# Peak Load Estimation Based on Consumer Heating Type Classification Powered by Deep Learning



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# PEAK LOAD ESTIMATION BASED ON CONSUMER HEATING TYPE CLASSIFICATION POWERED BY DEEP LEARNING

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## Abstract

The heating system of a building could significantly impact the aggregated electricity peak load. It is in the interest of the distribution system operators (DSOs) to both know what type of heating system that is connected to the grid, and the impact of end-users changing their heating system. Focusing on the transition from non-electric heating systems to heat pumps, this paper investigates its impact on peak load consumption. A state-of-the-art heating type classification method using smart meter data and deep learning was used to first classify the heating types of single-family dwellings. Building upon previous work, a multi-label approach was adopted with the classifier to accommodate buildings with multiple heating sources. To assess the impact of heating system changes, smart meter data were substituted with data from similar buildings equipped with heat pumps. This process was repeated for statistical confidence. A geographical analyses identify areas susceptible to a large peak load increase, demonstrating the practical application.

## 1 Introduction

In the scenario where buildings with non-electric heating systems transition to electricity-based heating systems, particularly heat pumps, there is a potential increase in electricity peak consumption, which could lead to bottlenecks in the grid. Hence, it is crucial for the distribution system operator (DSO) to monitor their customers' heating types to analyse any potential change in peak load. However, customers are often not obligated to notify the DSO about the heating system they use. On the other hand, a vast amount of data collected from smart meters presents a significant opportunity to automatically classify heating types without individually contacting customers.

Various approaches have been employed to classify the heating systems of buildings using smart meter measurements, including supervised [1–3] or unsupervised [4] machine learning. References [1–4] utilise conventional machine learning algorithms that rely on pre-defined features, whereas the deep-learning approach in [5] employs automatic feature extraction. One of the primary benefits of the deep-learning approach is its independence from expert-defined features, along with its demonstrated improvement in classification performance.

The impact on peak load in the electrical grid due to a change in heating type could be estimated using a bottom-up approach, e.g. with a building-stock model as in [6]. The main advantage of such an approach lies in its full control over the model and the various components affecting electrical consumption. However, its main challenge is the requirement for detailed consumer information on a local scale, including thermal characteristics, heating type usage, appliance usage, etc. Additionally, capturing end-user behaviour can be challenging. Nonetheless, it can serve as an efficient tool for evaluating different demand-side management schemes and future scenarios.

This paper aims to first extend the analysis of the proposed deep-learning classifier for heating types in [5] by considering all heating types, and secondly, to estimate and analyse how aggregated electricity peak consumption changes if consumers switch their heating systems from non-electric heating (NEH) to heat pumps. The main contributions of this paper include:

- Adapting the deep-learning framework in [5] to handle a mixture of heating types.
- Further evaluating the deep-learning framework by considering all heating types and assessing its impact on peak load estimation.
- Estimating peak load by replacement using smart meter data from buildings of similar types.

## 2 Methodology

### *2.1 Heating Type Classification by Deep Learning*

In this paper, we further evaluate the method proposed in [5] by considering six different types of heating systems and single-family dwellings (SFDs) with more than one heating system. The hierarchical LSTM-based network proposed therein offers an effective means of automatic feature learning from smart meter measurements and weather data to identify the installed heating type. An overview of the main modules is summarised in Fig. 1. The sequential data undergoes initial processing before being passed to the deep-learning network. In addition, we also include the heated area to improve the classification performance. Subsequently, two LSTM layers encode the complete multivariate time series into a single feature vector, which is then utilised for classifying heating types via a regular feed-forward neural network layer. Further details can be found in [5].

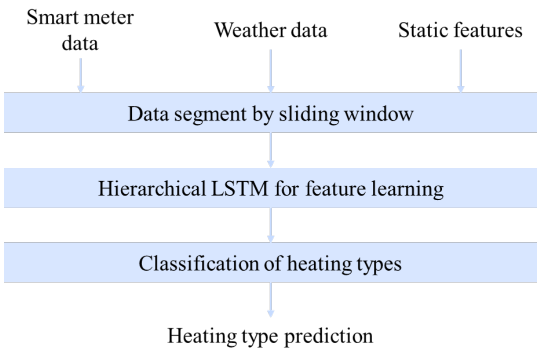


Fig. 1 Main modules of the deep-learning based network for heating type classification.

