Diagnostic Tools of energy performance for supermarkets using Artificial Neural Network algorithms

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Abstract

Supermarket performance monitoring is of vital importance to ensure systems perform adequately and guarantee operating costs and energy use are kept at a minimum. Furthermore, advanced monitoring techniques can allow early detection of equipment faults that could disrupt store operation. This paper details the development of a tool for performance monitoring and fault detection for supermarkets focusing on evaluating the *Store's Total Electricity Consumption* as well as individual systems, such as *Refrigeration, HVAC, Lighting and Boiler*. *Artificial Neural Network* (ANN) models are developed for each system to provide the energy baseline, which is modelled as a dependency between the energy consumption and suitable explanatory variables. The tool has two diagnostic levels. The first level broadly evaluates the systems performance, in terms of energy consumption, while the second level applies more rigorous criteria for fault detection of supermarket subsystems. A case study using data from a store in Southeast England is presented and results show remarkable accuracy for calculating hourly energy use, thus marking the ANN method as a viable tool for diagnosis purposes. Finally, the generic nature of the methodology

approach allows the development and application to other stores, effectively offering a valuable analytical tool for better running of supermarkets.

Keywords: Supermarket energy use, energy forecasting, diagnostics, fault detection, predicative maintenance, artificial neural networks.

1. Introduction

Of commercial buildings, supermarkets are one of the largest single end users of electricity, consuming considerable amounts of energy as part for their operation. According to estimates from DEFRA [1], in 2006, 6,578 supermarkets were operating in the UK consuming approximately 12 TWh_{el}, which is equal to 3.5% of the total UK electrical energy consumption [2]. The breakdown of the supermarket's electrical energy consumption to different end uses is as follows [3]:

- Refrigeration: 40% ~ 50%
- HVAC: 20% ~ 35%
- Lighting: 15% ~ 25%
- Hot water: 1% ~ 3%
- Others: 10% ~ 15% (e.g. bakery, rotisserie, HR offices, dry cleaning, etc.)

Electrical energy consumption accounts for approximately 80-90% of the energy use with the rest being attributed to gas or other fuels for space heating and hot water purposes [4].

The energy consumption of each store depends on a variety of parameters such as external weather conditions, size of sales area, opening hours, store layout, product mix, occupancy levels, the equipment used for food preparation and storage etc. One of the main drivers of energy demand is the ratio of food products against total products – the greater it is, the more energy intensive the store will be.

Considering the challenge of Climate Change in conjunction with UK's ambitious carbon emissions reduction targets i.e. cutting GHG emissions by 80% below 1990 levels by 2050 [5], it becomes apparent that energy conservation measures in supermarkets can substantially contribute to that direction, while also benefiting the companies' profits.

The achievement of UK's targets depends on both building 'greener' supermarkets as well as on the efficient operation of the existing estate. Careful examination and monitoring of the day-to-day energy performance of a supermarket is important for two main reasons. The first is to ensure that the overall energy consumption of the store and of each specific energy system installed is within the expected bounds, meaning that no energy is wasted. This evaluation will guarantee that no excess cost is incurred due to energy use and no excess carbon emissions are released due to higher than normal energy consumption figures. The second reason is to detect if any major faults have occurred that could risk the reliable and safe operation of the equipment as well as the quality of products in the supermarket. Adequate monitoring of these issues can yield great benefits to businesses who address them.

The objective of this work is to develop a diagnostic tool using Artificial Neural Network Algorithms for a supermarket. This tool will be used to evaluate the energy consumption of the store as a whole and of its individual energy systems separately (i.e. examine if energy use is higher than optimal). Additionally, another relevant function of the tool will be to detect any fault in the operation of the systems so predicative maintenance can take place and in turn avoid disruption of services.

2. Artificial Neural Networks

2.1. Algorithm Description

The concept of Artificial Neural Networks (ANN) was developed about fifty years ago, but it has been used for practical applications for approximately the last twenty years [6]. Artificial Neural Networks are one of the two major fields of Artificial Intelligence (AI) with the other one being Expert Systems [7]. ANN try to mimic the human brain learning process and are able to learn key information patterns in a multidimensional information domain [8]. According to Haykin [9], a neural network is defined as:

'A massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use'

As Kalogirou mentions in [7], ANN have been characterised as a “black box” model and unlike models that are based on physical principles, a detailed description of the modelled system configuration is not required. An ANN model can identify the relationship between input and output parameters by utilizing previously recorded data. Their main areas of application are classification, forecasting, control systems, and optimisation and decision making problems. The main advantage of ANN is that they can implicitly detect complex non-linear relationships between dependent and independent variables [7].

Fig. 1 shows an illustration of a typical multilayer feedforward neural network. Typically, this type of network utilises one input layer, one output layer and one or more hidden layers with several hidden nodes or hidden units. The purpose of the hidden layer is to add up more useful computation between the input and the output layer to improve the accuracy of the network. Each neuron is connected onto the next layer of neurons, through synaptic weights, with the connection being unidirectional and therefore this network architecture is characterised as *feedforward.* The connection weights are used to “store knowledge”. The number of neurons in the input and output layer are equal to the number of independent and dependent variables of the problem respectively [7].

