Multi Vector Energy Demand Modelling for Predicting Low-Carbon Electrical Heat Loads

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***Abstract*— The move to decarbonize heating through the adoption of heat pumps, will alter network load magnitudes and shapes at the low voltage (LV) distribution level. Due to the lack of monitoring at the distribution level, it is of interest to develop methods to infer LV network conditions in the absence of complete data. Limited uptake of domestic heat pumps in the UK limits presently available data to use for localized predictions sensitive to household specific time of use and magnitude variability. This work demonstrates a methodology for inferring potential future electrical heat load from existing household electrical and gas demand data, facilitating the prediction of future electrical heat load from limited data. Historical recurring load profiles from gas and electrical data are identified and generalized using a k-means clustering approach. The relation of these recurring load profiles with respect to each other is mapped using a through the construction of a Markov model with transition probabilities trained from household electrical and gas demand data. The use of this approach to infer future electrical heat load from implied premises occupancy and utilization is then demonstrated in a simple case study.**

Keywords—load modelling, low carbon heat, distribution networks

I. Introduction

The decarbonization of residential heating through the adoption of low-carbon heating solutions, such as heat pumps and increased building efficiency, is a major strategic priority for Europe [1] [2] , North America [3] and in general for developed nations with cold seasonal minimum temperatures and a high dependency on fossil fuels for heating. In both the UK and US, air-source heat pumps present a least-regrets option for typical residential buildings currently dependent on fossil fuels [1] [4]. Furthermore, steep increases in wholesale natural gas prices throughout 2021 [5] and ongoing at the time of writing are driving an immediate need to rapidly identify and implement heating solutions not dependent on natural gas as a matter of international energy security.

Against this backdrop, there are the specific technical challenges associated with high levels of heat pump uptake at the distribution level. Residential heat pumps are fundamentally a LV connected load and therefore characteristically have poor visibility and zero direct control by the distribution network operator [6]. Each heat pump connected to a distribution network is roughly equivalent to the addition of another household in terms of winter peak energy consumption and peak power [7]. The widespread connection of domestic heat pumps at the distribution level therefore stands to significantly alter existing distribution network load profiles, with corresponding risks to asset voltage and thermal ratings [8].

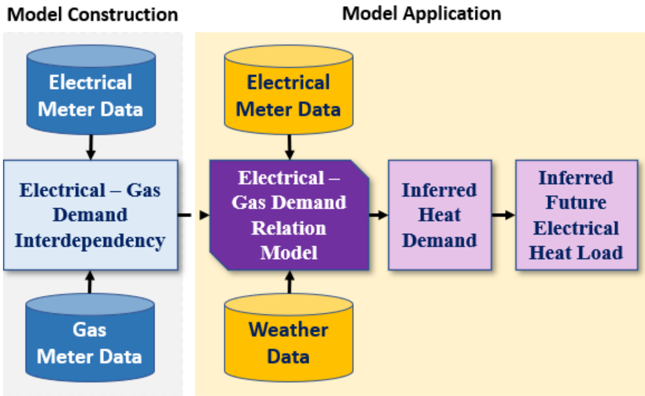

Fig. 1. Concept overview; electrical – gas interdepdency from metered households is exploited to construct heat demand predictions for future electrical heat load

To date the task of sufficiently characterizing potential network impacts has been addressed in part by academic studies, supported by industry and government driven projects [9] [10] that provide the bulk of the load data drawn from customer trials.

Previous research has examined transmission level impacts, and further work has been performed to develop LV network impacts based on insights derived from trial data [11]. An ongoing source of difficulty for forecasting future electrical heat load is localization of existing models or datasets to distribution network level scales. Protopapadaki et al. addressed this through the development of a parameter-based approach that correlated high-fidelity building parameters with building heat demand in order to predict local electrical heat load, sensitive to local geospatial dependencies [12]. Similarly, Flower et al. examined the heterogeneity of residential heat demand based on metadata available from census records and other local datasets [13].

