings in the trEASURE database follows the process outlined by [1], which we briefly summarize here. Building simulations were performed for different building archetypes and different performances of the building envelope (according to the current and past Norwegian building standards). The classification relies on the regression coefficients of daily-averaged energy consumption on the daily-averaged outdoor temperature, specifically during the coldest months (January, February, and March). However, for kindergartens (KG), schools (SC), and nursing homes (NH), there is currently lack of reference simulations to perform the classification using the aforementioned method.

Consequently, we opted for a different approach directly using the data generated by PROFet. $\Phi^P_{h,i,k}$ is the specific power for the building type $i \in (KG, SC, NH)$ with efficiency level $k \in (E, R)$ at hour $h \in [1:24]$. It enables calculating the predicted yearly-averaged specific power $\overline{\Phi}^P_{i,k} = \frac{1}{n}\sum_h \Phi^P_{h,i,k}$ for each building type and efficiency level. In PROFet, *very efficient* and *efficient* building categories are put into one, called *efficient (E)*. Similarly, we evaluated this quantity for real measurements from the Trondheim dataset for each building j, $\overline{\Phi}^T_{i,k,j} = \frac{1}{n}\sum_h \Phi^T_{h,i,k,j}$ (evaluated using its area A_j). Then, if the proximity of a real measurement from a kindergarten $\overline{\Phi}^T_{i,k,j}(W/m^2)$ was closer to the corresponding value $\overline{\Phi}^P_{i,k}(W/m^2)$ obtained from PROFet, we then classified the building to be of category k.

2.2 Trondheim municipality dataset

Data from over 80 buildings was collected by Trondheim municipality, including kindergartens, schools, and nursing homes. The dataset spans different years, from 2018 to 2022, although not all buildings have data for each year. After a thorough cleaning process, we narrowed down the dataset to 77 buildings: 29 kindergartens with a total area of 31,365 m^2, 31 schools with a total area of 190,084 m^2, and 17 nursing homes with a total area of 83,728 m^2. For validation, we focused on the year 2022. The dataset also includes outdoor dry bulb air temperature measurements from the Voll weather station in Trondheim for each individual year. While the dataset covers hourly electricity consumption and district heating data for the entire year, our focus is on the heating load, especially during the space-heating season.

2.3 Error metrics

To assess the performance of PROFet, we have considered the Coefficient of Variation of the Root Mean Square Error (CVRMSE) and the Normalized Mean Bias Error (NMBE) in accordance with ASHRAE Guideline 14-2014 using the formulas (1-2):

$$NMBE_j = \frac{1}{\overline{\Phi}_j^T} \sum_h (\Phi_{h,j}^T - \Phi_{h,i,k}^P) \tag{1}$$

$$CVRMSE_j = \frac{\sqrt{\frac{1}{n} \sum_h (\Phi_{h,j}^T - \Phi_{h,i,k}^P)^2}}{\overline{\Phi}_j^T} \tag{2}$$

3 Result

3.1 Categorization and identifying outliers

As previously outlined in the explanation of the categorization method, we classified the buildings into efficient and regular categories by comparing the measurement with estimations from PROFet. Specifically, we categorized 15 kindergartens as efficient and 14 as regular. For schools, there are 28 classified as efficient and 3 as regular. In the case of nursing homes, 14 buildings are categorized as efficient, and 3 are categorized as regular.

To identify outliers, we employed the Inter-Quartile Range (IQR) method [2]. This involved calculating the IQR, defined as the difference between the third quartile (Q3) and the first quartile (Q1) of the errors. Subsequently, we identified outliers that fell below the Lower Bound ($Q_1 - 1.5 \times IQR$) or exceeded the Upper Bound ($Q3 + 1.5 \times IQR$). Figures 1, 2, and 3 represent the categorization of buildings into efficient and regular, with CVRMSE and NMBE depicted on the axes. The outliers are visually identified by red triangles.

3.2 PROFet's performance

As mentioned earlier, our focus in this work is solely on District Heating (DH) consumption, and we do not consider electricity consumption. PROFet supplies data separately for Domestic Hot Water (DHW) and Space Heating (SH). Unfortunately, we lack actual measurements for DHW and SH separately in the Trondheim dataset. Consequently, we are provided only with DH measurements, and our evaluation focuses on assessing PROFet's performance in estimating the heating load.