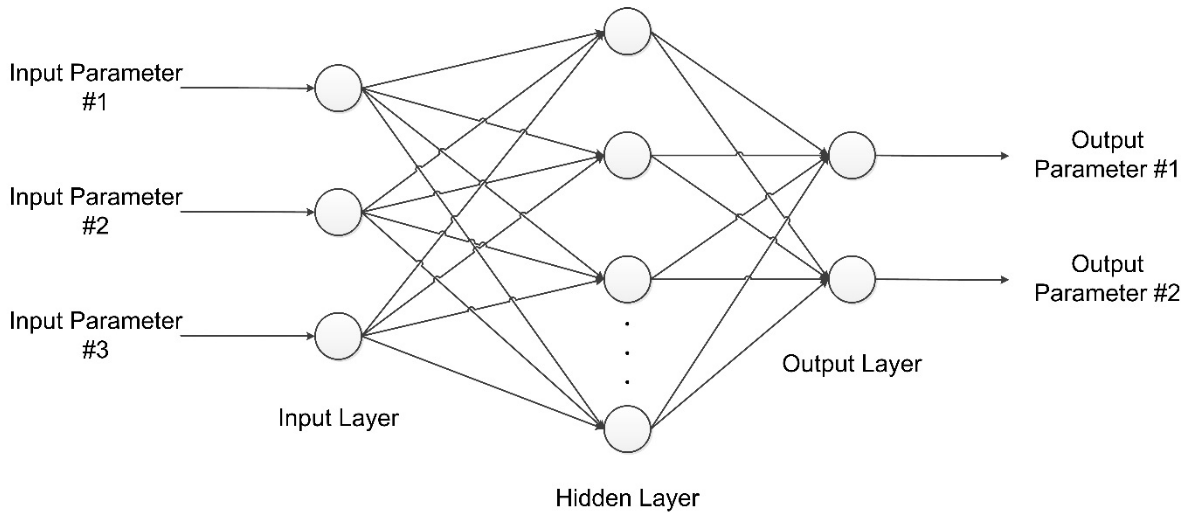

Figure 1. Feedforward Artificial Neural Network

The following step is to train the network. Training refers to the process finding the network parameters that lead to the best performance by minimisation of an error function. In neural network literature the term *learning rule* refers to the procedure of modifying the weights of a network. The network is fed with an input vector and a corresponding target-output vector. The network then uses the input to produce output which is compared to the targets. The learning rule is put into effect by adjusting the network weights to the error between the network output and the target values [7][10].

2.2. Artificial Neural Networks in Energy Systems Applications

Kalogirou [7][11] has provided very comprehensive reviews of ANN used in the energy field. Firstly, applications in the solar field are mentioned which include modelling and performance prediction of solar steam generators and solar water heating systems, as well as daily solar insolation prediction. A variety of ANN applications include HVAC systems, such as building thermal and cooling load prediction, energy consumption prediction and optimisation, and prediction of air flow in buildings. Applications for power generation systems are also reviewed; these include modelling of the combustion process, predictive control of the thermal plant and turbulent combustion modelling. Finally, Mohanraj et al [12] have reviewed applications of ANN that are related to refrigeration and heat pump systems. The applications outlined range from the energy consumption prediction of vapour compression refrigeration systems, chillers and heat pumps to modelling of different components such as condensers, compressors and cooling towers. The analysis also includes vapour absorption systems as well as applications where artificial neural networks have been used as predictive control systems.

Several studies are also available in the literature dealing with energy use in the Built Environment that utilise Artificial Neural Network techniques. Olofsson et al [13]used ANN to predict the annual heating demand for a number of residential buildings in the North Sweden using average indoor and outdoor daily parameters. A similar study was later conducted by Olofsson and Andersson [14] who developed an ANN model to predict the annual heating demand of residential buildings in the long-term, using short-term measured data – 2 to 5 weeks. González and Zamarreno [15] predicted the short-term electricity load of buildings using a ANN that feeds back a part of its outputs as inputs. The input parameters for the load forecast are current and predicted temperature values, the current load as well as the hour of the day and the day of the week. Rather than using a static approach for the prediction of energy usage in buildings, Yang et al [16] used accumulative training and sliding window training to perform on-line building energy consumption. Yalcintas [17] trained an ANN using energy consumption data of the pre-retrofit period of a building; hence, the model can be used to predict the energy usage of the pre-retrofit equipment in the post-retrofit period. By comparing, the model's output to the actual energy consumption data, an evaluation of the equipment retrofit is possible. Finally, a comparison between the ANN method and a building simulation model based on physical principles (EnergyPlus) is described in [18]. Both techniques show high accuracy in terms of energy forecasting, with the ANN being better in the short term prediction. On the other hand, it is possible to predict the energy consumption using ANN provided that previous measurements are available.

Neural Networks have also been widely used to develop diagnostic tools. Some of the applications include: electromechanical systems [19], power plants [20], industrial processes [21], Building Energy Management Systems (BEMS) [22] and electrical vapour compression chillers [23].

There are two different approaches in this application. The first is to use prediction techniques where the network is trained with optimal performance data and operates in parallel with the actual system. The network's output being the optimal performance of the system (in terms of energy consumption) is compared to that of the physical system. Any deviation can be interpreted either as prediction error or a fault in the system [24]. This approach is useful when data of faulty performance is not available. The second approach is to use a classification neural network. Using different classes for normal operation and specific types of faults in the system, the network can be trained to recognise whether the performance of the system can be characterised as normal or some specific error occurs [25]. This approach seems to give better results; however training data availability is the main obstacle.

The only study in the literature that involves the use of Artificial Neural Networks in a supermarket related energy application is the one by Datta et al [26]. In this study, the artificial neural networks method was used in order to predict the energy consumption of an existing supermarket in Scotland using a half-hourly step, for diagnosis purposes. The results showed that the energy consumption could be predicted with reasonable accuracy; however, apart from the development of the prediction element the study neither refers to the diagnostics part of the tool nor shows any results from its use.

2.3. Issues with Artificial Neural Networks

Limitations of the ANN method include overfitting and limited extrapolation ability. The first term refers to the network being trained to fit the data so well that it ends up learning some of the error in the dataset. Instead of learning the input-output patterns, it *memorises* them instead. Therefore, it loses the ability to generalise well. The Early Stopping technique can be utilised to prevent overfitting by introducing a validation set. Monitoring the error on the validation set during training, the process can be halted when the error reaches its minimum. A test set is finally used in order to estimate the generalisation error of the trained network [20].

Models developed using Artificial Neural Networks can achieve very high predictive performance for data that belong in the boundaries of the training set. However, they show very limited extrapolation ability. Therefore, in order to not lose the advantage of using ANN, it is essential that the range of the training dataset is representative of the real data that will be presented when the model is used [27].

3. Diagnostic Tool Development

3.1. Fault Detection

There are several approaches in dealing with fault occurrence in systems. The first and simplest is to take corrective action only after a system component fails to operate. This approach, however, is the most expensive method, since the system might need to be fully replaced or take time to repair. Moreover, if applied in a store environment, there could be adverse consequences for the products in the store e.g. inside a refrigerator cabinet. The second and most commonly used approach is to perform system maintenance at selected time intervals according to experience and recommendations given by manufacturers. The drawback of this method is that it does not consider the equipment’s condition i.e. whether its performance has deteriorated or not, thus missing the opportunity of being proactive. The final approach is to monitor the equipment’s performance and initiate maintenance action only when there is clear evidence of deteriorating performance. Systematic monitoring of the equipment can help prevent complete failure of the system, since faults can be detected at their early stages. In cases of performance degradation, monitoring can help determine the optimal maintenance schedule [28].