Within the UK, various industry projects have been undertaken to support the examination of potential electrical heat demand outputs versus existing distribution network asset ratings. Most recently, HEAT-up, led by SP Distribution [14] developed a methodology for identifying potential heat pump uptake sensitive to local influences such as physical property parameters and household demographics. Whilst providing a view of neighborhoods more or less likely to adopt electrical heat pump technology, this work did not examine the potential local variability in electrical heat load driven by variable physical and behavioral parameters such as building construction and demographics.

This is a peer reviewed, accepted author manuscript of the following research contribution: Anderson, A., Stephen, B., & McArthur, S. (2022). Multi vector energy demand modelling for predicting low-carbon heat loads. Paper presented at IEEE PES Innovative Smart Grid Technologies Europe 2022, Novi Sad, Serbia.

978-1-6654-8032-1/22/$31.00 ©2022 Crown

A. Aims

This work will examine the possibility of using existing household electrical meter data paired with gas meter data to infer household-specific heating activity, and therefore inform potential future electrical heat load and corresponding distribution network impact. By making the assumption that existing household gas demand data informs household-specific heating time of use and magnitude characteristics, this work seeks to explore whether these characteristics can be inferred through more commonly available household electrical meter demand data.

II. Methodology

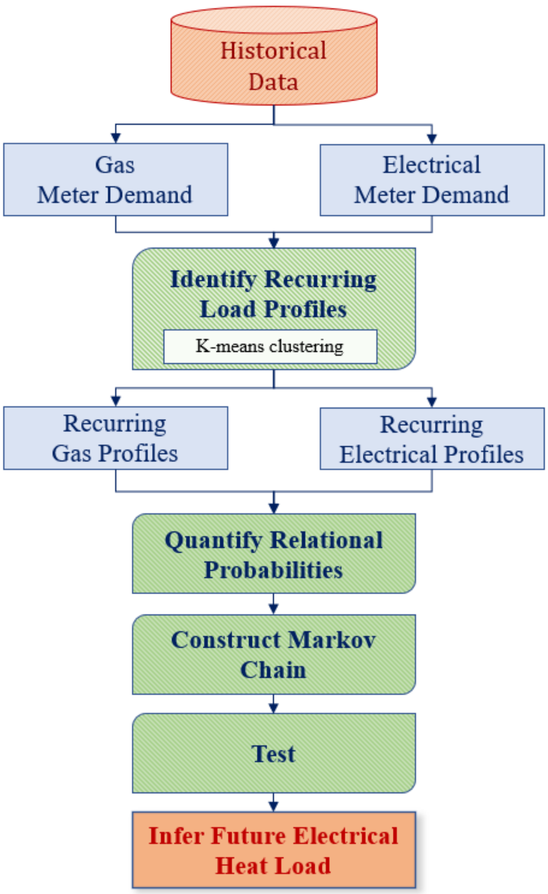

Fig. 2. Methodology for overall process for inferring future electricla heat load from historic household gas and electrical datasets

This work describes an approach for generating electrical heat load from existing household electrical meter data. Fig.1 demonstrates the relationships between the model construction, data and test components.

Firstly, paired sets of electrical and gas data for aggregations of households ranging are randomly selected from the training dataset. K-means clustering is applied to each customer aggregation in order to identify the three best fitting recurring gas and electrical load shapes. Each load shape consists of 48 half-hourly magnitudes that correspond to a 24-hour period.

In order to link the extracted load shapes to probability of occurrence, the occurrence of these load shape clusters with respect to time is quantified, and a corresponding probability transition matrix defined in order to construct a simple Markov chain that defines the probability a customer group will be in a specific gas-type cluster for a given electrical-type cluster.

The constructed model is then tested using electrical meter data as an input combined with the fitted shape and probability model in order to test how well existing gas demand can be inferred from electrical data. Further to this, the model is then applied to demonstrate future electrical heat load.