The method was evaluated on multiclass classification including three of the most common heating types; district heating (DH), exhaust air heat pump (EAHP), and direct electric heating (DEH). In this paper, we extend the analysis to cover all SFDs, where six groups of heating types were considered: NEH, ground source heat pump (GSHP), EAHP, air-to-water heat pump (AWHP), air-to-air heat pump (AAHP) and DEH. It's worth noting that NEH includes DH and heating types based on burning fuels. Since buildings may utilise multiple heating types, we propose a slight adaptation of the model. Specifically, we suggest a multi-label approach to utilise the distribution of heating types within each SFD to gain additional information during the training process for capturing the primary heating type. Otherwise, the use of other heating types is unaccounted for, potentially affecting the classification performance.

In the multiclass approach, each instance is assigned a unique heating type label $\boldsymbol{y}$, e.g. $\boldsymbol{y}_i = [1, 0, 0, 0, 0, 0]$ for the $i^{\text{th}}$ sample/customer. In the multi-label approach, multiple heating types can be assigned, e.g. $\boldsymbol{y}_i = [0.7, 0, 0, 0, 0.3]$. We consider a linear combination of heating types based on annual electricity usage obtained from the energy declaration [7], e.g. 70% NEH and 30% DEH. This flexibility is an advantage of the neural network-based model over conventional machine learning methods, such as k-nearest neighbours (k-NN) and support vector machines (SVM) [1, 3, 8], which do not naturally handle multi-label data.

In addition, to handle imbalance between the different categories during the training process, the classes are weighted according to:

$$w_c = \frac{\sum_{c=1}^{C} \sum_{i=1}^{N_{train}} y_{i,c}}{C \sum_{i=1}^{N_{train}}} \tag{1}$$

where $w_c$ is the weight for class $c$, $C$ the number of classes, $N_{train}$ the number of training samples.

### 2.2 Peak Load Estimation Based on Replacement

In this paper, we propose a simplistic approach to estimating a change in the peak load resulting from a change in heating types by substituting smart meter data from SFD of similar types within nearby geographical locations. The rationale is that geographically close buildings from the same building period, and with similar size, have similar building characteristics. At the same time, it is based on actual measurement data which offers the ability to capture coincidence in the electricity consumption between consumers of similar and different categories without the need to model it explicitly. This process can be repeated for statistical confidence. However, this approach has two main drawbacks. Firstly, it is limited by data availability; while we can replace smart meter data with that of consumers from nearby areas, we cannot analyse the entire region if there is a lack of data outside this region. Secondly, it cannot be used for different demand-side management tools that alter the electricity consumption profile as it uses historical measurements. Nevertheless, it can provide an estimation of peak load using only a few parameters: building year, heated area, heating type, geographical location, and smart meter measurements.

The nearest neighbour that falls outside the analysed area should fulfil the following criteria:

$$|Y_i - Y_j| \leq 5 \text{ years} \tag{2}$$

$$\left|A_i^{temp} - A_j^{temp}\right| \leq 10\text{m}^2 \tag{3}$$

where $Y$ represents the construction year, $A^{temp}$ denotes the heated area, $i$ denotes the index of the SFD changing heating type, and $j$ denotes the index of the nearest neighbour. If there are no buildings within the heated area criteria, the criteria are relaxed. The smart meter measurements are linearly scaled to match the heated area of the building.

## 3 Results

### 3.1 Experimental Data Description

The dataset comprises of hourly smart meter measurements [9] and weather data [10] from a Swedish city in 2016. Additionally, building characteristics (construction year and heated area) and the usage of heating types were collected from the buildings' energy declarations. Table 1 displays the number of SFDs with various mixes of heating types. Here, the primary heating type is defined as the most energy-intensive on an annual basis among the six listed categories. It's important to note that SFDs might have more than two heating types, which is not reflected in the table. SFDs with two successive missing values were linearly interpolated. If three or more successive missing data points were encountered, the SFD was excluded from the analysis, as interpolating data over a larger span was beyond the scope of this paper. Consequently, 7585 SFDs remained, representing 14.3% of the SFDs in the city in 2016 [11].