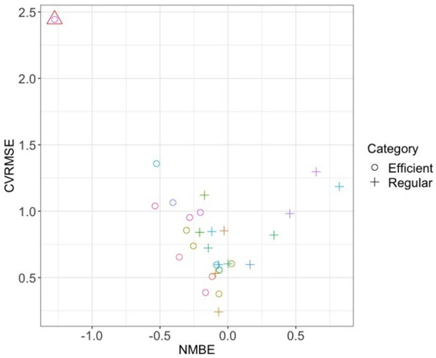

Figure 1. The errors and outliers for the kindergartens

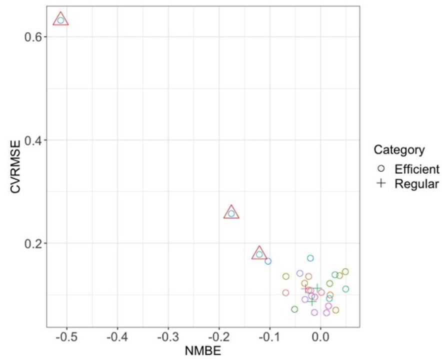

Figure 2. The errors and outliers for the schools

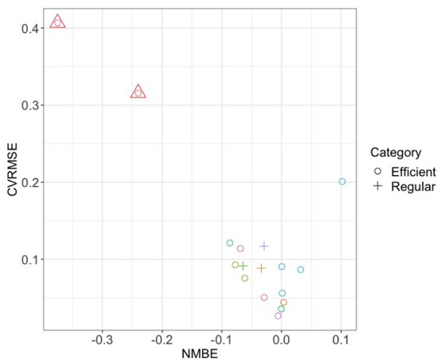

Figure 3. The errors and outliers for the nursing homes

Figure 4 displays the heating profile of efficient kindergartens in the year 2022 and its corresponding estimation from PROFet. Since PROFet generates hourly demand per square meter (W/m^2), we adjusted our data to be comparable. The following formula 3 was employed to calculate the hourly demand per square meter for each efficiency group.

$$\overline{\Phi}_{i,k,h} = \frac{\sum_j \Phi^T_{i,j,k,h}}{\sum_j A_{j,k}} \tag{3}$$

Table 1 illustrates the calculated errors for both heating and non-heating seasons. Additionally, it presents the peak demand during the heating season as estimated by PROFet alongside the actual load. We designated the period from April to October as the non-heating season.

According to the criteria specified in ASHRAE Guideline 14-2014, the model is expected to show an NMBE within the range of -0.1 to 0.1 and a CVRMSE not exceeding 0.3 in relation to hourly calibration data. However, PROFet did not meet these criteria using the 15 measured efficient kindergartens. For the 14 regular kindergartens, the prediction performance is better.

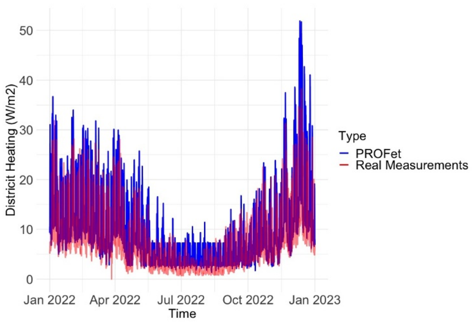

Figure 4. The real measurements and the PROFet estimation for the 15 efficient kindergartens

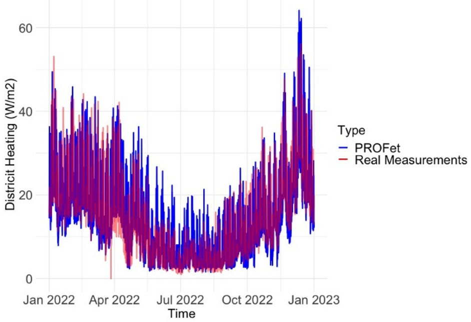

Figure 5. The real measurements and the PROFet estimation for the 14 regular kindergartens

Table 1. CVRMSE, NMBE, and peak loads for the 15 efficient kindergartens

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	-0.21	0.7	38	52
Non-heating	-0.36	0.87	-	-
Both	-0.27	0.81	-	-

As depicted in Figure 5 and Table 2, the estimation is more accurate compared to efficient kindergartens, even during the non-heating period.