A. Datasets

The Energy Demand Research Project (EDRP) dataset [15] was used in order to provide the electrical and gas meter data for this study. This project monitored 18,000 households in the UK with smart meters in order to collect energy usage data. This data is anonymized and has no direct geographic metadata but the households involved capture the breadth of UK housing stock and demographics. The trials began in 2007 and finished towards the end of 2010. ACORN demographic information is available in order to categorize demand behavior by demographics.

This work used a subset of 1,117 pairs of data which featured concurrent gas and electrical data for single households.

III. Recurring Load Profile Identification

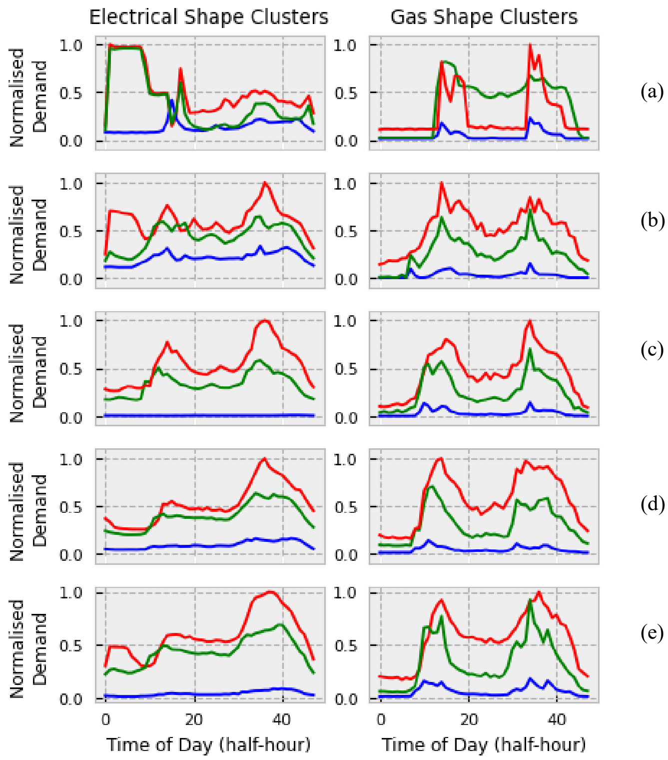

Fig. 3. Recurring Electrical Shape Clusters and recurring Gas Shape Clusters identified via k-means for a single household (a), five (b), ten (c), fifteen (d) and twenty (e) customer aggregations

In order to reduce the continuous time series data into recurring shape profiles, a simple k-means is applied to each customer set of electrical and gas demand data in order to group daily load profiles to the nearest defined clusters. Typically gas and electrical profiles retain the same basic shape but differ in magnitude depending on the season. In order to replicate this with an appropriate level of fidelity, three clusters were selected for each gas and electrical set for this particular study. Fig. 3fig demonstrates a set of obtained high, medium and low gas clusters (C_H^G, C_M^G, C_L^G) and corresponding electrical clusters (C_H^E, C_M^E, C_L^E)for randomized aggregations of 1, 5, 10, 15 and 20 customers, where each defined cluster C, consists of a set of 48 half hourly shapes. The convergence on a smoother cluster set versus number of customer is observable; this indicates that selected cluster sets have decreasing general applicability versus reduced number of customers. Similarly, for the customer groups illustrated, there is a broad correlation between time of day activity from low to high activity clusters for specific customer sets.

IV. Markov Model Construction

A. *Definition of Transition Probability Matrix*

Each customer group has been simplified from continuous time series data to three electrical and three gas clusters consisting of 48 half-hourly segments. The relationship of these clusters with respect to time for a randomized group of five customers over a two-year period is shown in Fig. 4.

