Deep learning approach electricity consumption monitoring

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1 Background

Many stakeholders can benefit from knowing the energy consumption of different devices within a home. It helps users understand their bills, retailers to plan tariff systems and distributors to plan network expansion. However, placing meters on all devices is expensive. Instead, we will determine device level power consumption based on half-hourly aggregated data available from smart meters. For many devices, validation of power consumption can be detected visually by trained observers. This project will seek "ground truth" use of several device types by visually inspecting the estimates of state-of-the-art disaggregation techniques, and sub-metering a small number of homes. This will allow the accuracy of the algorithms to be assessed and provide training data for more sophisticated supervised learning techniques.

Energy disaggregation is one of the emerging methods to build intelligent Energy Management Systems (EMS) for conservation and efficient consumption [1]. In principle, disaggregation is a form of blind-source separation where the aim is to reconstruct individual appliances power consumption from the house main reading. The disaggregation objective is to infer the consumption profiles for microwave, washing machine and kettle from the main consumption profile. This approach is referred to as Non-Intrusive Load Monitoring (NILM), where the main power reading is the only input required for a model to reconstruct the individual appliances profiles. However, unlike many of the conventional blind-source separation problems, disaggregation seems to be a non-trivial task. A typical household contains many appliances with different consumption signatures and various activity duration. With many devices being active at the same point of time this task become more challenging.

An alternative approach to NILM is to apply Intrusive methods, where meters are installed at each appliance to record direct consumption measurements [2]. While the latter method provides an accurate breakdown of consumption per appliances, their intrusive nature and the requirement for individual smart meter per appliance make them impractical and expensive [3]. In contrast, NILM methods are relatively cheap considering the requirement for a single smart meter only. Many countries are already changing their energy policies to mandate the installation of smart meters at every household. The new direction in metering is to to upgrade all the electricity network with smart meters. These meters provide real-time consumption feed to customers and utilities. These policy changes bring high potential for NILM systems, where they can be deployed at a large scale, utilising the existing infrastructure and available data sources. With such system, utilities can provide many benefits to customer, retailers, distributors and decision makers.

2 Motivation

This project is motivated by recent development in deep neural networks, which have revolutionised many machine learning domains such as machine translation and computer vision. Hence these techniques have the potential to provide outstanding results compared to conventional methods of energy disaggregation.

3 Objective and impact

The main objective of this project is to build NILM model based on Deep Neural Network Architectures. Stemming from this objective, the project aims to improve the accuracy of NILM models in the context of Deep Neural Network architecture. Secondly, what reinforcement learning techniques can be used for this specific case of energy disaggregation.

Obtaining trustworthy disaggregated estimation has a significant impact on customers, retailers, distribution companies and regulators. We summarise the project significance on different sectors as follow:

- Providing customers with a timely disaggregation information can help them alter their behaviour in order to reduce their total energy consumption. Studies suggest 3% to 10% reduction in consumption when customers are made aware of their consumption behaviour on the appliance level.

- Feedback given to both retailers and customers regarding reasons for consumption spikes can help reducing the number of complaints due to "bill shock" when, for example, hot or cold weather causes unusually high electricity consumption.

- Accurate disaggregation information will help the retailers designing new tariffs, such as time-of-use tariffs, which will become necessary as we move toward intermittent renewable, and solar which is minimal at the time of the current evening peak.

- Another aim of energy disaggregation is to find different trends in electricity usage. This information will support decision making in distribution companies by providing a better understanding of customers patterns. For example, are more people using air conditioners, are the same number of people using them for more hours, or are the air conditioners just using more power? This knowledge allows better planning of network capacity.

- Accurate disaggregation is essential for regulators to validate compliance with demand response contracts. This technology would enable emergency measures. For example, if air conditioner use had been banned when the transmission towers were blown down by the recent South Australian storm, then it may have been possible to prevent the tripping of the Victorian interconnect, preventing the state-wide blackout. Such a ban could only be implemented if there is a way to detect use of air conditioners.

References

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