Distribution System Load Synthesis through Smart Meter Data Analytics

Partik Kumar (2018EEZ8156)

The ability to assess energy consumption behaviour is important for utility companies in de signing effective demand reduction programs. Understanding household appliance usage patterns allows for more precise energy consumption behaviour assessment for a community load. Non Intrusive Load Monitoring (NILM) is a key tool in identifying appliance-level activities, offering significant insights into energy usage without the need for installing individual sensors at each appliance. NILM's ability to disaggregate household-level consumption into appliance-specific data directly contributes to distribution system load synthesis, enabling utility companies to derive insights about total load composition and its temporal variations from smart meter data.

Distribution system load synthesis involves reconstructing a detailed and accurate load profile for the entire distribution network by leveraging smart meter data analytics. NILM frameworks provide the foundation for this synthesis by identifying the contribution of various appliances to overall load, allowing for more precise modelling of load behaviour at the feeder, transformer, and community levels. NILM outcomes can also be utilized to build appliance recommendation systems, detect faulty appliances, improve load forecasting, and provide real-time feedback on energy consumption. However, existing NILM models suffer from two main challenges: limited accuracy and high computational complexity. As the number of appliances within a household increases, these challenges become even more pronounced, limiting the practical deployment of these models in real-world applications.

This thesis aims to address these limitations by proposing novel NILM frameworks that en hance both solution accuracy and computational efficiency. The proposed frameworks integrate several advancements, including the modelling of inter-appliance operational dependencies, con siderations of the differential in appliance operating states over time, and appliance switching and operating duration patterns into the NILM modelling process. These innovations make the frame works particularly well-suited for low-sampling-rate datasets typically captured by utility-installed smart meters, ensuring their applicability in real-world energy management systems.

The thesis develops NILM models based on optimization techniques, the factorial hidden Markov model (FHMM), and machine learning approaches. To validate the proposed frameworks, case studies are performed using three publicly available NILM datasets: AMPds, REDD, and UKDALE.These datasets, collected from different geographic regions, allow for a comprehensive evaluation of the models across varying household conditions and data characteristics. The results demonstrate that the proposed frameworks outperform state-of-the-art NILM models in terms of both accuracy and solving time. In some cases, the accuracy is significantly higher, while in others, the proposed frameworks provide comparable accuracy with much lower computational complex ity, making them more practical for real-world deployment.

The research presented in this thesis lays the groundwork for further advancements in NILM and its applications, including demand flexibility estimation, appliance recommendation systems, and real-time energy monitoring systems. By addressing the challenges of existing NILM models, this work contributes to the development of robust, fast, and accurate NILM frameworks that can be applied to real-world energy management tasks.

Key Terms: LoadSynthesis, Non-Intrusive Load Monitoring, Factorial Hidden Markov Model, Change Point Detection, Load Disaggregation, and Energy Consumption Behaviour.