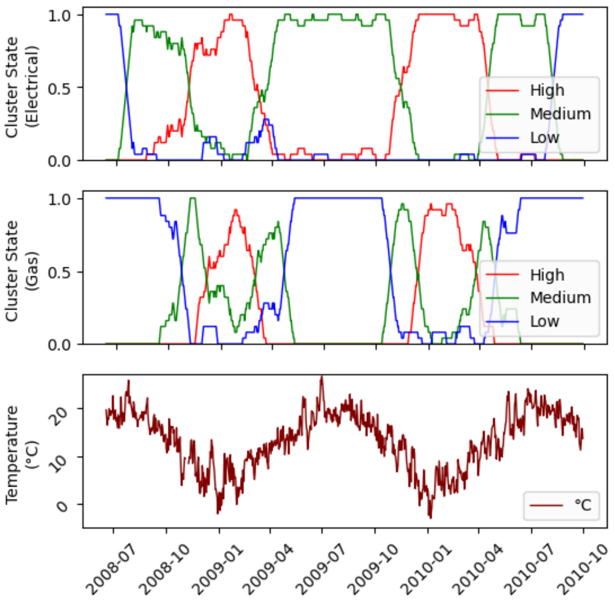

Fig. 4. Demonstratation of Gas cluster state (top) and Electrical cluster state (middle) and daily average temperature (bottom) with respect to time, for a five-household aggregation

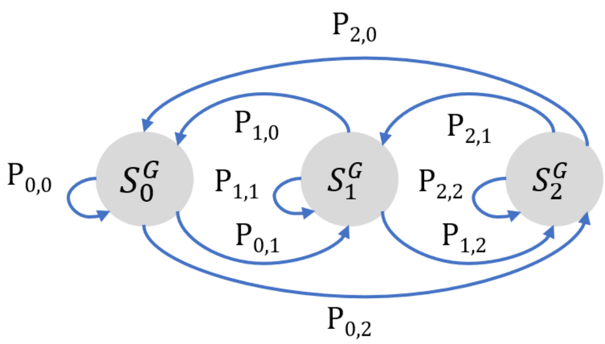

Fig. 5. Generic three-state Markov chain element for model; for each known electrical state S_n^E there are three possible gas states S_0^G , S_1^G and S_2^G with corresponding transition proabilities

For this application the electrical cluster state is known, and therefore the probabilities of the gas cluster state given the known electrical state is of interest. For each electrical state S_n^E, there is a corresponding transition probability matrix for the gas transition states. This is then represented generically as a 3x3 transition probability matrix as shown in (1), where each row sum is equal to 1, as per (2).

$$P(S_n^E) = \begin{bmatrix} P_{0,0}^G & P_{0,0}^G & P_{2,0}^G \\ P_{0,1}^G & P_{1,1}^G & P_{2,1}^G \\ P_{0,2}^G & P_{1,2}^G & P_{2,2}^G \end{bmatrix} \tag{1}$$

$$\forall x \sum_{i=0}^{3} P_{x,i} = 1 \tag{2}$$

B. *Extraction of Customer Specific Transition Probabilities*

For each state S_n, the number of occurrences in the paired demand data was computed and then scaled by the total length of the paired demand data L. For each discrete electrical state S_0^E, S_1^E, and S_2^E, the corresponding probability of the gas states, S_0^G, S_0^G and S_0^G was determined as per (3). The output of this process is to provide a probabilistic prediction of gas state based on electrical state.

$$P_{n,m}^G = \frac{\sum S_{n,m}^G}{L} \tag{3}$$

V. Model Testing

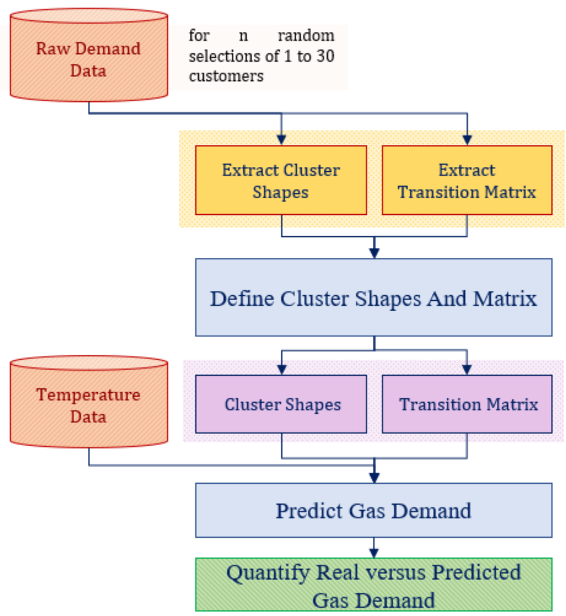

Fig. 6. Workflow for extracting cluster shapes and transition matrices from training datasets, application of global shapes and matrices to raw test electrical demand data in order to construct a quantifiable prediction