In order to evaluate the performance of the store or a system as well as to detect any faults, the operation of the store/system must be compared to some reference behaviour. There are two basic ways to establish this [29]:

The first approach is called *energy benchmarking* and it includes the comparison of the system with the current or previous performance of a similar system. This method can only provide an approximate assessment of the relative performance depending on the similarity between the two systems. Benchmarking is not popular with performance monitoring systems and is used as a quick way to assess a system's performance. The second method is called *energy baselining*, in which the reference behaviour is defined as the previous (historically best) or ideal (theoretical) performance of the system. In this case, a model for the energy consumption of the store or the examined system must be created. Since supermarkets tend to have different configurations, it becomes challenging to find a store with similar characteristics as a benchmark; hence, the second approach has been chosen for this work [29].

3.2. Artificial Neural Network Models

In order to develop an Artificial Neural Network model the first step is to determine the dependent and the independent variables of the problem. In order to determine them one must have a priori knowledge about the behaviour of the system. Since the model is for energy consumption prediction, the dependent variable will be the energy consumption either for the total store or for an individual system. The independent variables will be factors that affect the energy consumption of the systems examined. Furthermore, careful consideration is also needed in order to avoid overparameterisation of the neural network that could lead to overfitting.

The first factor that determines the shape of the load profile is the calendar date. Supermarkets have different energy consumption during weekdays and weekends due to different opening hours and different shopping habits. Moreover, there is a differentiation through the hours of the day. Therefore, *Day Of The Week* and *Hour Of The Day* are the two first input variables. Other important factors are weather data such as temperature, humidity, daylight illuminance and wind speed. Finally, other external factors such as occupancy level of the store could influence the energy consumption of its systems.

The majority of supermarkets in the UK solely log temperature values for the internal and external environment. In order to avoid overparameterisation and enhance the replicability of the model, the only weather related variables that are used are indoor and outdoor temperature as well as light sensor readings for the case of the lighting system. The ANN design concepts for each case described above can be seen in Fig. 2. Note that for the HVAC system, two internal temperature values have been used in order to account for the different locations of the Air Handling Units (AHUs) inside the store.

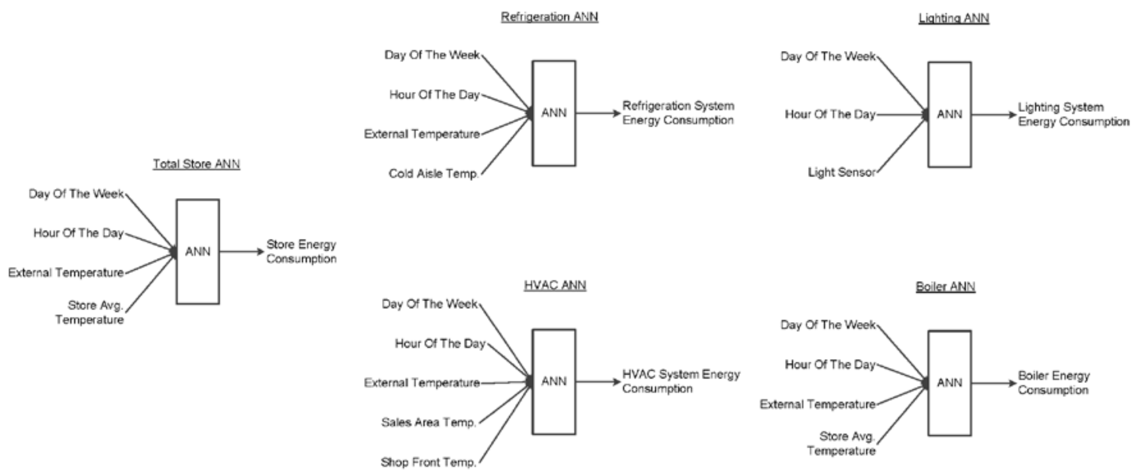

Figure 2. ANN Model Design Concepts

All the models are fed with hourly values of the influencing parameters (time variables, and temperatures or light intensity) corresponding to each hour of the day and day of the week as well as with the corresponding energy consumption value. Five months of data have been used for the training of the models. As a result, after each network is trained, it is able to predict the hourly energy consumption of the store and of each specific energy system. Apart from point predictions, the tool also gives the prediction bound for each hour of the day, which indicates the range in which the energy consumption should be with a 90% confidence using the *Resampling* technique [30]. In this method, the confidence intervals are calculated from the residuals derived from calculations within a known dataset. The assumption necessary for the calculations is that the distribution of errors observed in the dataset used is going to be similar to the distribution of errors when the model uses unseen data. One of the common issues with this method is the limited availability of data, since every bit of data available is usually used to train the model. However, using the training dataset may lead to acceptable results if care is taken to avoid overfitting [31].

At this point, the power of the Artificial Neural Networks method must be stressed and this is better illustrated with an example. For instance, if a classical modelling approach was selected, in order to build the refrigeration model, separate submodels would have to be built for the compressor, the condenser, the evaporator, the expansion valve and the cabinets. These submodels would have several inputs each and they would have to be built specifically for the system in the examined store. This would also mean that extensive information about the system's configuration and layout would be required, which might not be available or it would be difficult to obtain. Finally, the model would not be easy to replicate for other sites, as it would need to be significantly altered in order to be applied on another system in a different store (e.g. because of different system configuration, different refrigerant etc). On the other hand, the ANN refrigeration model is not system-specific and it uses only four input variables, which makes it a very generic application. Moreover, the variables used are monitored and logged in the majority of supermarkets; therefore it could be easily applied to any supermarket or system, provided the data is available.

3.2.1. Network Architecture

In the majority of papers that investigate energy demand forecasting reviewed by Hippert et al [32] and Ismail et al [33] the *multi-layer feedforward* architecture was used. Moreover, Datta and Tassou [34] have shown this specific architecture can provide better results than Radial Basis Function (RBF) networks. Therefore, for this study the multi-layer feedforward architecture has been used to build the prediction component of the diagnostic tool.

3.2.2. Data Pre-Processing

The first step of the pre-processing phase is to split the dataset into three different subsets, since the *Early Stopping* technique will be used to avoid overfitting: a *training set*, a *validation set* and a *test set*. The greatest percentage of data must be used for the training set, with less data left for the validation and the test set. The division into the three sets has been done by assigning 70% of the data to the training set, 15% to the validation and the final 15% to the test set.

Before the data is fed to the network, it has to be normalised to eliminate any bias for one input variable over the others, by using the same range for all the variables. It is particularly valuable when inputs are generally on broadly different scales. The normalisation range lies between 0 to 1 when a logistic sigmoid transfer function is used and -1 to +1 when a linear or tangent hyperbolic transfer function is used.

