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Development of an Intelligent System for Smart Home Energy Disaggregation Using Stacked Denoising Autoencoders

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Abstract

Energy sustainability remains one of the biggest challenges for the Philippines' energy sector with 51% of the demand coming from the residential and commercial sectors. Intelligent energy monitoring systems play a key role with the opportunity to contribute sizeable amount of energy savings by providing meaningful consumption feedback to home owners. While smart meters provide an ideal ubiquitous energy monitoring solution, these devices lack appliance-level feedback. In this study, we present a concept of augmenting smart utility meters with an energy disaggregation method using Stacked Denoising Autoencoders to provide appliance-level feedback to home owners. We evaluate the results using absolute mean loss and proportion of energy correctly assigned as metrics for the signal disaggregation. The results show that the model was able to decompose an aggregate appliance signal and provide an itemized appliance-level power consumption.

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1. Introduction

In 2014, the Department of Energy Philippine Power Statistics have identified that the combined residential and commercial power consumption alone comprises 51% of the total electricity demand for the year and is expected to grow in the upcoming years[1]. This large consumer base presents a key opportunity for intelligent energy management systems to play a substantial role as part of the nation's energy sustainability solution.

Studies have shown that providing households with intelligent energy monitoring solutions with meaningful appliance consumption feedback results in significant energy savings as high as 12% of the total energy consumption[2]. Thus, micro-scale management of residential and commercial power usage can contribute sizeable difference in the long run creating an enormous potential market for intelligent energy monitoring systems.

Commercially available are household monitoring solutions consisting of wireless sensor networks and smart plugs with software packages that provide appliance level data along with visual interfaces and personalized recommendations. However, these solutions have drawbacks such as cost per appliance monitor and installation effort[3]. Another study by Louis et al also has shown that majority of these energy monitoring solutions failed to take into account the collective consumption of these devices and actually contributed to an increase energy usage by as much as 15.9%[4]. Smart utility meters offer an ideal ubiquitous energy monitoring solution that provides minimal cost, maintenance, and installation effort. However, one major drawback is the lack of appliance level feedback[3].

In this paper, we present the development of an energy disaggregation method to augment a custom embedded smart utility meter as an intelligent home energy management system capable of providing appliance level feedback and recommendations to the home owner.

2. Energy Disaggregation Framework

Energy Disaggregation, also known as Non-Intrusive Load Monitoring (NILM), is the process of disaggregating appliance level feedback from an aggregate electricity consumption signal of residential and commercial units[5]. The emergence of energy disaggregation research is generally attributed to George Hart in the late 1980's for his study of Non-intrusive Appliance Load Monitoring (NALM) utilizing abrupt changes of reactive and real power to discriminate the on and off state of appliances across a household[6].

Numerous researches in energy disaggregation has since been published and majority of which can be categorized into two methods: event identification and load disaggregation. Researches on appliance event identification have been performed utilizing custom high frequency data gathering hardware and using methods such as transient noise generated by mechanical switch, spectral transients harmonics, and electromagnetic interference (EMI) noise emitted by appliances to identify the current appliances in used[5,7].

Researches on load disaggregation focuses on methods for decomposing low frequency aggregate data into an appliance level breakdown. These data are typically from 1 second up to hourly data gathered by smart utility meters. Various researches utilizing methods such as Discriminative Sparse Coding[8] and Factorial Hidden Markov Models[9] have been studied in order to extract the specific appliance signal from an aggregate whole-house consumption. Deep Learning approaches for energy disaggregation were investigated by Kelly[10] which demonstrated several Deep Learning architectures such as Recurrent Neural Networks (RNN), Deep Neural Networks (DNN), and Autoencoders. The work was later expanded by Nascimento[11] focusing on the Long Short Term Memory (LSTM) and Convolutional Neural Networks (CNN) implementations for energy disaggregation. Both of these studies has established the idea of utilizing deep learning models for energy disaggregation with a great degree of success on data with a relative low sampling frequency.

In this study, we pursue the use of Deep Learning as a machine learning framework for energy disaggregation. One particular Deep Learning architecture of interest for this study are Denoising Autoencoders (dAE)[12]. Similar studies particularly in signal processing applications such as the one by Lu et al[13] have exhibited that training a stack of dAE using a noisy-clean pair of speech data enabled the resulting model to reconstruct a clean speech from a noisy input. A later study by Xu et al[14] has shown that noisy-clean pair data with additional complex noise patterns allowed the network to develop a generalized model that suppresses noise and reconstruct a clean speech signal.

In this study, we propose an approach on energy disaggregation utilizing Stacked dAE as a reconstruction problem