FUTURE RESIDENTIAL ENERGY DEMAND MODELLING – A DATA DRIVEN APPROACH

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Overview

The objective of greenhouse gas-neutral economies and associated advancements in low-carbon technologies lead to a transformation of the way electricity and heat are supplied and consumed. Lower capital costs of renewable energy technologies, coupled with rising energy procurement expenses, have encouraged the adoption of decentralized, on-site generation systems such as photovoltaics, heat pumps, and electric vehicles. This transformation increases overall electricity demand but also reshapes load profiles in ways that necessitate new modeling approaches. Understanding the fundamental drivers, notably occupant behavior, is vital, as the electrification of mobility and heating accelerates, leading to pronounced variability and potential flexibility in consumption patterns.

In response, advanced models incorporating occupant-centric data and sector coupling are required to accurately capture the interconnected behavior of domestic appliances, space heating, and electric vehicle charging. The use of emerging artificial intelligence techniques, particularly neural network-based methods from the field of natural language processing, is promising for generating realistic occupant activity and mobility schedules. These synthetic schedules lay the foundation for holistic simulations of residential energy demand profiles across multiple domains, thereby enabling robust analyses of cost-minimal building energy systems and the broader impacts on energy infrastructures.

Methods

To capture the complexity of household-level occupant behavior in a unified framework, we propose a novel single-step neural network approach that jointly models individual activities and mobility states for all household members. This integrated architecture circumvents the limitations of multi-step processes, where mobility and at-home activities are generated separately and then merged, e.g. [1]. By treating an entire household as the fundamental modeling entity, correlations among individuals - such as synchronization of meal times or simultaneous departures - are directly learned.

Drawing from representative time use and mobility datasets, we train deep neural network models to process multi-day activity sequences at a high temporal resolution. Each input consists of demographic variables (e.g., age, occupation), along with temporal information (e.g., day of the week) encoded through sinusoidal and embedding layers. The networks allow for the detection of complex dependencies that span multiple days and multiple individuals within the same household.

From the resulting synthetic schedules, we derive consistent electricity demand profiles by assigning relevant household appliances, heating loads (e.g., heat pumps), and charging events for electric vehicles to each modeled activity state. This holistic method enables the generation of realistic, intra-household-correlated energy demand data, thereby providing a robust basis for assessing future flexibility potentials of the household sector.

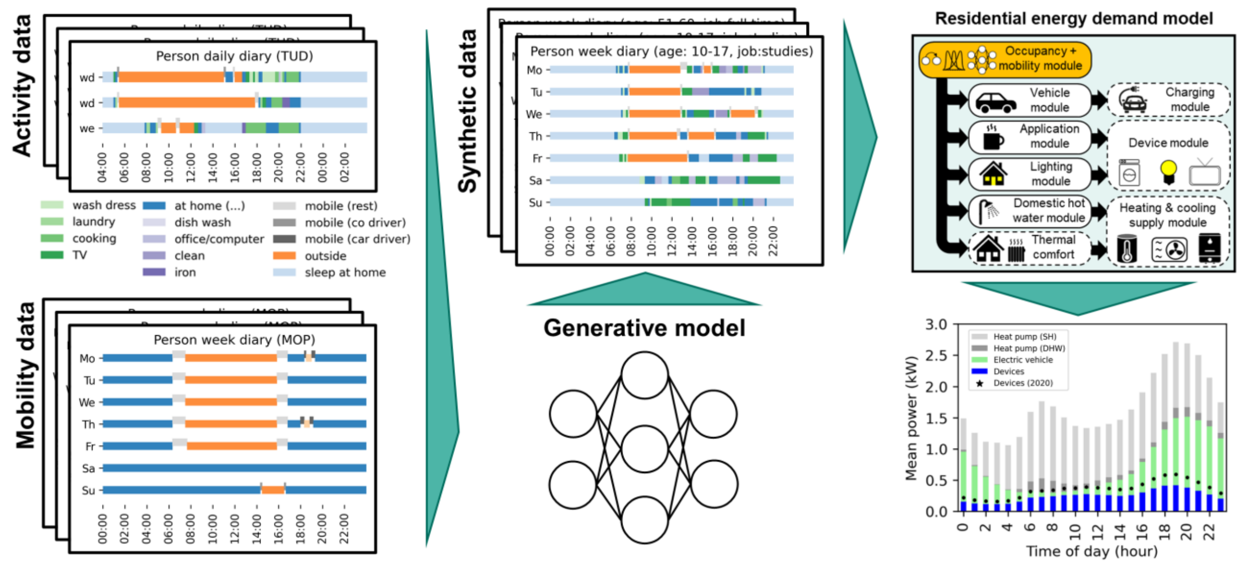

Figure 1: graphical representation of the proposed data driven approach for consistent residential energy demand modelling

Results

The proposed single-step neural network demonstrates represents empirical data well and can generate high-quality synthetic household activity data with regard to fidelity, diversity, and generalization [2]. Day-to-day autocorrelation, state duration, and inter-individual synchronization are captured more effectively than baseline approaches. Household members' shared activities and mobility patterns exhibit realistic consistency. The model thereby delivers high-quality activity schedules that extend beyond one day, forming the basis for consistent, multi-day electricity demand profiles, including heating and mobility demand.

Conclusions

By integrating large-scale time use and mobility datasets in a single-step, household-level modeling approach, we overcome the limitations of traditional Markov-based methods [3]. Our deep neural network framework captures complex, long-term dependencies while reflecting intra-household correlations critical for realistic activity and mobility patterns. This enables the generation of multi-day occupant schedules that not only mirror observed behavior but also facilitate consistent demand profiles for domestic appliances, electrified heating, and electric vehicles. Consequently, analysts and decision-makers can evaluate diverse decarbonization pathways and flexibility scenarios with increased accuracy.

References

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