Using Geodesic Acceleration with LevMar to Maximize Smart Home Energy Management

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Home energy optimization is increasing in research interest as smart technologies in appliances and other home devices are increasing in popularity, particularly as manufacturers move to produce appliances and devices which work in conjunction with the Internet. Home energy optimization has the potential to reduce energy consumption through "smart energy management" of appliances. 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 support home energy management (HEM) systems 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 geodesic acceleration.

INTRODUCTION

Home energy optimization in increasing in 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 appliances. 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 the larger concept, "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 explained 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 devices such as the currently available 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 suggesting changes in behavior. A common example is using the washing machine or dishwasher during off-peak times rather than during peak power consumption periods. These appliances can be controlled by a user who is alerted to off-peak periods by the utility company; the user can remotely turn on the appliances using a remote device such as a mobile phone. Similarly, if a consumer leaves a lamp or other device on, they can be alerted to the use of energy at peak-pricing periods; so they can make the choice to turn off these devices to save on energy consumption.

With the goal of improving the efficiency of power consumption, artificial intelligence (AI) can play an important role. Artificial intelligence can be used to make decisions on behalf of the user to manage home devices, e.g., turn off and on devices during peak and off-peak periods respectively. With this in mind, there is a need to make communication and information systems that can be used to increase the efficiency and effectiveness of automated home management.

Home Area Networks (HAN) utilize a communication path among smart meters, home appliances and devices (Hiew et al 2014). The HAN enables consumers to collect information about their power consumption behavior and the electricity consumption costs via in-home display devices. This is a vast improvement over the traditional (labor-intensive and periodic) electric energy metering system, whose precision is not accurate nor timely enough to provide any practical energy cost savings to the customer.

LITERATURE REVIEW

Agarwal et al. (2010) determined that most building electrical systems run on a set schedule without consideration of occupancy status or user needs. Addressing this concern, the authors deployed sensor technology to measure occupancy status. In order to interact with sensors, an occupancy detection was developed along with a wireless network and occupancy server. They deployed their system in ten offices over a two-week interval for data collection purposes. Using the data collected in the aforementioned step, the authors performed a simulation, which indicates that they are able to produce a 10%-15% savings with variations explained by daily outdoor temperature fluctuations.

Wireless Networks (WNs) have been widely recognized as a technology promising to improve several aspects of smart energy technologies (Collotta et al, 2015; 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).

Machine to machine (M2M) communication has shown great promise in a wide variety of domains. Niyato, Xiao, and Wang (2011) applied the M2M approach to the smart grid and revealed that M2M is typically embedded in electronic devices. They further explained that M2M enables connectivity, functions as middleware, provides M2M component connectivity, and the communication network facilitates M2M communication between gateways and M2M servers. To demonstrate their methods, authors looked at a scenario within 1 sq. km. and 250 nodes served by a WAN base station. Finally, they recommend open research possibilities and suggest that the cost of HEMS can be minimized with an M2M approach.

Erol-Kantarci and Mouftah (2011) evaluated an in-home energy management system (iHEM). iHEM was compared with optimization-based residential energy management (OREM). The authors demonstrated that iHEM has the potential to lower costs when peak pricing is employed. OREM had a total lower cost and was deemed more flexible, permitting communication with devices and sensors. When employed in this scenario, it was successful in reducing the cost to consumers.

Hu and Li (2013) proposed SHEMS, or smart home energy management systems, where machine learning was integrated with sensing and communication technologies for all aspects of home energy management. A naïve Bayes classifier and hidden Markov models were applied to predict human activity, and thereby energy consumption, via data collected from sensors. Results were validated via simulation and demonstrate how the design can be adapted to many scenarios. Additional models were introduced by Han et al (2014) and Chen et al (2013). In their models, the SHEM relied on matching present generation values with demand by controlling the energy consumption of appliances and optimizing their operation at the user side.

Asare-Bediako, Ribeiro, and Kling (2012) researched the optimization of smart home energy systems (SHEMS). The authors sought to analyze how the implementation of SHEMS could be used to improve the efficiency of energy consumption. Home energy consumption provides many challenges that need to be addressed. The study used a MATLAB simulation to look at the various aspects of SHEMS. Key findings included the importance of electricity consumption and the need for an energy-aware system. A solution such as a SHEMS cost-optimization for demand peaks and valleys is critical. Conservatism, cost, and privacy will be key barriers to the future adoption of smart home energy systems.