Using the transition probability defined in (1) combined with the cluster shapes derived in Section III, it is now possible to generate a predicted gas state and demand shape based on electrical state. In order to incorporate sensitivity to local temperature, this is further modified as per (4) by using the temperature versus daily demand relationship provided in [16].

$$D^{G}_{n,m} = P(S^{E}_{n}) * m * T^{°C} + c \quad (4)$$

In order to test the performance of the model the workflow shown in Fig. 6 is applied. Randomized sets of customers from 1 to 30 are drawn from the training dataset, with the corresponding cluster shapes and transition matrices derived for each set. The defined clusters and transition probabilities, coupled with UK daily average temperature data [17], are then applied to the raw electrical demand data for the specific customer set in order to construct a prediction for gas demand.

The output of this process is to generate a half-hourly predicted gas demand generated using the shapes from the training data, which can be compared versus the half-hourly real demand of the randomized test dataset. Fig. 7 demonstrates the known electrical demand, the real gas demand and the inferred gas demand from the developed model for a one-month winter period for an aggregation of fifteen customers. The half-hourly prediction combined with 12-hourly rolling average is displayed for each demand type. Fig. 8 illustrates the mean percentage error for customer group sizes from 1 to 30, with corresponding standard deviation.

A. Results

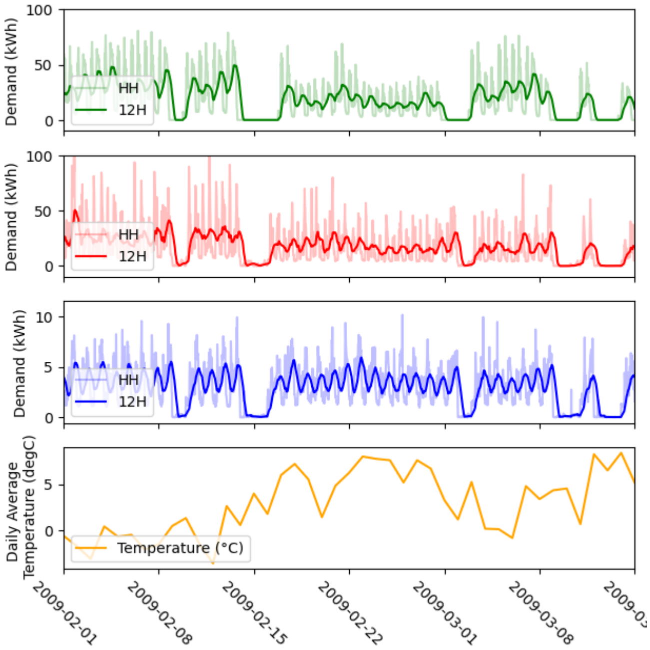

Fig. 7. Predicted Gas demand (top), actual Gas demand (middle) and actual Electrical Demand (bottom) for single group of fifteen customers over a one-month winter period

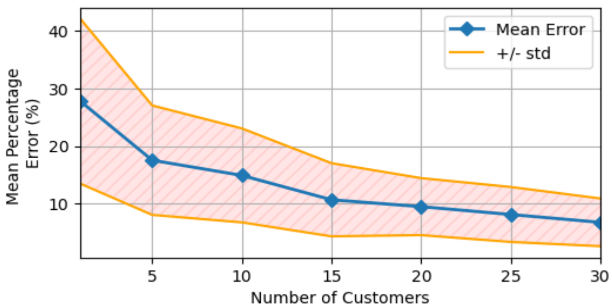

Fig. 8. Mean percentage error for seasonal peak daily demand versus number of customers