Table 2. CVRMSE, NMBE, and peak loads for the 14 regular kindergartens

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	0.07	0.37	56	64
Non-heating	-0.07	0.54	-	-
Both	0.02	0.44	-	-

We observe a similar situation for schools, where the tool performance is superior for the 3 regular schools compared to 28 efficient ones. The results for efficient schools are depicted in Figure 6 and Table 3.

Table 3. CVRMSE, NMBE, and peak loads for the 28 efficient schools

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	0.07	0.41	36	33
Non-heating	-0.38	0.68	-	-
Both	-0.07	0.51	-	-

For regular schools, we have achieved quite acceptable errors based on ASHRAE Guideline 14-2014, as illustrated in Table 4. The results of the estimation are depicted in Figure 7.

For the nursing home buildings, we observe the most accurate estimation in terms of errors and peak load. As depicted in Table 5 and Figure 8 for the 14 efficient nursing homes, the errors align with ASHRAE Guideline 14-2014, and the peak loads are very close.

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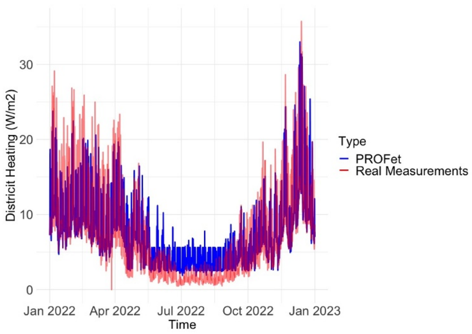

Figure 6. The real measurements and the PROFet estimation for the 28 efficient schools

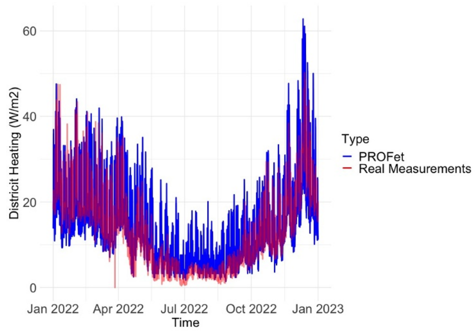

Figure 7. The real measurements and the PROFet estimation for the 3 regular schools

Table 4. CVRMSE, NMBE, and peak loads for the 3 regular schools

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	0.03	0.35	50	63
Non-heating	-0.35	0.69	-	-
Both	-0.09	0.5	-	-

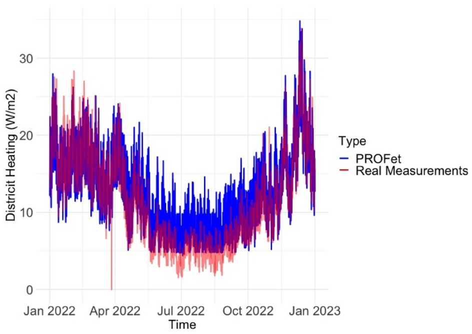

Figure 8. The real measurements and the PROFet estimation for the 14 efficient nursing homes

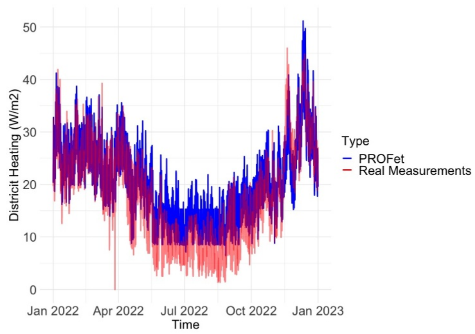

Figure 9. The real measurements and the PROFet estimation for the 3 regular nursing homes

Table 5. CVRMSE, NMBE, and peak loads for the 14 efficient nursing homes

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	0.01	0.14	34	35
Non-heating	-0.31	0.4	-	-
Both	-0.11	0.24	-	-

Finally, for the 3 regular nursing home buildings, we observe an acceptable load estimation for the heating season based on the errors. The results are depicted in Table 6 and Figure 9.

