USING ANN WITH GEODESIC ACCELERATION TO MAXIMIZE SMART ENERGY MANAGEMENT

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ABSTRACT

Home energy optimization is an increasing research interest as smart technologies in appliances and other home devices are replacing traditional items, particularly as manufacturers move to produce appliances and devices that work in conjunction with the Internet. Home energy optimization has the potential to reduce the use of energy through "smart energy management" of appliance demand for energy. Information and communications technologies (ICTs) help achieve energy savings with the goal of reducing greenhouse gas emissions and attaining effective environmental protection in several contexts including electricity generation and distribution. This "smart energy management" is utilized at the residential customer level through "smart homes." This paper compares two artificial neural networks (ANN) used to as a support for a home energy management (HEM) system based on Bluetooth low energy, called BluHEMS. The purpose of the algorithms is to optimize energy use in a typical residential home. The first ANN uses the Levenberg-Marquardt algorithm and the second uses the Levenberg-Marquardt algorithm enhanced by a second order correction known as the geodesic acceleration.

KEYWORDS

Artificial Intelligence, Optimization, Green Computing, Home Energy Management, Smart Energy Management, Neural Networks

INTRODUCTION

Home energy optimization has become an increasing research interest as smart technologies in appliances and other home devices are replacing traditional items, particularly as manufacturers move to produce appliances and devices that work in conjunction with the Internet. Home energy optimization has the potential to reduce the use of energy through "smart energy management" of appliance demand for energy. Information and communications technologies (ICTs) help achieve energy savings with the goal of reducing greenhouse gas emissions and attaining effective environmental protection in several contexts including electricity generation and distribution. This “smart energy management” is utilized at the residential customer level through “smart homes.” Smart home energy management has led researchers such as Chen et al (2013), Han et al (2014), and Collota et al (2017) to focus on “smart homes” as critical partners in reducing energy consumption and thereby reducing greenhouse emissions and achieving large-scale energy savings. As stated by Collota et al (2017), intelligent metering management systems and incentives such as demand response programs, time-of-use, and real-time pricing, are applied by utilities to encourage customers to reduce their load during peak load hours.

A smart home is a home equipped with lighting, heating, appliances, and electronic devices that can be controlled remotely by phone or computer. Use of these technologies can reduce energy consumption by providing consumption profiles of appliances to the consumers and helping them to change their behavior. A common example of how this would be the use the washing machine or dishwasher during off peak times rather than during peak period and being controlled by a user being alerted by the utility company that an off-peak period is occurring and the user remotely turning on the device using their computerized device from wherever they are. Similarly, if a consumer leaves on a lamp or computer device, the user could be alerted that they device is consuming a peak energy cost and make the choice to turn off the device to save on energy consumption.

With the ability of artificial intelligence (AI) to act on behalf of the user to manage home devices, e.g., turn on and off devices during off peak and peak periods respectively, there is a need for methods to make communication and information systems more efficient and effective in automated management. The end goal is to improve efficiency of power delivery and use.

Home Area Networks (HAN) is one such use of smart homes and smart grids. HANs utilize a communication path among smart meters, home appliances and devices (Hiew et al 2014). The HAN enables consumers to collect information about their consumption behaviors and the electricity usage costs via in-home display devices. This is a vast improvement over the traditional electric energy metering system, whose precision is not accurate nor timely enough to be of any energy cost savings to the customer.

Smart Home Energy Management Systems (SHEM) have been introduced by researchers such as (Han et al, 2014, Chen et al, 2013). SHEM rely on matching present generation values with demand by controlling the energy consumption of appliances and optimizing their operation at the user side. Wireless Networks (WNs) have been widely recognized as a technology promising to improve several aspects (Collotta et al, 2015) of smart energy technologies (Wang and Granelli, 2014), especially those that deal with power generation, bidirectional delivery, utilization and seamless monitoring, providing an energy efficient, reliable and low-cost solution for control management (Collota et al 2017, Feng et al, 2015).

SYSTEM MODEL

We present the smart home energy model proposed by Collota et al (2017) in Figure 1 to illustrate how a SHEM system would work.

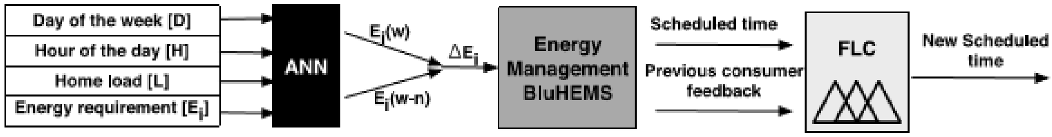

Figure 1. Architecture of the proposed energy management system. reprinted from Collota et al (2017)