3.2.3. Number of Hidden Layers

In terms of number of hidden layers for the developed network, there is no theoretical research that could determine the optimum number [33]. However, multi-layer feedforward networks with one hidden layer have been characterised as *universal approximators.* In 1987, Hecht-Nielsen [35], using Kolmogorov's theorem [36], proved that any continuous function can be represented by a neural network with only one hidden layer and exactly *2n+1* nodes, where *n* is the number of input nodes. Yet, since the *2n+1* figure is valid only for the activation function that Hecht-Nielsen used, the next step should be to examine the number of neurons in the hidden layer [37].

3.2.4. Number of Hidden Neurons

Even though the number of input and output neurons are predefined in a way (equal to the number of independent and dependent variables of the problem examined), the number of hidden neurons has to be calculated. There are plenty of empirical formulas in order to determine the optimal number of neurons in the hidden layer, however, in this study an experimentation method is utilised. Having determined all the other network parameters, the network is trained for a number of hidden neurons from 1 to 40. Each candidate design is trained for 10 times, using different initial weight values, and the Mean Square Error (MSE) values in the training set, validation and test set are stored. The optimal number of neurons is the one that gives the lower MSE in the test set.

3.2.5. Learning Algorithm and Transfer Functions

The performance of the ANN models is optimised, using the number of neurons in the hidden layer as well as learning algorithms and transfer/activation functions as the architecture parameters. The approach that was used was the trial and error in order to identify the architecture that leads to the smallest error in the test set.

In this study five different learning algorithms were use; these are:

- Levenberg-Marquardt backpropagation [38][39];
- Resilient backpropagation [40];
- Gradient descent with momentum and adaptive learning rate backpropagation [41];
- Conjugate gradient backpropagation with Powell-Beale restarts [42], and
- Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton backpropagation [43]

For every learning algorithm, three types of activation functions were used for the hidden and output layer; these are:

- Linear (purelin);
- Hyperbolic tangent sigmoid (tansig);
- Logistic sigmoid (logsig)

The following step is to train the ANN models until satisfactory results have been achieved. Then, the model's output is fed along with the actual energy consumption from the monitoring systems to the diagnostic part of the tool described in the following section.

3.3. Two-level diagnostic tool

At this stage, as was previously mentioned, there are two levels of diagnosis. In the first level, the actual total daily energy consumption of the store or the system is compared to the predicted consumption. If the actual value exceeds the predicted by 10% or more, then the performance is labelled as *Bad*. If the performance exceeds the predicted value by 5% to 10%, then the performance is characterised as *Average*. In every other case the performance can be classified as *Good*. The process flow chart of the first diagnostic level can be seen in Fig. 3a.

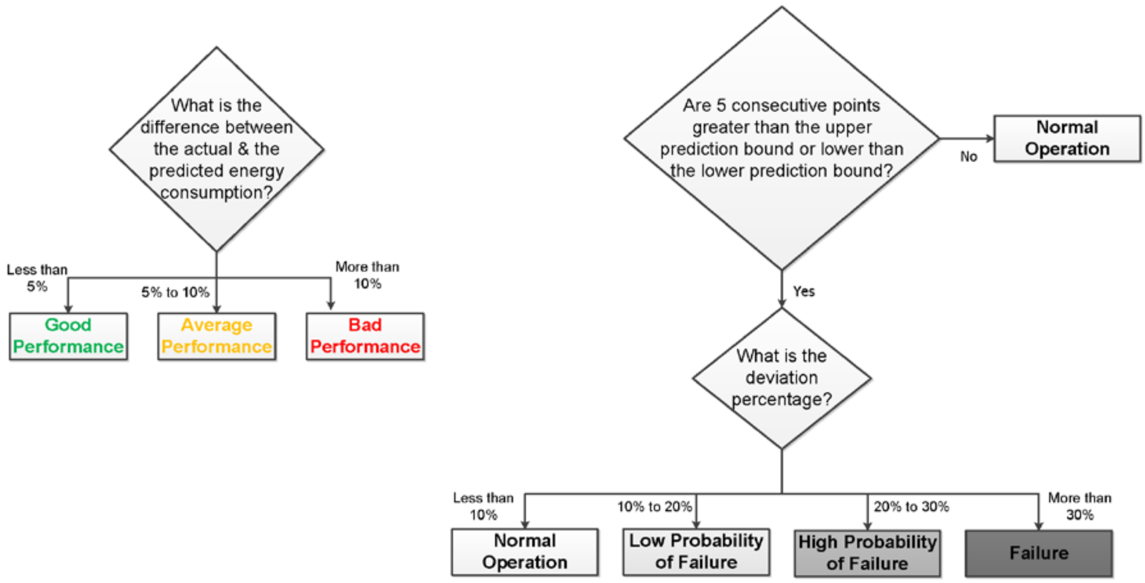

Figure 3. a. First Diagnostic Level, b. Second Diagnostic Level of the Tool Developed

The second diagnostic level is applied only in the case of the different subsystems to identify if the operation is normal or some fault has occurred. At the final diagnostic level, the energy consumption of each store system is not compared to the predicted value, but to the confidence bounds instead. The concept of this level is the following: Even if the energy consumption of each subsystem is not equal to the predicted value, if it lies inside the confidence bounds, the operation of the system can be classified as normal, since this deviation from the predicted value could be due to factors other than system fault. Moreover, following the same approach as Kalogirou did in [24], if the energy consumption for one hour is outside the confidence bounds, this cannot necessarily be attributed to some fault incident, since something else might be the cause of it *e.g.* a frozen cabinet door being accidentally left open by a customer. Nevertheless, if there are five or more consecutive points/hourly values, where the energy consumption is outside the confidence bounds, the likelihood of a fault occurrence is high. According to Kalogirou [24], the choice of five (5) consecutive values was found to be a "good compromise between false alarms and early detection". The deviation from the confidence bounds can be from both the upper and lower bound signifying either some fault that leads to excess energy consumption or some fault that ceases the operation of a component respectively.

For the diagnosis purpose, four different modes of operation have been created, similar to [24]: *Normal Operation, Low Probability Of Failure, High Probability Of Failure, and Failure*, corresponding to deviation from the confidence bounds of less than 10%, 10 to 20%, 20 to 30%, and 30% or more respectively. The concept of the second diagnostic level has been schematically depicted in Fig. 3b. The tool cannot however, identify the exact cause of the fault in each system. Once a fault has been detected, the maintenance team must be notified to examine the operation of the system more closely.