Pipattanasomporn, Kuzlu, and Rahman (2012) studied a HEM algorithm for managing high consumption households. Their algorithm is important in demand response within households. The authors performed a simulation on a 2500 sq. ft. home and ranked the importance of various systems such as water temperature and HVAC levels. Results indicate the algorithm can keep a home's power consumption below the demand limit; however, home occupants may need to sacrifice comforts in order to achieve peak efficiency.

Zhao, Lee, Shin, and Song (2013) investigated efficient scheduling methods for home power usage and consumption in the smart grid. Their objective was to deploy energy management systems in the home to reduce demand at peak times. The authors based their approach on receiving a demand signal from the electricity provider to detail peak usage times. An optimization-based approach complete with a genetic algorithm and tested via a simulation was developed. Results of the simulation on a combination RTP and IBR pricing model demonstrated that when applied in this scenario results are favorable for both energy providers and consumers.

Ozturk, Senthilkumar, Kumar, and Lee (2013) developed a system to expand demand response via automated scheduling of appliance operations. Demand response and time of use based pricing scenarios seek to inform and control consumer demand for power during peak periods. Furthering this method, they develop a decision support system which is used to forecast occupant demand based on an adaptive neural fuzzy instance system (ANFIS). Implementing the ANFIS on a self-organizing home energy network, results indicated that ANFIS is a suitable mechanism to learn user behaviors and develop models to buffer electricity demand through automated appliance scheduling.

Similarly, home energy management systems (HEMS) are designed to lower the cost of energy for consumers. One issue is the effects of HEMS with HVAC systems. To address this, Jo, Kim, and Joo (2013) propose a smart home heating and air conditioning management system via optimal scheduling management. This model takes into account customer convenience with available low-cost energy resources. The model has the potential to lower consumer costs via optimization scheduling and could be employed in a wide range of scenarios.

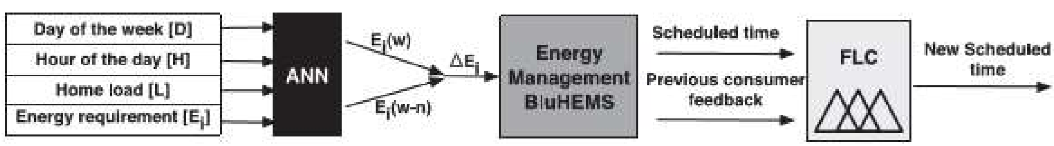
Anvari-Moghaddam, Monsef, and Rahimi-Kian (2015) developed a linear programming model to balance comfort and efficiency in smart home management. Oftentimes, there are conflicting objectives, such as comfort and efficiency that need to be considered from an optimization point of view. To address this concern, a multi-objective mixed integer non-linear programming method was developed. To compare this approach with other methods, multiple simulations using real-world data were employed. Results showed that balancing system and user constraints could be addressed with the potential to reduce energy usage while maintaining user comfort.

D.-M. Han and Lim (2010a, 2010b) and J. Han, Choi, Park, Lee, and Kim (2014) investigated ZigBee and PLC to consider both load management and demand response. First, the research examined standard practices for demand and load management. Next, ZigBee was deployed with sensor networks, which divided tasks into appropriate components complete with a new routing protocol dis-joint multi-path based routing (DMPR). The DMPR improved the performance of ZigBee networks through more efficient routing. Next, a system was proposed using PLCs and a home server to gather and analyze information from the network to aid in making intelligent decisions to control home energy usage based on statistical analysis. In all instances, ZigBee combined with sensor technology was shown to improve Smart Home Energy Networks.

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, an 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. The Levenberg-Marquardt algorithm is a technique for solving nonlinear least squares problems. Least squares problems arise in the context of fitting a parameterized function to a set of measured data points by minimizing the sum of the squares of the errors between the data points and the function. Nonlinear least squares methods iteratively reduce the sum of the squares of the errors between the function and the measured data points through a sequence of updates to parameter values. The Levenberg-Marquardt curve-fitting method is a combination of two minimization methods: the gradient descent method and the Gauss-Newton method.