The main elements of the system are BluHEMS - a home energy management (HEM) system based on Bluetooth low energy - for monitoring and controlling the electrical appliances, planning a convenient start time for them, a FLC to manage both the scheduling of home appliances and the feedback of consumers, and an ANN, for forecasting of energy requirements. Collota et al (2017) proposed an ANN to overcome the main limitations of the lack of an automated system capable to make choices based on both the actual energy consumption values and of predicted ones limitation. The system proposed by Collota et al (2017) involves communications among smart appliances and BluHEMS through a wireless network. BluHEMS, assisted by the FLC, allows the switching on of the appliance or suggests to the consumer which is the more appropriate start time, taking into account both the available stored energy in the storage system and the updated prices in that time slot. The consumer can decide whether to accept the schedule proposed by BluHEMS. Several parameters, such as the day of the week, the hour of the day and the home load, are taken into account in order to train an ANN model aiming at forecasting the energy requirements. The output of the ANN is used to feed BluHEMS, and the FLC, with the goal of reducing home electricity consumption charges, decreasing the electricity bill of the consumer by shifting the appliances' operation from peak demand hours to off-peak ones.

ANN USING GEODESIC ACCELERATION TO IMPROVE THE PERFORMANCE OF THE LEVMAR ALGORITHM

It has been shown numerically that the performance of the Levenberg-Marquardt algorithm can be improved by including a second order correction known as the geodesic acceleration. Unlike other methods which include second derivative information, the geodesic acceleration does not attempt to improve the Gauss-Newton approximate Hessian, but rather is an extension of the small-residual approximation to cubic order. In deriving geodesic acceleration, we note that the small-residual approximation is complemented by a small-curvature approximation. This latter approximation provides a much broader justification for the Gauss-Newton approximate Hessian and Levenberg-Marquardt algorithm. In particular, it is justifiable even if the best fit residuals are large, is dependent only on the model and not on the data being fit, and is applicable for the entire course of the algorithm and not just the region near the minimum. (Transtrum & Sethna, 2012).

PERFORMANCE EVALUTION

To assess the performance of the proposed model, a simulation using the Network Simulator Version-3 (GNS3). The simulation followed the approach proposed by Collota et al (2017) and evaluated in terms of HEM performance and the network performance in a typical home automation scenario, as depicted in Figure 2.

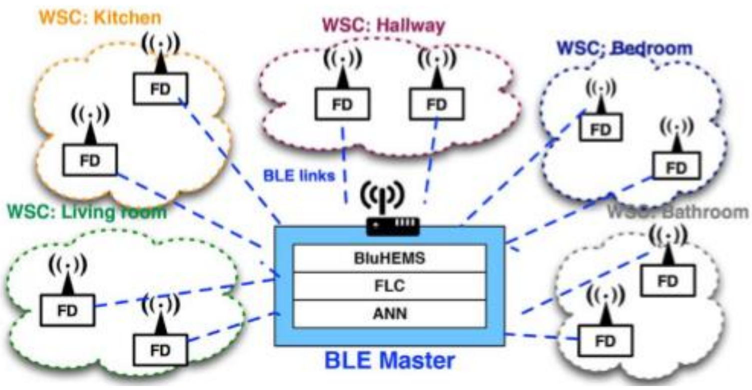

Figure 2. Sample Wireless HAN architecture based on BLE reprinted from Collota

The evaluation scenario the simulations have been performed making a comparison between the BluHEMSANN model and the BluHEMSANN-E model. The only differences between the models is the addition of geodesic acceleration to the LevMar algorithm to train the neural network. We retained the approach of taking into account of the consumers' feedback. The simulation scenario like Collota et al (2017) contained several loads represented by a washer, a dryer, a dishwasher, a hairdryer, a dehumidifier and a coffeemaker. The duration (minutes) and the energy consumption (kWh) of these appliances are vendor specific but we used reference values for average load per cycle given. An extra load was included with an electricity consumption varying between 0 kWh and 5 kWh randomly. Regarding the load, 80% of it was considered miscellaneous while the remaining 20% was related to standby appliances. The peak hours fall from 8 AM to 2 PM, the switching on of an appliance has been considered as a Poisson distribution and the requests generated randomly. Regarding to the configuration parameters, the threshold value of power has been set to 1 kWh, the threshold value of delay has been set to 24 hours, simulations duration has been between 5 days and 365 days (1 year) and the first 5 days are spared for warm up. The electricity consumption pattern measured in a generic single day is depicted in Figure 3 with hours on the x axis and consumption on the y axis.

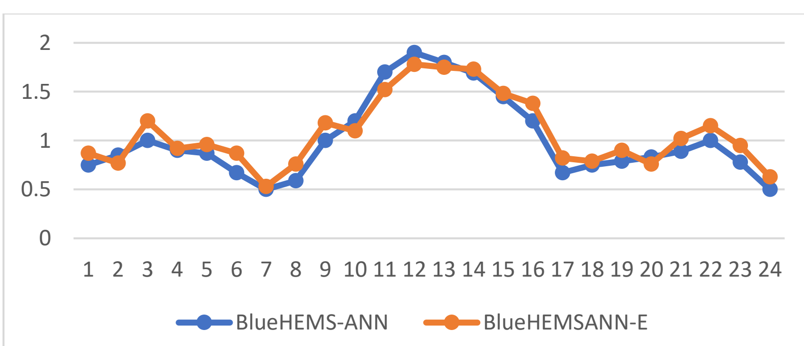

Figure 3-Electricity Energy Consumption Comparison

The percentage of load in peak hours is a ratio between the amount of load in peak hours to the total load. High value of this ratio results in high electricity charges due to pricing tariffs.