In order to provide more information to the user, the tool calculates the difference between the predicted energy consumption and the actual energy consumption for the day in terms of absolute energy units (kWh) and deviation percentage (%), as well as the incurring difference in cost of energy (£) as well as CO_2 ($kgCO_2$) emissions. These pieces of information are given as an output in an information panel along with the visualisation of the results. For the calculation of the cost and emissions difference the following factors, displayed in Table 1, have been used for the calculations.

Table 1. Cost and Emission Factors used for the calculations

Cost per kWh electric (£/kWh$_e$)	0.0863
Cost per kWh thermal (£/kWh$_{th}$)	0.0366
CO_2 emissions per kWh electric	0.55
CO_2 emissions per kWh thermal	0.013

The tool has been developed, from the ANN Model to the visualisation of the results, using MATLAB and the included Neural Network Toolbox [44].

4. Case study store

A case study applying the developed tool has been carried out, taking its data from a UK supermarket located in Kent, opened in February 2011. The store has a sales area of 35,759 ft^2 or 3,300 m^2 and its opening hours are from 8am to 10pm on weekdays and Saturdays, and from 10am to 4pm on Sundays. To give a better insight to supermarket energy use, the results of an energy audit of the store are presented. Thorough monitoring capabilities allow us access to energy consumption data for the store every 30 minutes. Fig. 4a shows the breakdown of energy use for the store on an annual basis.

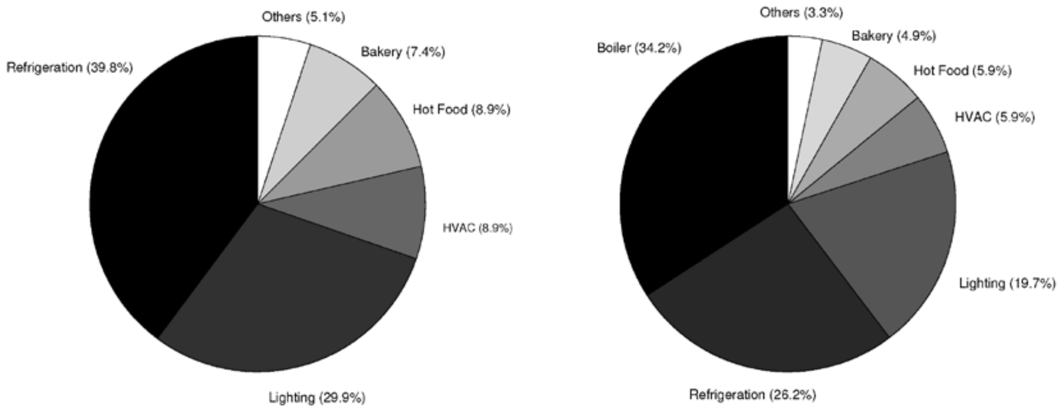

Figure 4. a. Electrical Energy Consumption Pie b. Electrical and Thermal Energy Consumption Pie

In terms of electrical energy, the *refrigeration system* is the major consumer with almost 40% of the total energy. The *lighting* system at the store consumes approximately 30% of the energy with the HVAC system consuming about 8.9% of the electrical energy. Considerable amounts of energy are consumed in the *Hot Food and Bakery ovens*, corresponding to 8.9% and 7.4% of the total respectively. Finally, the category *Others* in the graph refers to energy consumed outside the sales area such as the manager's office, meeting rooms, etc. Hence, it can be said that this energy pie resembles the breakdown of energy use, according to [3], mentioned in the introduction.

If heat is taken into account, then the breakdown of energy use changes dramatically. From Fig. 4b, it can be seen that the *Boiler* consumes about 34.2% of the total energy of the store; providing both hot water and space heating services. Together with the HVAC system they constitute 40% of the total energy use.

Overall, on an annual basis the store in terms of electrical energy consumes more than 1,500 MWh that incurs an electrical energy bill equal approximately equal to £150,000 per annum. Concerning thermal energy, the annual energy use is equal to 740 MWh. The store has a biomass boiler to cover of the heat demand, hence the annual cost is calculated to be approximately equal to £27,000.

These cost figures make the need for an energy consumption evaluation and diagnostic tool evident, since commercial businesses operate with tight margins and reducing operating costs increases their profit line.

Analysis of the load profiles of the energy systems at the store will facilitate understanding of interactions between the systems and determination of optimal energy saving strategies. From the grid's perspective, the power drawn on a typical day of the store is shown in Fig. 5.