In the gradient descent method, the sum of the squared errors is reduced by updating the parameters in the steepest descent direction. The gradient descent method converges well for problems with simple objective functions. For problems with thousands of parameters, gradient descent methods are sometimes the only viable choice. The gradient of the chi-squared objective function with respect to the parameters is:

$$\frac{\partial}{\partial \mathbf{p}}\chi^2 = 2(\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p}))^{\mathsf{T}}\mathbf{W}\frac{\partial}{\partial \mathbf{p}}(\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p})) \tag{1}$$

$$= -2(\mathbf{y} - \hat{\mathbf{y}}(\mathbf{p}))^{\mathsf{T}}\mathbf{W}\left[\frac{\partial \hat{\mathbf{y}}(\mathbf{p})}{\partial \mathbf{p}}\right] \tag{2}$$

$$= -2(\mathbf{y} - \hat{\mathbf{y}})^{\mathsf{T}}\mathbf{W}\mathbf{J} \tag{3}$$

where the $m \times n$ Jacobian matrix $[\partial\hat{\mathbf{y}}/\partial\mathbf{p}]$ represents the local sensitivity of the function $\hat{y}$ to variation in the parameters $\mathbf{p}$. For notational simplicity, the variable $\mathbf{J}$ will be used for $[\partial\hat{\mathbf{y}}/\partial\mathbf{p}]$. The parameter update $\mathbf{h}$ that moves the parameters in the direction of steepest descent is given by $h_{gd} = \alpha\mathbf{J}^{\mathbf{T}}\mathbf{W}(\mathbf{y} - \hat{\mathbf{y}})$ where the positive scalar determines the length of the step in the steepest-descent direction.

In the Gauss-Newton method, the sum of the squared errors is reduced by assuming the least-squares function is locally quadratic and finding the minimum of the quadratic. It presumes that the objective function is approximately quadratic in the parameters near the optimal solution. For moderately-sized problems, the Gauss-Newton method typically converges much faster than gradient-descent methods. The function evaluated with perturbed model parameters may be locally approximated through a first-order Taylor series expansion.

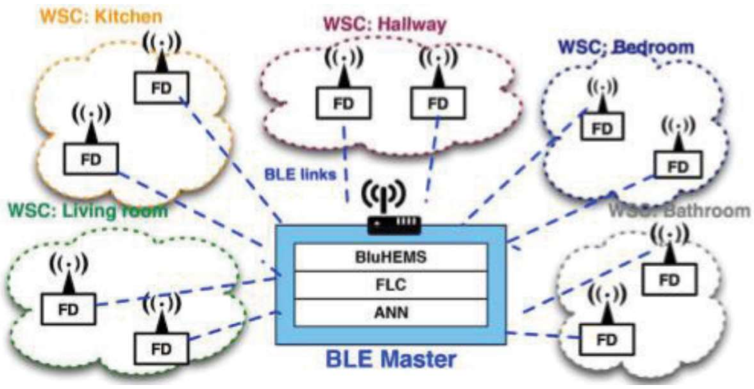
The Levenberg-Marquardt method acts more like a gradient-descent method when the parameters are far from their optimal value, and, acts more like the Gauss-Newton method when the parameters are close to their optimal value. (Levenberg, 1944; Lourakis, 2005). Many variations of the Levenberg-Marquardt have been published in papers and in code such as Grammes (n.d.), Lourakis (2005), Press, et al (1992), Gavin (2017), and Shrager et al, (2006).

Geodesic refers to the shortest possible line between two points on a sphere or other curved surface. Unlike other methods which include second derivative information, the geodesic acceleration does not attempt to improve the Gauss-Newton approximation to the Hessian matrix, but rather is an extension of the small-residual approximation to cubic order. In deriving geodesic acceleration, the small-residual approximation is complemented by a small-curvature approximation. This latter approximation provides a much broader justification for the Gauss-Newton approximation to the 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 EVALUATION

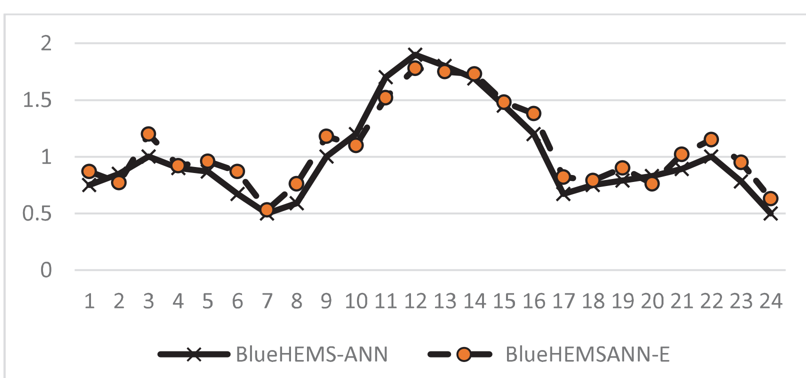
To assess the performance of the proposed model, a simulation using the Network Simulator Version-3 (GNS3). The simulation followed the approach proposed by Collota et al (2017) and evaluated in terms of HEM performance and the network performance in a typical home automation scenario, as depicted in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