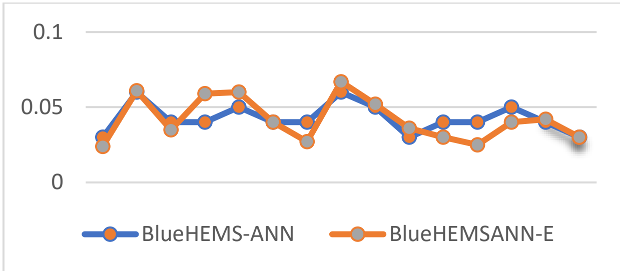

Figure 4 . Load of the appliances ratio during peak hours.

Figure 4 shows the contribution of the appliances on the average peak load is shown. Consistent with the results from Collota et al (2017), both the BlueHEMS-ANN and the BlueHEMSANN-E have almost 0.1 of the load generated by the appliances takes place during peak periods although the enhanced system performed better as the number of days increased.

The results obtained by the simulations are shown in Tables 1 and 2. These simulations have been performed to obtain the configuration of the ANN that achieves the best performance. The inputs of the neural network are given by the sum of the embedding dimensions. A higher number of inputs leads to a significant accumulation of data in memory and could have reduced capacity in terms of memory. The reduction in the number of inputs also improves memory management. For consistency with Collota, the training parameters used in the simulations are the following:

• performance goal: 7×10^{-3};
• learning rate: 0.4;
• maximum failure number for validation: 30;
• Marquardt adjustment parameter: 0.07.

Table 1. Performance of ANN with LevMar Algorithm (BlueHEMS-ANN)

Neurons in Hidden Layer	Training Cycles	MSE	RMSE	MAE	MAPE
10	125	926.7E-5	837.8E-5	7887.0E-5	60.6E-5
20	137	928.0E-5	2291.0E-5	207.0E-5	4562.0E-5
30	104	947.8E-5	387.0E-5	57.7E-5	452.2E-5
40	167	20.7E-5	34.2E-5	3.4E-5	34.2E-5
50	198	973.9E-5	222.6E-5	23.3E-5	70.5E-5
60	219	374.6E-5	172.7E-5	21.9E-5	944.3E-5
70	155	54.2E-5	197.1E-5	6352.0E-5	520.7E-5
80	137	676.2E-5	45.7E-5	32.0E-5	96.3E-5
90	196	89.2E-5	523.7E-5	9033.0E-5	526.8E-5

100	148	2910.0E-5	39.2E-5	960.4E-5	3970.0E-5

Table 2. Performance of ANN with LevMar Algorithm with Geodesic Acceleration (BlueHEMSANN-E)

Neurons in Hidden Layer	Training Cycles	MSE	RMSE	MAE	MAPE
10	119	6854.7E-5	4.9E-5	6.0E-5	3303.0E-5
20	146	5627.9E-5	826.1E-5	7701.0E-5	476.3E-5
30	105	363.5E-5	5106.9E-5	65.5E-5	9670.1E-5
40	124	9.7E-5	3.2E-5	1.4E-5	1.7E-5
50	279	55.8E-5	889.2E-5	186.1E-5	5874.4E-5
60	255	19.8E-5	4134.6E-5	136.2E-5	9.5E-5
70	182	3228.0E-5	8113.4E-5	1910.1E-5	362.6E-5
80	131	706.6E-5	35.9E-5	64.1E-5	4878.9E-5
90	262	611.4E-5	231.3E-5	662.5E-5	18.7E-5
100	137	969.7E-5	9943.4E-5	94.1E-5	6.5E-5

Both algorithms performed best at 40 nodes as indicated by the lowest performance indicators. A t-test comparing the means of the Electricity Energy Consumption and Load of the appliances ratio during peak hours showed a significant difference in the energy consumption at a p-value of .005 which indicates the enhanced algorithm did improve the performance of the LevMar algorithm. However, a t-test of the load ratio did not have a significant difference between the two algorithms.

CONCLUSION AND NEXT STEPS

In this work an Artificial Neural Network (ANN) enhanced with geodesic acceleration for BluHEMS was shown to potentially improve the problem of peak load management using the available data obtained by the Home Energy Management (HEM) system. The proposed mechanism provides the possibility to improve forecasting the energy consumption conditions and the home energy requirements at different times of the day or on different days of the week. The next step is to simulate energy management without the input from the consumer and with more modern wireless technologies such as TVs.

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