VI. Inference of Future Electrical Heat Load from Electrical Heat

A simple multiplier is applied to transform the inferred gas demand into an equivalent electrical heat load via the coefficient of performance (COP). A static coefficient of performance is used but for specific studies a COP sensitive to temperature conditions and specific manufacturer heat pump ratings could be applied. Fig. 9 demonstrates electrical heat load derived from electrical meter state for a customer group size of 15, with penetrations ranging from 25% to 100%.

$$D^{E}_{m,n} = \frac{D^{G}_{m,n}}{COP} \quad (4)$$

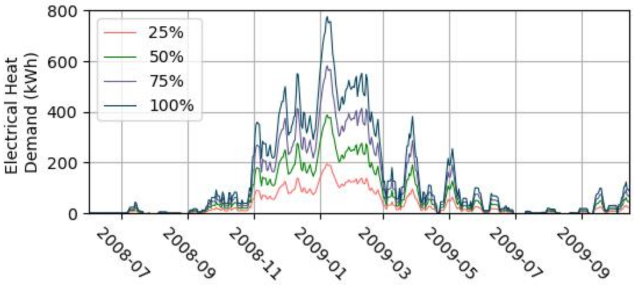

Fig. 9. Daily electrical heat load inferred from electrical meter state for 15 customer aggregation

VII. Discussion

In order to facilitate penetrations of LV-connected domestic electrical heat pumps to target levels [18], appropriate tools must be developed in order to better characterize the local LV network impacts incurred by high penetrations. The proposed model in this study outlines an approach for generating half-hourly electrical heat load profiles on the basis of existing household electrical and gas meter data. This provides a demonstration of how limited available datasets can be used to derive improved insights for future electrical heat load in a power distribution network context, traditionally constrained by limited data availability. It is envisioned that this model could be coupled with a networks type study paired with existing smart meter data in order to forecast potential electrical heat load with respect to local asset ratings.

The developed approach simplifies existing customer demand data into three cluster shapes, with further magnitude refinement sensitive to local daily average temperature. Due to the exploitation of electrical household meter demand, this approach could be used to infer future electrical heat load for off-gas households which are considered a high priority in the UK strategy for electrical heat pump installation [1].

Fig. 7 demonstrates that the simplified shapes obtained via k-means are able to generally follow the time of use characteristics of household gas demand. Coupled with historical temperature data, these template shapes are then scaled sensitive to local daily temperature at the time of measurement. However, this methodology is reliant on appropriate source electrical meter data. The training dataset offers only a limited representation of potential UK household heating routine diversity, and therefore presents a limited view of household electrical to gas dependency. Further testing and cross-examination versus present and future household meter datasets [19] is desirable in order to more thoroughly quantify this relationship.

Similarly, this methodology is reliant upon the assumption that the majority proportion of household gas demand is due to heat load as opposed to cooking or other auxiliary non-temperature dependent functions. Therefore, when translating this approach to examine specific distribution network impacts, the local context for non-heat type gas demand should be incorporated.

VIII. Conclusion

Decarbonisation of heating poses a threat to distribution networks that could stall its widespread adoption. Better models of uptake and consequence are required to quantify these risks to distribution feeders posed by residential premises with heat pumps. This work has demonstrated a concept for inferring future electrical heat load at a half-hourly resolution, using monitored electrical demand data, local temperature data and relational probabilities extracted from historic gas demand data as inputs. This facilitates the prediction of future electrical heat load for distribution networks in the absence of evidence from large scale installations [18]. The developed methodology complements existing works as this offers a household specific magnitude and time of use prediction, from the associated metered electrical load, as opposed to the highly averaged results of previous works [11].

This methodology represents a broad approach to developing household specific predictions based on inferred premises utilization and further work could be applied in order to develop more refined time of use estimations rather than fitting data to 24-hour shape patterns. Further development to more completely quantify the relationship between existing electrical demand and household heat demand could be performed, particularly developing further sensitivity to time of use dependencies between electrical and gas load.

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