Table 1 Number of buildings according to the primary and secondary heating types in the data set.

| | | Secondary heating type | | | | | |
|---|---|---|---|---|---|---|---|
| | | NEH | GSHP | AWHP | EAHP | AAHP | DEH |
| **Primary heating type (%)** | NEH | 1666 | 1 | 0 | 33 | 56 | 754 |
| | GSHP | 103 | 539 | 2 | 8 | 13 | 213 |
| | AWHP | 32 | 0 | 160 | 1 | 17 | 121 |
| | EAHP | 100 | 1 | 1 | 537 | 18 | 239 |
| | AAHP | 9 | 2 | 2 | 6 | 8 | 431 |
| | DEH | 159 | 10 | 10 | 139 | 723 | 1471 |

### *3.2 Classification of Heating Type*

The classification of primary heating types was carried out by incorporating the proposed multi-label approach. Six types of heating were considered: NEH, DEH, and four types of heat pumps: GSHP, AWHP, EAHP, AAHP. The consumer set was divided into a 60%/20%/20% train/validation/test set, ensuring an equal distribution of primary heating types across each set. The split was resampled to get an average generalisation performance. This involved dividing the dataset into five equal folds, with each fold being tested once, and the remaining data being split into training and validation. Notably, the model was retrained and reevaluated for each fold. Model hyperparameters were determined through a grid search over selected hyperparameters, with the combination yielding the highest averaged f1-score on the validation set across all six categories being selected. Further details on the hyperparameters are available in [5].

The performance on the test set for each heating type is depicted in Table 2 and Table 3. It can be observed that the performance decreased compared to the analysis in [5], which is understandable given the dataset includes more heating types and the added complexity of classifying SFDs with a mix of heating types. Nonetheless, the precision and recall demonstrate that the categories are to some extent distinguishable, even though misclassification occurs. The model showed high precision and recall for NEH. The model was however not able to distinguish AAHP from DEH. This could be attributed to buildings with AAHP being reliant on DEH for domestic hot water production, but also due to reduced coefficient of performance (COP) with decreasing outdoor temperature. Additionally, misclassifications between the two types of waterborne heat pumps (GSHP and AWHP) suggest similarities in their characteristics. On the other hand, more training samples of AWHP could possibly increase the precision and recall of this class. Moreover, misclassifications of EAHP, GSHP and AWHP as DEH may be attributed to a higher energy intensity of these samples, possibly due to supplementary electric heating or poor efficiency of the heat pump. This should be further investigated.

Table 2 Confusion matrix of the test performance using the proposed deep-learning framework. Values are averaged $\pm$ standard deviation over five runs normalised to the class size.

| | | Predicted heating type (%) | | | | | |
|---|---|---|---|---|---|---|---|
| | | NEH | GSHP | AWHP | EAHP | AAHP | DEH |
| **Actual[d] heating type (%)** | NEH | 89.8 $\pm$1.2 | 4.1 $\pm$0.8 | 1.0 $\pm$0.6 | 1.2 $\pm$0.5 | 0.3 $\pm$0.2 | 3.7 $\pm$1.0 |
| | GSHP | 3.1 $\pm$0.8 | 63.9 $\pm$2.8 | 13.3 $\pm$4.7 | 7.7 $\pm$0.8 | 0.5 $\pm$0.4 | 11.5 $\pm$2.7 |
| | AWHP | 1.8 $\pm$1.5 | 23.2 $\pm$10.9 | 44.7 $\pm$8.7 | 11.8 $\pm$3.5 | 0.3 $\pm$0.6 | 18.1 $\pm$4.0 |
| | EAHP | 0.4 $\pm$0.4 | 6.5 $\pm$1.0 | 5.7 $\pm$2.3 | 68.6 $\pm$2.4 | 0.2 $\pm$0.4 | 18.5 $\pm$2.1 |
| | AAHP | 1.7 $\pm$0.9 | 7.9 $\pm$2.4 | 3.1 $\pm$1.3 | 5.9 $\pm$2.3 | 1.1 $\pm$0.0 | 80.4 $\pm$1.4 |
| | DEH | 2.4 $\pm$0.6 | 8.3 $\pm$1.0 | 5.3 $\pm$2.3 | 8.4 $\pm$2.0 | 1.3 $\pm$0.8 | 74.2 $\pm$2.9 |