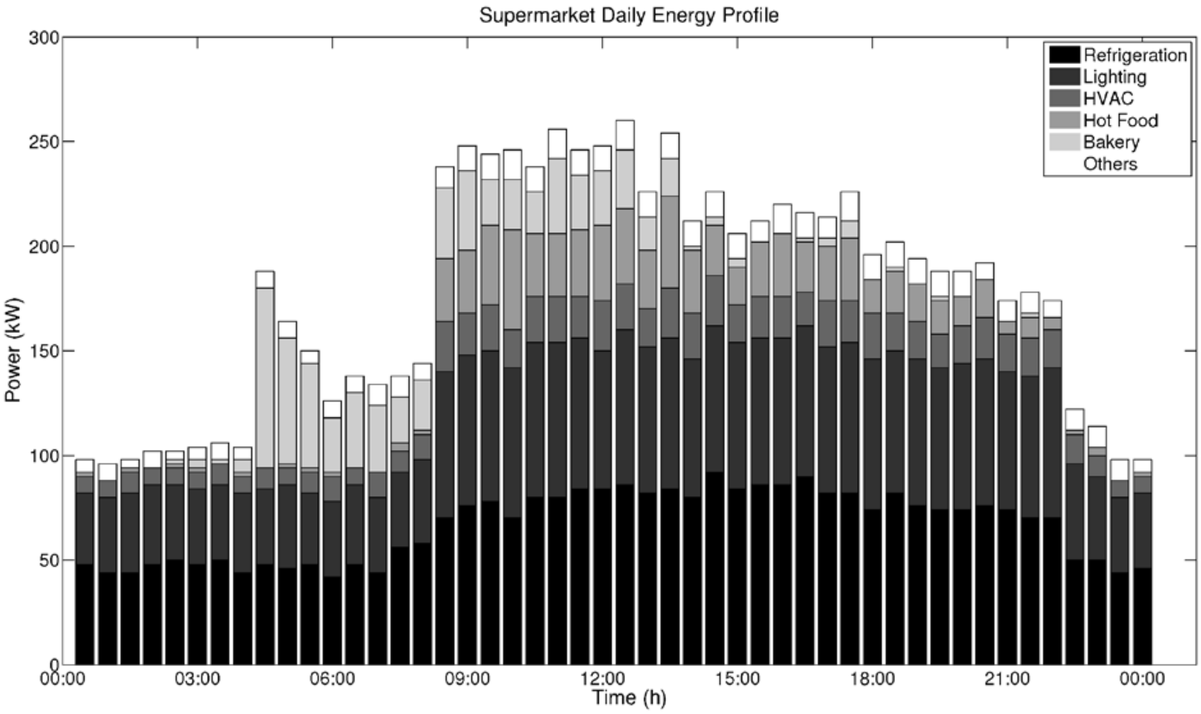

Figure 5. Typical weekday electricity load profile at examined store

One can firstly notice that the store consumes more energy during trading hours (when the store is open). From the power profile, it becomes evident that from 11pm to 4 am, when the store is closed, it operates at base load. Then at around 4.30am there is a peak in power demand due to the Bakery ovens turning on but then it decreases once they have reached their operating temperature. The next peak is observed at 8am, when the store opens, due to the turning on of Air-Handling Units, Hot Food Ovens and Lighting. The energy consumption then remains relatively constant during trading hours, only to be reduced when the store is closed.

5. Results and Discussion

The results for the ANN models development can be seen in Table 2. In all the cases the best performing algorithm was the *Levenberg-Marquardt*. The table also includes the network architecture parameters in terms of number of neurons in the hidden layer and transfer functions. It becomes evident that there is not one combination of parameters that gives the best results, hence it is important to optimise the network rather than randomly choose its parameters.

Table 2. ANN Models Development & Accuracy Results

		Total Store	**Refrigeration**	**Lighting**	**HVAC**	**Boiler**
Learning Algorithm		Levenberg - Marquardt				
Network Parameters	**Number of Hidden Neurons**	34	33	11	30	28
	Hidden Layer Transfer Function	tansig	tansig	logsig	tansig	logsig
	Output Layer Transfer Function	logsig	purelin	logsig	logsig	logsig
Accuracy Results	**R-value**	0.9808	0.9682	0.9777	0.8870	0.9708
	Mean Absolute Percentage Error (%)	4.79	7.9	5.64	36.9	6.52

The second section of the table contains the R-values and the Average Prediction Error for the ANN models developed. The results show that satisfactory performance has been achieved for all the models, except for the HVAC model. The reason is that the energy consumption of the HVAC system is not only driven by temperature value, hence additional parameters such as the Variable Speed Drive (VSD) control logic should be utilised.

To illustrate the accuracy of the models developed, Fig. 6 compares the total energy consumption of the store given by the ANN model to the actual values, over a week's period, where it can be seen that the two curves fall very close to each other. The network accurately predicts the energy consumption peak in the morning when the bakery starts, as well as when the store starts trading. It also performs well predicting the fluctuations of the load throught the day. Moreover, it has "learned" to recognise the different days of the week and therefore the energy consumption on Sunday, corresponds to the energy profile for that day with fewer trading hours compared to the other days.

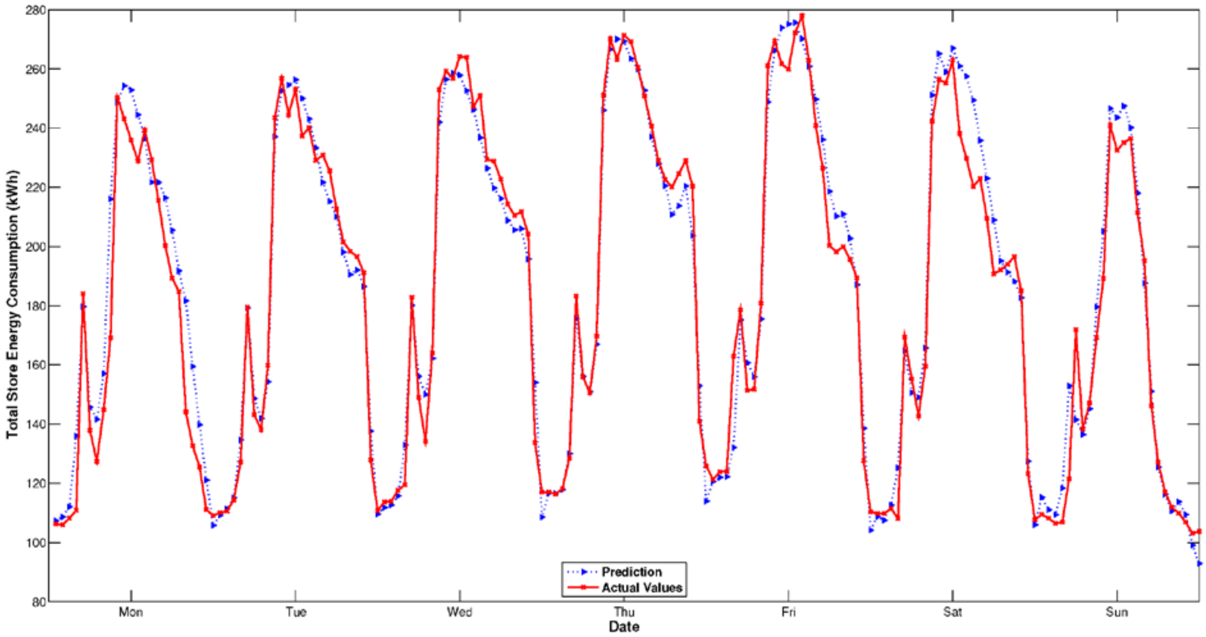

Figure 6. Comparison between predicted and actual data over a week's period using the ANN developed for the Total Store Energy Consumption

Running the tool for the store's total energy consumption, the output will look like that in Fig. 7. In this case, the tool's output is for a day in May and it is evident the store's energy consumption profile matches very closely the predicted energy consumption and therefore the performance is labelled as good. On the other hand, Fig. 8 shows an example of the tool's output for the store's total energy consumption on a Bad Performance Day. The reason that the performance has been labelled as Bad is that the total daily energy consumption is higher than the expected by almost 18%, hence above the 10% threshold for the Bad Performance label.

