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Investigating Weather Inputs for Neural Networks in Home Energy Management Systems

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ABSTRACT

The increase in energy demand within smart homes has generated corresponding demand for smart grids and home energy management systems (HEMSs) aimed at helping consumers construct efficient energy use plans and electricity cost savings. Neural Networks (NNs) are being implemented to enable efficient HEMS operation. Examining the effects of weather on a data set that is used for an applied NN in a HEMS could help to optimize energy efficiency. This study finds that information from weather forecasting can play a significant role in designing NNs to support energy management systems (EMSs). Accurate modeling of the energy demand is critical for a HEMS to be effective. Foregoing weather data inputs altogether when designing NNs leads to less specific outputs, resulting in less efficient network response. And, although reliable forecasting provides many benefits when managing energy distribution, NN algorithms must account for forecasting errors if network inputs require more than 24-hour advance notice. NNs for HEMSs forecasting require weather inputs to accurately predict energy demand by accounting for substantially different and continually changing environmental factors.

Introduction

The housing sector energy demand will continue to expand as worldwide population rises (AlFaris et al., 2017). This demand has driven the development of smart grids and home energy management systems (HEMSs) to help consumers construct more efficient energy use plans and save on electricity. Energy Management Systems (EMSs) provide the framework to help organizations monitor, control, and continuously improve their environmental performance by efficiently controlling energy flow. This research considers several weather variables common to HEMSs, including sky cover, dew point, relative humidity, temperature, and wind speed. EMSs are integral to integration of renewable energies by providing power grids the flexibility needed to enable the accommodation of power generated with renewable energy sources (Almughram et al., 2022). EMSs, however, are inconsistent in terms of overall energy supply and do not always match with the energy demand cycle. Neural networks (NNs) are computer programs that link different nodes to form connections and create an operating environment that is similar to that of neurons in the brain. NNs are used to predict the level of energy a home will demand, along with when the demand will happen. Efficient EMS-based NNs can therefore cut down on electricity usage, benefiting both the user's economic interests and the broader environment.

This research focuses on how weather impacts the efficacy of the data set that is used as an input sample for NNs. (see fig. 1):