FIGURE 2
SAMPLE WIRELESS HAN ARCHITECTURE BASED ON BLE REPRINTED FROM COLLOTA



The evaluation scenario of the simulations was performed making a comparison between the BluHEMSANN model and the BluHEMSANN-E model. The only difference between the models is the addition of geodesic acceleration to the LevMar algorithm to train the neural network. The authors retained the approach of including the consumers' feedback. The simulation scenario like Collota et al (2017) contained several loads represented by a washer, a dryer, a dishwasher, and a dehumidifier which are appliances the network can run while the user is away from home. 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 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. The high value of this ratio results in high electricity charges due to pricing tariffs.

FIGURE 4
LOAD OF THE APPLIANCES RATIO DURING PEAK HOURS

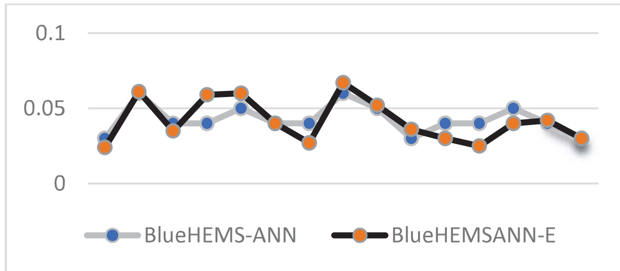


Figure 4 shows the contribution of the appliances on the average peak load is shown. Consistent with the results from Collota et al (2017), both the BlueHEMS-ANN and the BlueHEMSANN-E have almost 0.1 of the load generated by the appliances takes place during peak periods although the enhanced system 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 et al (2017), 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	123	8.75E-03	8.50E-03	6.77E-02	5.75E-04
20	132	8.18E-03	2.35E-02	2.10E-03	4.27E-02
30	105	9.43E-03	3.87E-03	6.33E-04	5.54E-03
40	162	2.46E-04	3.02E-04	1.76E-05	3.64E-04
50	204	9.74E-03	2.19E-03	1.97E-04	9.31E-04
60	218	3.70E-03	1.76E-03	5.32E-04	7.86E-03
70	154	5.19E-04	1.93E-03	5.37E-02	6.26E-03
80	129	6.76E-03	4.34E-04	1.92E-04	4.41E-04
90	195	8.53E-04	5.27E-03	6.84E-02	1.26E-02
100	158	2.91E-02	4.16E-04	7.83E-03	2.38E-02

TABLE 2
PERFORMANCE OF ANN WITH LEVMAR ALGORITHM ENHANCED WITH GEODESIC ACCELERATION (BLUEHEMSANN-E)

Neurons in Hidden Layer	Training Cycles	MSE	RMSE	MAE	MAPE
10	124	6.86E-02	7.51E-05	4.64E-05	3.31E-02
20	137	5.63E-02	8.27E-03	7.70E-02	4.79E-03
30	102	3.59E-03	5.10E-02	6.10E-04	9.67E-02
40	127	1.14E-04	9.43E-06	1.68E-05	4.09E-05
50	289	5.90E-04	8.90E-03	1.83E-03	5.88E-02
60	260	2.05E-04	4.14E-02	1.38E-03	1.01E-04
70	188	3.22E-02	8.11E-02	1.91E-02	3.59E-03
80	139	7.04E-03	3.11E-04	6.20E-04	4.88E-02
90	271	6.16E-03	2.36E-03	6.67E-03	2.26E-04
100	140	9.70E-03	9.94E-02	9.76E-04	3.09E-05

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 had a p-value of .07 which indicates there was not 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. Future research actions may simulate energy management without input from the consumer and with a more modern use of appliances and wireless technologies such as recording streaming videos for later consumption, home temperature regulation, and lighting.

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