Table 3 Test performance of the deep-learning classifier using multi-label targets. All performance values in the table are averaged $\pm$ standard deviation over five runs*.

| Heating type | Precision (%) | Recall (%) | $F_1$−score (%) | Total accuracy (%) |
|---|---|---|---|---|
| NEH | $95.6 \pm 1.0$ | $89.8 \pm 1.3$ | $92.6 \pm 0.1$ | |
| GSHP | $54.1 \pm 3.7$ | $63.9 \pm 2.8$ | $58.5 \pm 2.4$ | |
| AWHP | $31.2 \pm 5.6$ | $44.7 \pm 8.7$ | $36.2 \pm 4.7$ | $71.8 \pm 1.3$ |
| EAHP | $62.2 \pm 2.7$ | $68.6 \pm 2.4$ | $65.2 \pm 1.8$ | |
| AAHP | $10.7 \pm 3.6$ | $1.1 \pm 0.0$ | $2.0 \pm 0.1$ | |
| DEH | $70.3 \pm 1.3$ | $74.2 \pm 2.9$ | $72.2 \pm 1.8$ | |

* By dataset re-partitions, followed by re-training and re-testing.

### *3.3 Peak Load Estimation*

The peak load analysis focuses on the impact of NEH consumers transitioning to heat pumps. As NEH systems as the main heating type often are distributed via a water-borne system, we consider the transition to heat pumps with the same type of heat distribution, i.e. GSHP or AWHP. The analysis entails aggregation of randomly selected consumers of the considered heating types, and conducting geographical analyses.

*3.3.1 N Aggregated Customers:* Fig. 2a shows the peak load of 50 randomly selected aggregated SFDs with NEH, replaced

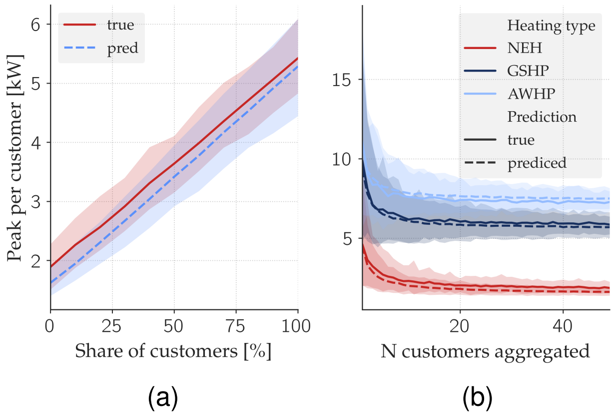


Fig. 2 Aggregated peak load of randomly selected SFD, repeated 100 times for statistical confidence. a) shows $N = 50$ aggregated SFD with NEH as the primary heating type, replaced by SFD with either GSHP or AWHP. The share of customers indicates the number of customers with heat pumps. b) shows the results of $N$ aggregated customers of each category. The shaded area represents the 95% confidence interval.

by SFDs of similar type with GSHP or AWHP, repeated 100 times for statistical confidence. The analysis considers both energy declaration categories and classifications from the deep-learning model. All SFD are re-categorised based on the model obtained from the training and validation set, repeated for all folds. A linear trend can be seen as the proportion of heat pumps increases, nearly tripling the peak load. Additionally, there is only a minor difference between the categories extracted from the energy declaration and the predicted categories from the classification. The difference diminishes as the number of heat pumps increases. Initial deviations may be attributed to the model classifying some NEH samples as heat pumps or DEH. Given the model's high classification rate with NEH, this suggests that misclassified samples are likely more energy-intensive than typical NEH buildings, possibly due to a change in heating system, or the usage of supplementary heating. Notably, previous analyses have indicated that some SFD has changed the heating system since the energy declaration was issued [5], indicating that some energy declarations may be outdated.

Due to the coincidence factors being more or less constant (see Fig. 2b ), the results (aggregated peak/N customers) would look similar for various numbers of aggregated customers, with deviations apparent only for a small number of aggregated customers (N<15). Furthermore, no significant difference exists between coincidence factors for the class label taken from the energy declaration, and those from classifications with deep-learning, suggesting that misclassifications may not significantly impact post-analysis results.