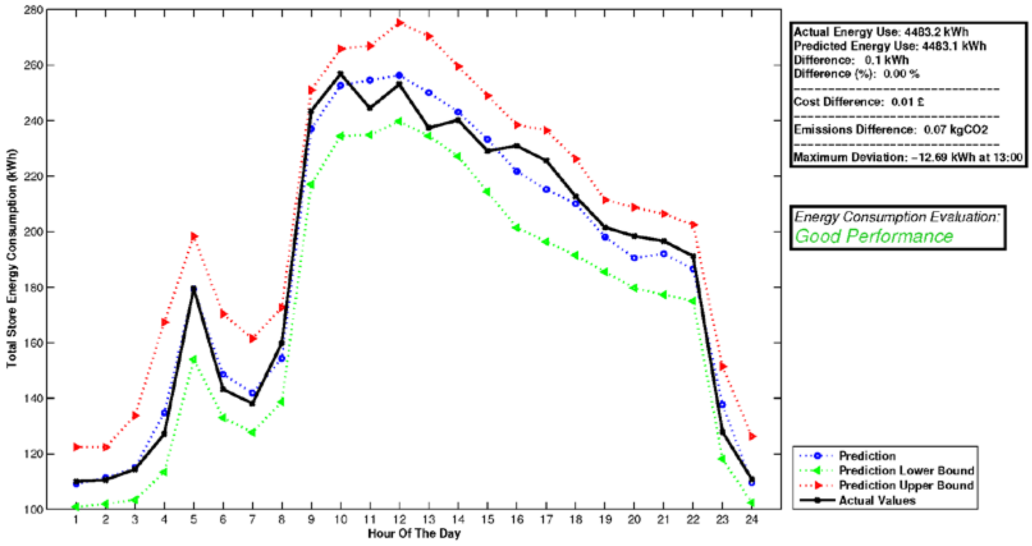

Figure 7. Diagnostics tool output for Total Store on a Good Performance Day

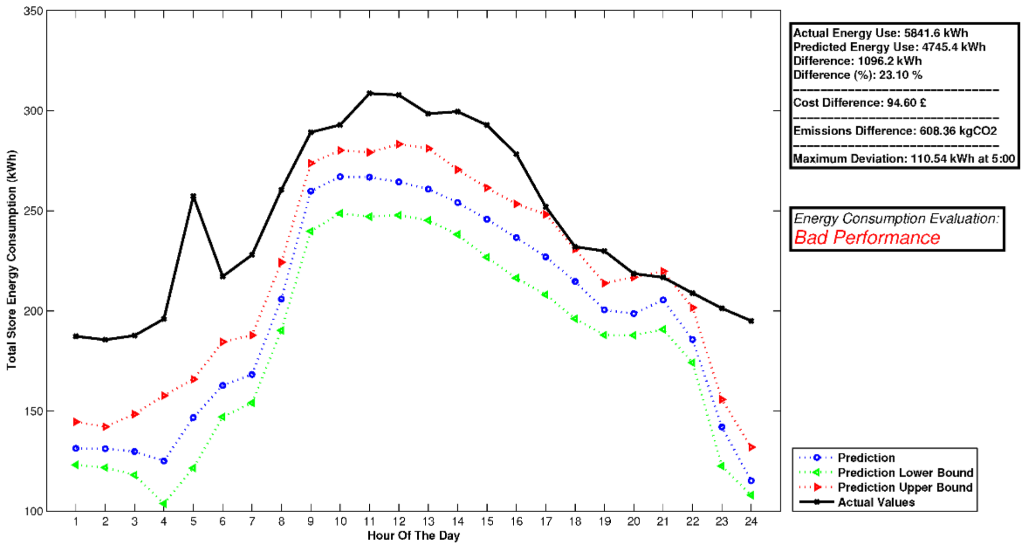

Figure 8. Diagnostics tool output for Total Store on a Bad Performance Day

Running the tool solely for the store's energy consumption, one cannot get any insight on the individual systems performance. Hence, the tool must be also executed for the individual systems. Example outputs of the tool for the different systems are presented as follows.

Fig. 9 shows the output of the tool for the refrigeration day on a Good Performance day, since from the information panel, next to the plot, inside Fig. 9, it can be seen that the overall energy consumed in the day is 1.22% less than the expected. From the panel, it can also be seen that this performance leads to £1.49 savings as well as a reduction in CO_2 emissions of 9.55 kg. Since the energy consumption profile follows the expected profile relatively close without exceeding the confidence bounds, the Operation Diagnosis is Normal Operation.

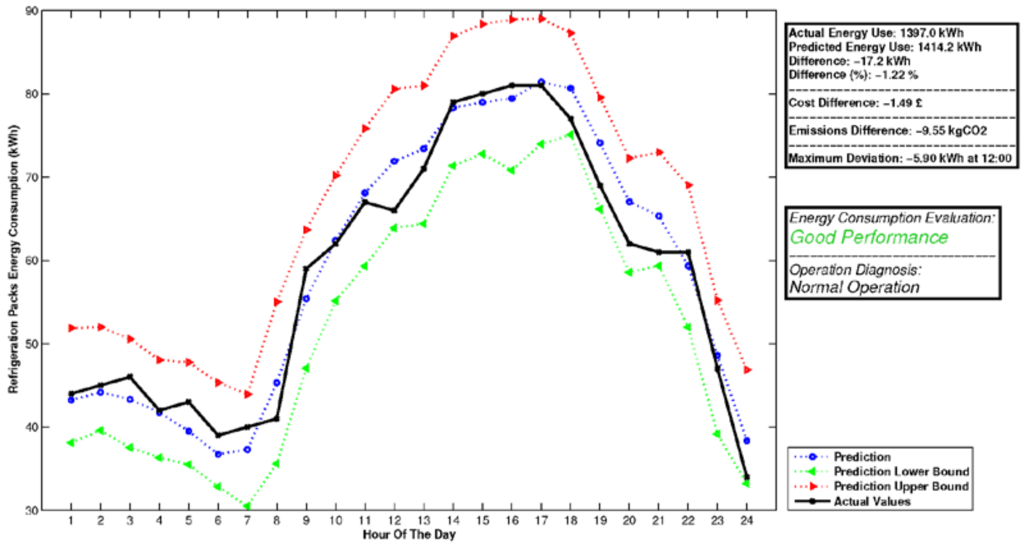

Figure 9. Diagnostic Tool Output for Refrigeration System on a Good Performance and Normal Operation Day

Fig. 10 presents the output of the tool for a hypothetical day, when there is *High Probability of Failure.* In this case, an incident that has kept the energy consumption at very high levels has occurred *e.g.* a broken condenser fan, resulting in a *Bad Performance* from an energy consumption perspective. The deviation from the upper prediction bound is for more than 5 hours and at levels, which according to the criteria set in Section 3.3., designate that there is a High Probability of Failure.