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Table 6. CVRMSE, NMBE, and peak loads for the 3 regular nursing homes

Season	NMBE	CVRMSE	Actual peak load	Estimated peak load
Heating	-0.01	0.15	46	51
Non-heating	-0.31	0.39	-	-
Both	-0.13	0.25	-	-

In addition to NMBE and CVRMSE, we have included the coefficient of determination (R^2) measurements for the entire period corresponding to each building type and category, as shown in Table 7.

$$R_j^2 = 1 - \frac{\sum_h (\Phi_{h,j}^T - \Phi_{h,i,k}^P)^2}{\sum_h (\Phi_{h,j}^T - \overline{\Phi}_{h,j}^T)^2} \tag{4}$$

Table 7. CVRMSE, NMBE, and peak loads for the 3 regular nursing homes

Building type and category	R^2
15 Efficient kindergartens	-0.014
14 Regular kindergartens	0.56
28 Efficient schools	0.59
3 Regular schools	0.55
14 Efficient nursing homes	0.79
3 Regular nursing homes	0.75

Table 7 verifies the earlier error measurements, highlighting the poorest estimations observed for efficient kindergartens in terms of NMBE and CVRMSE, further supported by a low R^2. For the remaining cases, R^2 values are nearly equal, except for nursing homes exhibiting the highest R^2, consistent with the previously noted lowest errors. We have also included the duration curves for various building types and categories. As depicted in Figure 10, the real measurements curve (red) does not completely align with the PROFet curve for efficient kindergartens. In contrast, for regular kindergartens, we observe a more favourable situation. Both efficient and regular schools exhibit almost a similar pattern, while both efficient and regular nursing homes show better alignment for high loads compared to the rest.

Another figure included here displays the hourly average heating loads, as depicted in Figure 11.

Figure 11 affirms that PROFet struggles to accurately estimate loads during non-heating seasons.

4 Discussion

Firstly, PROFet faces challenges in accurately estimating the heating load outside the space-heating season and consistently tends to overestimate them. This discrepancy may be attributed to various factors, such as vacation periods or a substantial difference in load between the heating and non-heating seasons. In buildings such as kindergartens and schools, which operate during working hours on weekdays, a significant contrast is observed in the load estimation between efficient and regular buildings. Notably, the estimation accuracy is higher for regular buildings in these contexts. Conversely, for nursing homes, the situation differs, and the results are promising in both categories. This pattern is also evident in peak loads.