*3.3.2 Geographical Analysis:* A geographical analysis was conducted to assess the impact of a scenario in which all buildings with NEH transition to either GSHP or AWHP. This analysis demonstrates the practical application of heating type classification. Predictions based on the classifier were utilized, with the estimated peak loads averaged across the different data splits. The results are comparable to using class categories directly from the energy declaration, which indicates the usefulness of the classification on consumers with unknown heating type. Fig. 3a displays the geographical distribution SFDs, while Fig. 3b illustrates the share of NEH as the primary heating type. It's important to note that this analysis covered only 14.3% of the total number of SFDs in the area [11]. This due to limitations in past years' collected measurements. For comprehensive coverage, all SFD should undergo classification utilising smart meter measurements. Furthermore, Fig. 3c depicts the original aggregated peak load of the areas, whereas the new peak estimated by replacing smart meter measurements from similar SFDs can be observed in Fig. 3d. This estimation aids in identifying areas at risk of increased peak load due to SFDs transitioning from NEH to heat pumps. In general, it can be seen that the peak load increase is proportionate to the share of heat pumps, as depicted in Fig. 3b. However, variations may occur depending on the coincidence factor between consumers, which can be influenced by the category, as shown in Fig. 2b.

## 4 Conclusion

This paper evaluates a deep-learning model for heating type classification and its impact on peak load. Specifically, the study analyses the effects of single-family households (SFDs) transitioning from non-electric heating (NEH) to heat pumps by replacing smart meter data from similar types of SFD. It was observed that the classification performance decreased compared to the previous analysis, likely due to the dataset's inclusion of more heating types and the complexity of SFDs with multiple heating sources. However, precision and recall metrics suggest that the categories remain partially distinguishable, despite instances of misclassification. The peak load analysis reveals only a minor difference between true and predicted class labels, indicating that the classification model effectively groups similar types of buildings. This underscores the application of the classification model. Future work will involve further analysis of misclassified samples and comparison of peak load estimation with replacement versus a bottom-up approach.

## 5 Acknowledgments

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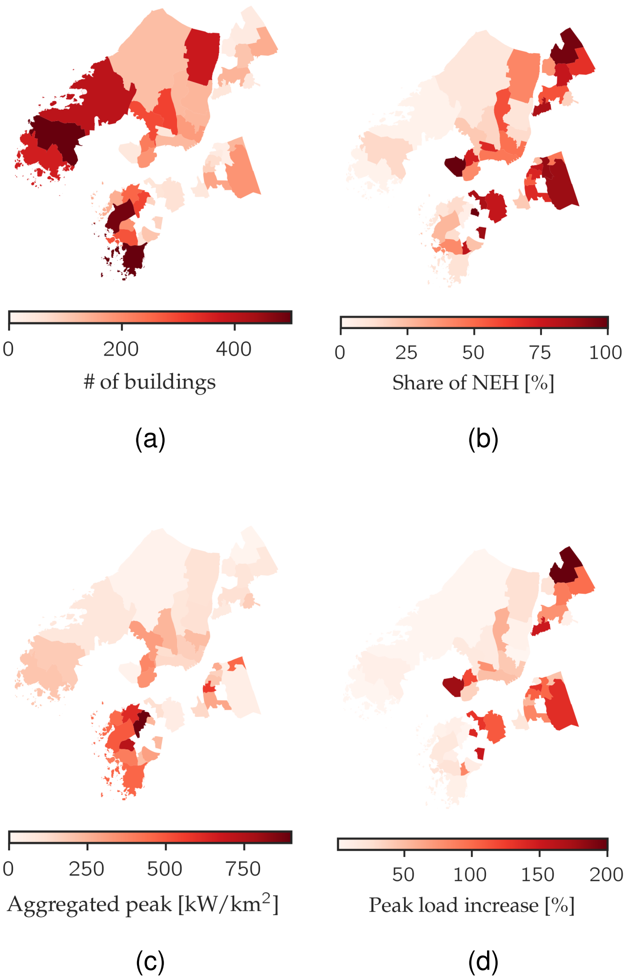


Fig. 3 Geographical distribution illustrated for a) the number of consumers, b) the share of SFD with NEH as the primary heating type, c) the original aggregated peak load, and d) the increase in peak load when 100% of buildings with NEH switch to either GSHP or AWHP.

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