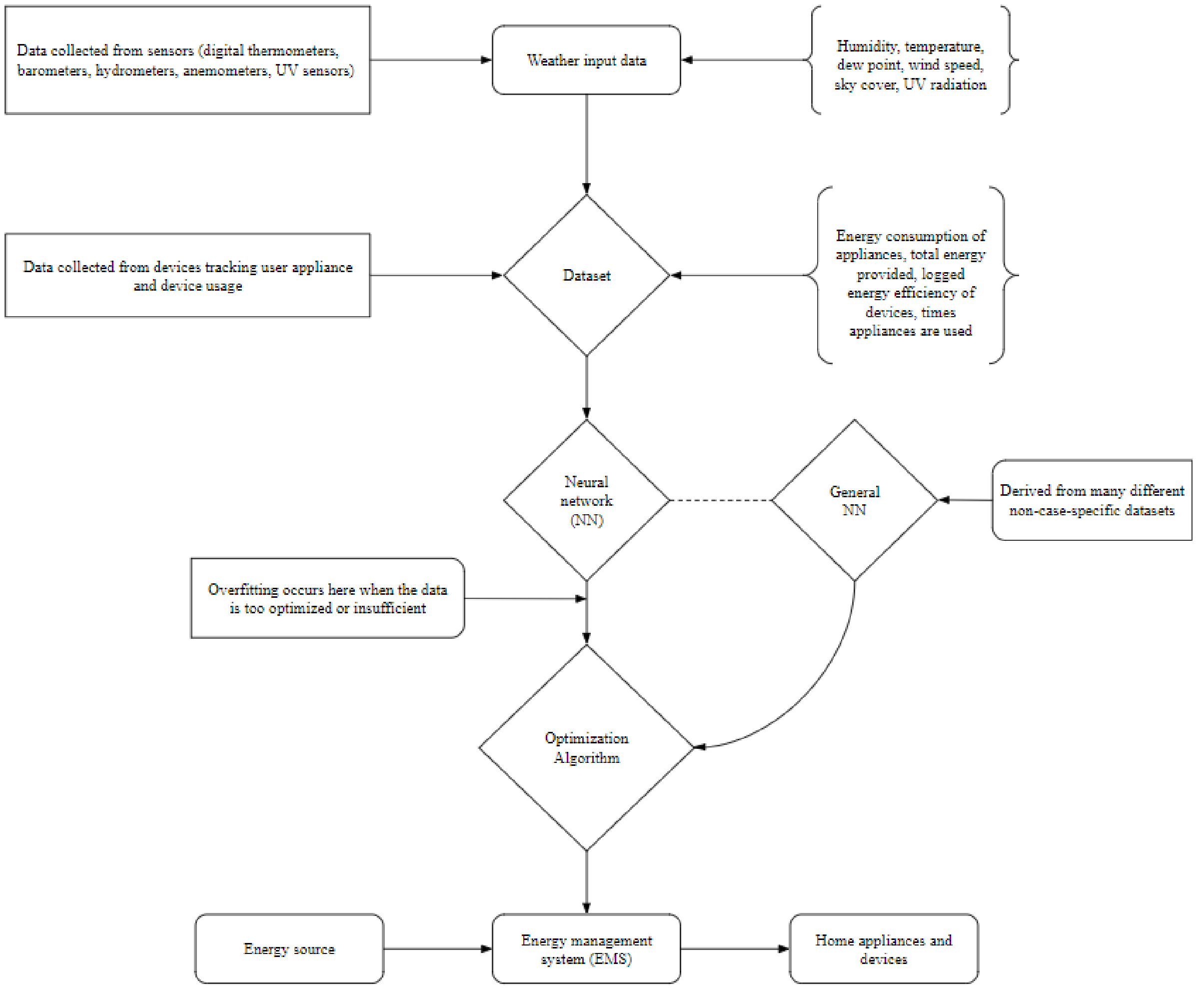

Figure 1. Focus on Neural Network Inputs within Household Energy Demand Flow

NN-based EMS applications in homes have increased significantly in the last 10 years (Lissa et al., 2021). Constructing accurate energy demands based on outputs from these applications is critical to effective HEMS energy distribution and management. When developing EMS applications, small data sets can limit the learning capabilities of the NN and lead to an inaccurate model. With NNs developed from small data samples, the NN will be limited in its prediction capabilities. In regard to input variables for the NN, too many can lead to overfitting, as the NN will attempt to fit the model to irrelevant or noisy variables (Aggarwal, 2018). The problem with overfitting is that the proposed model may provide inaccurate energy demand predictions and may not perform well for all types of data because the NN is trained too tightly to the initial data set. Overfitting has proven to be a rising problem and calls for corresponding action in terms of developing methods to provide more general datasets for inputs [5]. Examining the effects of weather on a dataset that is used for an applied NN in a HEMS can be beneficial for understanding how to further optimize the energy efficiency provided by the application of the results of such networks. This would ultimately help to inform the building of robust NNs that can predict demand for many homes.

Method

For this research, I used search engines google scholar and semantic scholar. When performing the literature review, I used the keywords “home energy management system”, “neural network”, and “forecasting”. I focused on articles with keywords “energy management system”, “genetic algorithm”, “optimization”, and “demand side management”. Inclusion criteria involved articles published in the last decade, focusing on the impact of weather on energy consumption. Exclusion criteria involved articles not including weather as an input parameter to a NN, or not relevant to HEMS. Statistical analysis involved identifying trends in energy usage based on weather variables.

Results

Reference	Energy type	Parameters included in NN	Results
“Design of a Home Energy Management System by Online Neural Networks” (Ciabattoni et al., 2013)	Solar (PV)	Oven, washing machine, dishwasher, and PV production: 3 homes	Energy gathered increase 8%, Energy absorbed decrease 25%
“Day-Ahead Photovoltaic Forecasting: A Comparison of the Most Effective Techniques” (Nespoli et al., 2019)	Solar (PV)	Feed forward NNs measuring solar illumination and air temperature: PV plant	Lower # of standby units, Cost reduction in operating power
“Weather forecasting error in solar energy forecasting” (Sangrody et al., 2017)	Solar (PV)	Weather variables including sky cover, dew point, relative humidity, temperature, and wind speed	1-day forecasting approx. 5% error, 5-day forecasting approx. 30% error
“Weather forecasting error in solar energy forecasting” (Sangrody et al., 2017)	Solar (PV)	Weather variables including sky cover, dew point, relative humidity, temperature, and wind speed	Overestimation of forecasts values versus real observed weather variables for: sky cover (25-35%), dew point (3-5%), relative humidity (9-12%), and temperature (3-5%); Underestimation of wind (3-4%)
“Day-Ahead Photovoltaic Forecasting: A Comparison of the Most Effective Techniques” (Nespoli et al., 2019)	Solar (PV) and climatic	ANNs solar irradiance, air temperature, clear sky condition	Mean Absolute Error (MAE) between 1% and 5%, with slight advantage for the hybrid method under some conditions. Between 4% and 32% less mean absolute error (for 4 of the 6 days identified) when using daily