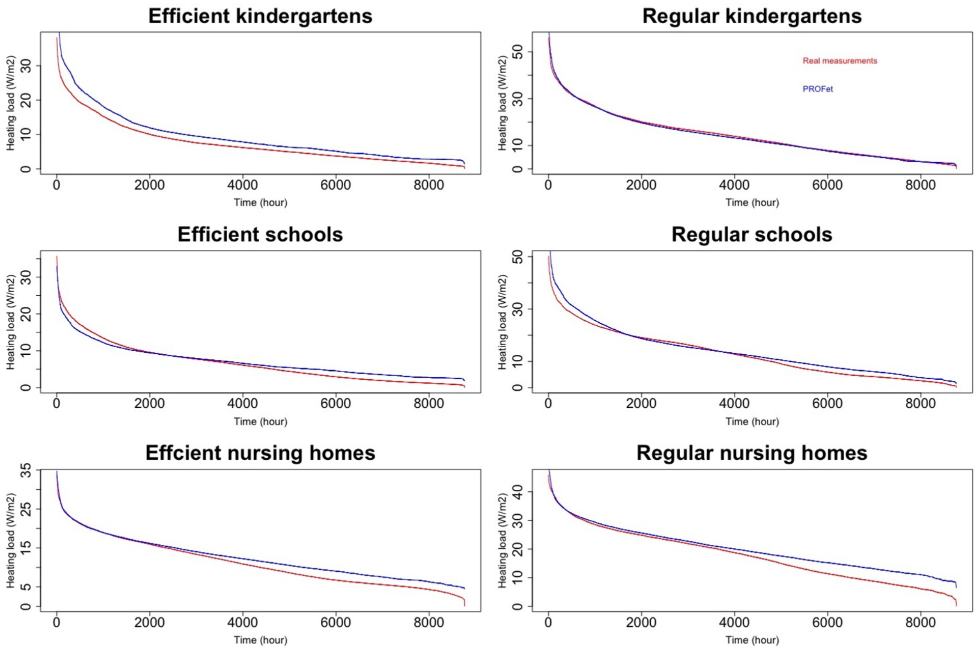

Figure 10. The duration curve for different building types and categories

5 Conclusion

This study aimed to validate load profiles from the PROFet model using out-of-sample datasets from the Trondheim municipality. The validation of building categories in PROFet was successful for nursing homes. For the heating season, the statistical indicators are acceptable according to ASHRAE Guideline 14-2014. However, apart from nursing homes, the most challenging case is observed for efficient kindergartens. For regular kindergartens, NMBE is within the boundary defined by the guideline, and CVRMSE is close to the specified limit in the guideline. A similar trend is observed for schools, where the performance of regular schools is better than that of efficient schools. In both cases, NMBE is within the boundary defined by the guideline, and CVRMSE is close to the specified limit.

6 Future work

In this study, we did not carefully consider holidays, weekends, and weekdays. For future research, we plan to incorporate these factors. It is essential to develop a more effective method for categorizing buildings into efficient and regular structures. Therefore, it is advisable to implement a more robust and precise method. PROFet estimates both Domestic Hot Water (DHW) and Space Heating (SH), but the actual measurements do not distinguish between them, as we only have data for District Heating (DH). To address this aspect of PROFet, we propose using disaggregation methods on our actual measurements. This study is based on one year of data. To enhance the robustness of our findings, we can extend the analysis to multiple years and compare the results. In addition, some categories, especially for regular buildings, had a limited number of buildings. It is therefore questionable whether the mean

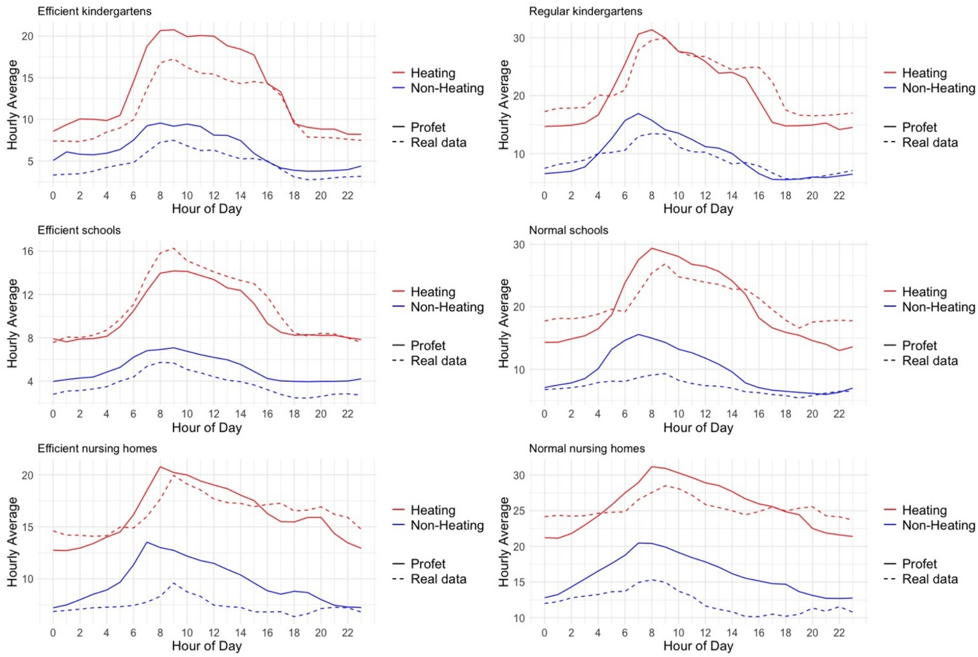

Figure 11. Hourly average heating load for different building types and categories

load of these limited number of buildings can be considered as representative of an aggregated load evaluated by the tool. In this study, we utilized outdoor temperature data from only one weather station. However, the outdoor temperature typically varies between different parts of the city. In future work, it is advisable to incorporate data from multiple stations by either averaging across all stations or using a distance-weighted average to obtain more representative outdoor temperature data.

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