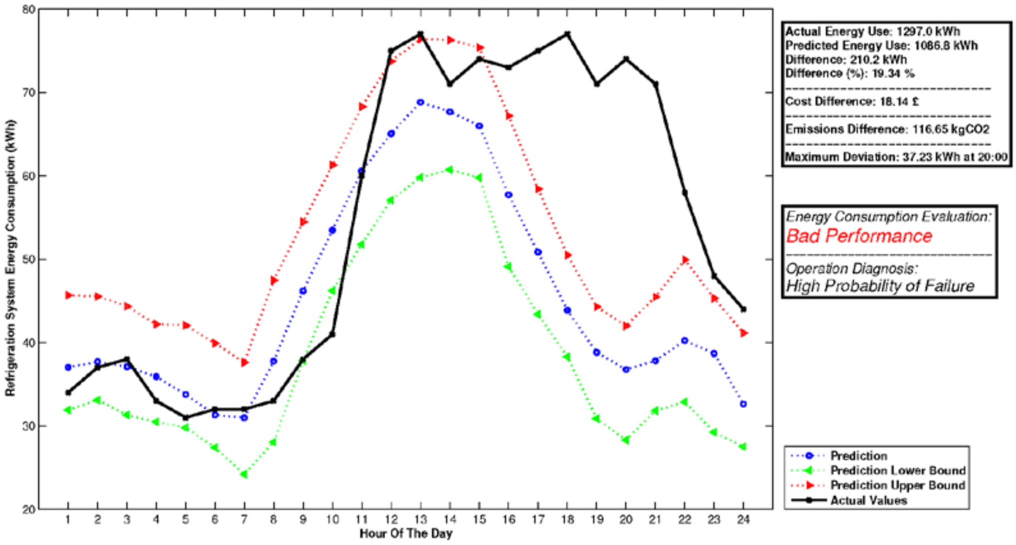

Figure 10. Diagnostic Tool Output for Refrigeration System on a Bad Performance with High Probability of Failure

Apart from increased energy consumption, system failure can also lead to reduced energy consumption due to component failure, for example. The tool's output for the boiler system for the day that failure has occurred can be seen in Fig. 11. From the information panel on the right, it can be seen that the actual energy consumption is by 46% smaller than the predicted value. However, in this case, this does not indicate good energy performance, since this has occurred due to component failure. Hence, in the tool's output, the *Energy Consumption Evaluation* has been omitted since it would indicate *Good Performance.*

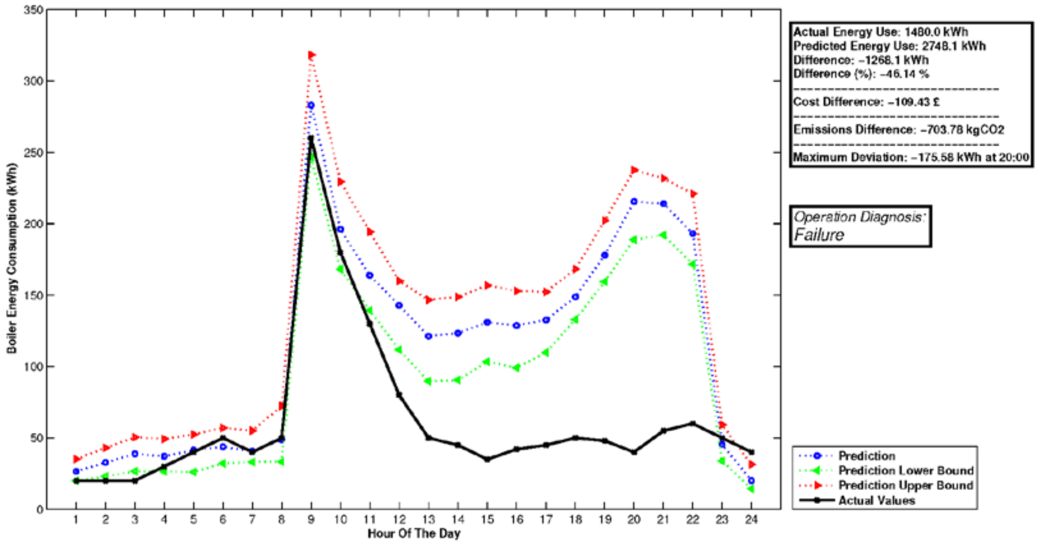

Figure 11. Diagnostic Tool Output for Boiler System on a Day when Failure has occurred

6. Conclusions

The developed tool can be used by two categories of people involved in the operation of a supermarket. Firstly, it can be used by the manager of the store to ensure that no energy is wasted in its operation that could cause excessive cost in the energy bill of the store, thus giving the manager the ability to become proactive in what is going within his/her work environment. Likewise, a specialised energy team can supervise many sites in a time-effective manner to ensure stores perform as expected. Moreover, the maintenance team could utilise the tool to monitor the performance of the energy systems installed in order to detect and repair any faults before they disrupt the operation of the store *aka* predicative maintenance. Finally, it can be used to help them determine the optimal maintenance schedule taking into account the state of the equipment.

The model developed uses weather data as well as the day of the week and hour of the day parameters to predict the expected energy consumption. The data needed for the training of the models came from the advanced remote monitoring systems that were installed in the store; data quality was of utmost importance for the model development. The results in the study showed that a simple neural network structure can provide predictions of the energy consumption of the store and its systems with a reasonable degree of accuracy, as shown by the Mean Absolute Percentage Error (MAPE). Since the tool's development process requires data that is available in most retail stores, this tool can be applied for different stores, by training a particular ANN for each one, offering wider diagnostic capabilities.

Overall, Artificial Neural Networks is a generic technique that can be used to identify relationships between inputs and outputs. It requires less expertise and effort compared to traditional modelling approaches. This project proved their applicability for the development of a diagnostic tool for the energy systems in a supermarket. Finally, the use of the method is not limited only to diagnostic tools, but it can also be applied in other applications such as in energy prediction applications in order to allow demand response assessments or even for purchasing electricity in the spot market.

7. Future work

In terms of future work, the models developed could be integrated in the monitoring tools that the store uses in order to enhance the adoption and use of the tool by the people involved in the store operation. As soon as the data that the tool needs as input is logged in the monitoring system, the diagnostic tool can provide the performance evaluation and fault detection results automatically, so that the corresponding store's manager and maintenance team receive the daily output of the tool at the end of each day, *e.g.* via email.

Finally, another way to improve the neural network model is to automate it in a way that the neural network model can draw new data added in the monitoring systems of the supermarket and retrain periodically in order to update its training status, *e.g.* every month. The training dataset can be infused with newly collected measurements. This way the network can be up to date and be able to identify both the local (*e.g.* daily) and the global (*e.g.* seasonal) energy variation. With this approach the model will continually adapt to new data and it will be able to reflect any changes.

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