			weather forecast.
"How people use thermostats in homes: A review" (Peffer et al., 2011)	HVAC	N/A	Residential thermostats consume 42% of the total residential energy and up to 9% of the total energy consumption in the U.S.
"How people use thermostats in homes: A review" (Peffer et al., 2011)	HVAC	N/A	Less than 50% of consumers use programmable thermostats to control ventilation, respond to electricity price signals, and interact with home area network
"Household Power Demand Prediction Using Evolutionary Ensemble Neural Network Pool with Multiple Network Structures" (Ai et al., 2019)		real-time power reading of the household, forecast of the power demand of the coming 10 seconds	ensemble NN pool achieving > 30% reduction in error, attributing better results than ANNs devoted solely to a one household input

Discussion

Weather as an Input for HEMS NNs

Information from weather forecasting plays a significant and vital role when designing NNs for HEMS applications. Sharma identifies weather as the most vital input when modeling photovoltaic (PV) related artificial NNs (ANNs) given weather's dominant effect on PV output (Sharma et al., 2023). Incorporating weather into the dataset being provided for the input layer of the NN is virtually a necessity, as weather plays a large part in determining when certain systems, like PV arrays and HVAC systems, should be operating within a home. Benmouiza posits that more precise weather forecasting plays an increasingly important role in electric energy planning and management due to the integration of PV solar systems into power networks (Benmouiza, 2022). Obtaining precise weather forecasting leads to more efficient energy management for EMS applications, which are increasingly using NNs to model home energy demand. According to the Department of Engineering and Information in Italy, the consumption of the energy gathered from PV cells, or solar panels, can improve up to 8%, and the amount of energy absorbed can be reduced by up to 25% when a NN is applied while using the given weather information as an input (Ciabattoni et al., 2013). This type of reduction in home energy demand, if employed by multiple homes within a region, would have a significant impact on the overall demand for energy for that region.

Accurately modeling energy demand is critical for HEMS effectiveness. Weather forecasting affects energy distribution. More specifically, reliable forecasting affects downstream energy distribution and management. With reliable forecasts, system operators can handle uncertainty and fluctuation in energy demand. The availability of reliable forecasts allows distribution and transmission operators to cope with intermittent PV plant production, avoid problems in balancing power generation and load demand, enhance the stability of the system, and reduce the cost of secondary energy support services (Nespoli et al., 2019). Accurate forecasts enhance reliability and reduce costs by allowing efficient solar energy trading and secure distribution. Getting these accurate forecasts is not possible without weather as a parameter input. In addition, efficient forecasting leads to a lower number of standby units and reduced cost for the operation of the entire power system (Nespoli et al., 2019). Accurately modeling the energy demand within homes leads to more efficient distribution of energy supply, along with better balancing of related energy system costs.

When designing NNs for energy consumption, much of the network's optimized efficiency stems from information assuming weather predictions are accurate. Predicting weather, however, is difficult. In comparing observed versus predicted 6-day forecast results from an ANN focused on solar energy, Sangrody found weather prediction error ranged between 5% at day one to almost 30% by day five (Sangrody et al., 2017). Errors of this magnitude indicate weather predictions are far from accurate. NNs must account for these errors when applying weather inputs. Accounting for these errors will help validate use of weather forecasting for NN based EMS applications.

Weather is an important input parameter for EMS because it affects how much power a home consumes. In terms of energy consumption, most households in the U.S. use thermostats to control the heating and cooling system in their home (Peffer et al., 2011). In 2005, approximately 97% of households in the U.S. had a heating system and over 75% had air conditioning. Peffer determined residential thermostats consume 42% of the total residential energy and up to 9% of the total energy consumption in the U.S–a substantial portion of both fuel and electrical energy (Peffer et al., 2011). Weather directly affects decisions associated with determining the level of energy required to make a home comfortable by adjusting temperature. In terms of overall energy demand, making homes feel comfortable requires a substantial amount of power.

Variance in weather can be substantially different for each and every home. Some home environments are subjected to much greater variance in weather phenomena. More extreme weather environments must be recognized and subsequently algorithmically accounted for when generating HEMSs (Hawkins, 2004). For instance, compiling data for predictable weather regions would lead to fairly accurate forecasting. The forecast data from these stable weather regions would be effective for training the overall model within the general dataset. These generalities must be conditioned to incorporate forecast information from regional data sets. An energy demand architect cannot generate a simple algorithm accounting for differences between a consumer turning on energy for someone from a stable climate region (e.g., San Diego, California) compared to a more extreme weather region (e.g., Jackson Hole, Wyoming). Specifically, significant variations in weather are brought into focus when considering such outliers, as tracking weather can lead to many variations in results (Hawkins, 2004). Variability between model forecast data and actual weather data must be addressed when considering HEMS data sets.

Although weather forecasting introduces variation that is difficult to model and therefore difficult to predict, the absence of weather data within a NN based EMS would compromise the accuracy of energy demand predictions, as weather conditions strongly influence energy demand and production. NN based EMSs that did not include weather as an input parameter would be more dependent on other relevant parameters, including historical energy consumption patterns and energy system loading. Sangrody found that solar PV generation forecasting generally relied upon observed weather data, whereas energy forecasting was more likely based on forecasted weather data (Sangrody et al., 2017). Their results using NOAA forecasting data indicated overestimation of forecast values compared to real observed weather variables for sky cover (25-35%), dew point (3-5%), relative humidity (9-12%), and temperature (3-5%), and underestimation of wind (3-4%) (Sangrody et al., 2017). Weather forecasting may result in overestimation and underestimation in energy forecasting. This study further determined that using observed weather data in lieu of forecasted data led to less efficient energy allocation. Since these parameters are less specific, placing greater reliance on parameters that do not include weather forecasting led to less efficient energy demand prediction.

Human choice will continue to disrupt the ability to accurately project energy demand within a home. Installing programmable thermostats is intended to save energy, yet recent studies found that homes with programmable thermostats can use more energy than those controlled manually depending on how—or if—they are used (Peffer et al., 2011). Much time and attention has been devoted to increasing thermostat capability, including adding programmable features that allow thermostats to control ventilation, respond to electricity price signals, and interact with a home area network. Consumers, however, have been slow to adopt these features, with less than 50% implementing these capabilities (Peffer et al., 2011). Because humans are not opting to employ automated capabilities, the energy demand related to thermostat control (one of the leading sources for demand) will continue to be inefficient. Adoption of NNs providing automated thermostat response within homes would improve HEMSs by reducing energy demand locally. Coupling weather forecasting data with programmable thermostats would enable more accurate predictions for demand side power forecasting due to HEMSs having information necessary to determine when to operate HVAC systems. Including weather forecasts within NNs would help optimize thermostat settings for energy efficiency.

There are energy forecasting models that do not use weather as a data input. One study conducted by the Department of Energy in Italy in 2019 compared two artificial NNs (ANNs) using an hourly series of climatic and PV system inputs covering one year, clustered to distinguish sunny from cloudy days (Nespoli et al., 2019). One forecasting method feeds only on the available dataset, the other is a hybrid method relying upon daily weather forecasts. The comparison identified that both methods were good at estimating sunny days conditions, with mean absolute error (MAE) between 1% and 5% for all cases, with a slight advantage for the hybrid method under some conditions (Nespoli et al., 2019). The results also indicated less efficiency during cloudy days for both methods, attributing between 4% and 32% less mean absolute error (for 4 of the 6 days identified) when coupling the daily weather forecast. Ultimately, NNs with weather forecasting demonstrated smaller error across all conditions.

Conclusion

Weather is a necessary input variable for NNs to efficiently predict home power consumption. The consideration of continually changing environmental factors is essential for predicting home energy demand because they majorly affect the usage of home appliances, both those controlled weather-accordingly and those activated by the user at different times. In these cases, a NN can either help to control weather-dependent appliances almost entirely or can make predictions about how the user in question will manage the appliances in accordance to time and will adjust the home's power plan accordingly. For EMSs that govern the regional management of homes, more general NNs must also be taken into account. While being more effective for the management of multiple homes, these EMSs will include some oversights in data, and therefore have a loss in efficiency, due to inability to account for each device within a home. Weather will continue to be a dominant factor in determining inputs to NNs for HEMSs as it directly affects energy distribution, loading, production, and trading. Incorporating weather parameters into NNs for energy forecasting enhances the EMS model's ability to adapt to dynamic environmental conditions, resulting in more accurate prediction of energy demand within the home, and ultimately as those efficiencies go on to affect broader regional energy demand.

Examining the effects of weather on a dataset that is used for an applied NN in a HEMS can be beneficial for understanding how to further optimize the energy efficiency provided by the application of the results of such networks. Including weather inputs could lead to overfitting, especially for any networks established using a small network input base with highly tailored inputs. Additional research is required to determine the network scale sufficient for maintaining weather inputs without being affected by overfitting, as both sets that are too general and those that are too specific have been documented. Additional research is also needed to further understand the variability of human choice and its impact on energy management when responding to weather conditions.

Limitations

Weather forecasting is one of many design factors that influence overall residential energy use when developing HEMSs. When designing EMS applications, weather forecasting is critical for all of the reasons cited above. A few additional factors impact overall residential energy use enough to warrant further study, including prevalence of miscellaneous electrical loads (MELs), and determining the network scale sufficient for maintaining weather inputs without being affected by overfitting. Accounting for these two factors would help deliver more viable HEMS solutions.

Miscellaneous electrical load (MEL) is the collective consumption of electronic devices and appliances that do not fit within standard categories similar to lighting, heating, cooling, and ventilation. These loads typically include devices such as computers, printers, video equipment, chargers, and other small electronic devices. A study by the University of Texas in 2015 identified a growing percentage of MEL significantly impacting residential building energy use (Dong et al., 2016). MEL contributed approximately 15–25% of a typical home's energy use and was projected to increase by 52% by 2040. Given its substantial projected increase, understanding and managing MEL is crucial for optimizing energy efficiency within HEMSs. Introducing this factor would help generate more predictable energy use data sets in the near future.

Training a network on a single home inhibits several problems. The limited data will cause the NN to fit too tightly to the single home. Using gathered weather data in a small data set in terms of input for the given NN can lead to the network proposing inefficient energy consumption patterns. For example, a team from the National University of Computer and Emerging Sciences in Pakistan created a model that they applied to a real home for about one and a half years, finding upwards of 35% error between real data and forecast when accounting for extreme weather conditions (Ismail et al., 2021). One must also consider that data collected from one specific home could be drastically different from that collected from another based on its surrounding topography, infrastructure, and energy resources, amongst other factors. For an effective model to be created, the sample size must be much larger, including homes from a large variety of landscapes, climate zones, cities, and other varying sets. Abu-Mostafa recommends, when establishing NNs, using data for at-least 10 times each parameter involved to get a proper result (Abu-Mostafa et al., 2012.) For example, a NN with 3 weights should employ 30 data points. Another study from 2023 determined deep learning model performance is directly related to the number of training samples, meaning larger number of training samples leads to better model performance (Li et al., 2023). Therefore, a NN dependent on data from a single residency may prove to be effective for that particular home, but when the differences are factored in, overfitting is widely apparent, with energy- and cost-efficiencies being much less optimized generally.

Another method for addressing smaller data set bias would be to use larger data sets when employing the model. This could be accomplished by either using a much larger data model to conduct the initial training or aggregating multiple smaller models to achieve a meaningful representation of a higher order community sample. The University of Norway employed an ensemble NN pool method in 2019 achieving > 30% reduction in error than ANNs devoted solely to a one-household input (Ai et al., 2019). Inputs from larger data sets would provide better adaptation to community and larger changing energy needs. Another study from the Middle East conducted in 2022 used an expansion algorithm with data from 169 residential customers to refine and ultimately improve energy consumption predictions for short term loads when compared to deep learning models based on much smaller data sets (Shaikh et al., 2022). Managing these multiple inputs or larger data sets would likely, however, require greater storage and computational capacity.

Such cases where overfitting would hypothetically impact these efficiency factors, as opposed to a more comprehensive data set providing a given home with more efficiency in such categories, would also require the same amount of money to implement for less functional results. This means that the productivity ratio, which is the ratio of the output to the input in terms of amounts of work or value measured by time or qualities of something that make it tradeable; in this case the ratio of money invested to money saved by implementation of the NN, is lower than it could be. In implementing a NN where overfitting is prevalent in the results, the process of testing and revising the NN would also require more time and resources being committed, whereas the problem could have been avoided by a broader input dataset leading to more efficient results directly.

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