

Load Profile Generator and Load Forecasting for a Renewable Based Microgrid Using Self Organizing Maps and Neural Networks

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Abstract— In this paper, two methods for generating the daily load profile and forecasting in isolated small communities are proposed. In these communities, the energy supply is difficult to predict because it is not always available, is limited according to some schedules and is highly dependent on the consumption behavior of each community member. The first method is proposed to be used before the implementation of the microgrid in the design state, and it includes a household classifier based on a Self Organizing Map (SOM) that provides load patterns by the use of the socio-economic characteristics of the community obtained in a survey. The second method is used after the implementation of the microgrid, in the operation state, and consists of a neural network with on-line learning for the load forecasting. The neural network model is trained with real-data of load and it is designed to stay adapted according to the availability of measured data. Both proposals are tested in a real-life microgrid located in Huatacondo, in northern Chile (project ESUSCON). The results show that the estimated daily load profile of the community can be very well approximated with the SOM classifier. On the other hand, the neural network can forecast the load of the community reasonably well two-days ahead. Both proposals are currently being used in a key module of the energy management system (EMS) in the real microgrid to optimize the real uninterrupted load for 24-hour energy supply service.

Index Terms—Self-organizing Map (SOM), neural networks, load forecasting, Energy Management System (EMS), microgrid.

I. INTRODUCTION

The load behaviour of a microgrid presents more non smoothness and high frequency changes than the observed in traditional high-scale power systems. Given the small-size of the microgrid, any change in the electricity usage may have a significant effect on the load of the microgrid. Thus, conventional methodologies are not suitable for real-application in the forecasting of load in microgrids, making necessary the development of new techniques that deal with the higher uncertainty of the load behavior, its high volatility, etc.

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For solving the load forecasting problem, brain-like and computational intelligence techniques, such as neural networks, have been widely used. In this context, a radial basis function network for short-term load forecast of a microgrid located in a building in Hong-Kong was proposed by Xu et al. [1]. Chan et al. [2] proposed a multiple classifier system for the short-term load forecast of microgrids. This classifier was combined with neural networks, multilayer perceptron and radial basis functions, and the results were evaluated using real load data. Additionally, other techniques like wavelets analysis have been used as a complementary tool, for example in characterizing different load profiles [3].

Evolutionary algorithms have also been used for determining the inputs of predictive models such as type of day, temperature, etc., [4]. Amajady et al. [5] proposed a new bi-level strategy for short-term-load forecasting. In the upper level a stochastic search technique (Differential Evolution) was used to optimize the parameters of the feature selection algorithm and in the lower level another forecast engine (Neural networks and Evolutionary Algorithms) was used for the predictions. The proposed method was evaluated with real-life data from a university campus in Canada.

As a complementary tool in load forecasting methodologies, which is important for the optimal operation of the microgrid, we have the identification of the connected loads on the basis of their consumption behavior, and their classification according to some patterns of consumption. Kim et al. [6] consider an automatic meter reading system that is used for generating typical load profiles at distribution transformers. The generated profile is constructed based on load profiles obtained through fuzzy clustering and classification techniques. However, this method is only applicable to traditional distribution systems. In the case of microgrids, obtaining profile results is a more difficult task given the high variation and uncertainty of the load behavior.

Regarding domestic energy consumption, Mori et al. [7] propose a short-term load forecasting method that uses an input data classifier based on Kohonen neural networks. Valero et al. [8] combine both multilayer perceptron and Self Organizing Maps (SOM) for classifying and using the historical data. The main advantage of the SOM is its capacity to automatically show an intuitive description of the data similarity [9]. Sánchez et al. [10] use SOM for classifying the demand patterns of electricity customers on the basis of database measurements. Verdú et al. [11] consider a SOM classifier that uses the socio-economic characteristics of energy used when load data is not available.

In this paper, we describe the implementation of an SOM to generate the load profile for the design of microgrids in terms of unit sizes. Most of the research in the literature on the generation of electricity demand profiles is based on real-time measurements. In this proposal, we include only socio-economic aspects and some variables related to the consumption behavior of the community. The electricity forecast demand has been studied; however, there are few existing developments applied to microgrids which explicitly consider the characteristics of the demand, characteristics which are very different from those in traditional power systems.

Also, in this paper, we propose for the operation of the microgrids an on-line neural network for load predictions, currently used as a key module in the energy management system (EMS) of a real microgrid system implemented in the north of Chile. Then, to keep track of changes in the behavior of the consumption, the parameters of the neural network models are continuously adapted including also the on-line measurements.

The paper is organized as follows: In Section II, the load profile generation method based on SOM is described. Section III details the applied load forecasting using a neural network with on-line learning. In Section IV, the results for the real microgrid project ESUSCON are shown and discussed. In Section V the conclusions and suggestions for further research are presented.

II. LOAD PROFILE GENERATION BASED ON SOM

A. Self-Organizing Map (SOM)

This section describes the self organization maps (SOM) developed by Kohonen [12][13]. One of the main features of the Kohonen's SOM is their capability to classify complex sets of patterns in an unsupervised way, by extracting some classification criteria from the data, which are expressed and used later in a non-explicit manner [8]. This classification is carried out by using the distribution of an input space V_i , over an output space V_o (usually of a lower dimension), and preserving the topological properties of the patterns in the input space.

The output space is defined by a set of neurons generally arranged over a plane or a line, in a rectangular or hexagonal shape, where a neighborhood function is defined as shown in Fig. 1. The self-organized network must extract the important features, patterns, regularities, correlations or categories in the input data, and incorporate them in its internal structure of connections and links. The neurons must self-organize themselves based on the external stimuli, i.e., according to the inputs.

After the learning process, an input vector $\vec{x} = (x_1, \dots, x_n)$ will activate the neuron j of the output space if the weighting vector $\vec{w}_j = (\omega_{j1}, \dots, \omega_{jn})$ has the lesser distance to the input vector x . In this way, the vector \vec{w}_j is considered to be the prototype of the input space region whose vectors activate the neuron j (the so called winning neuron). In this way, two vectors with similar inputs according to the relations defined in V_i will activate the same neuron or two different but near neurons of the output space.

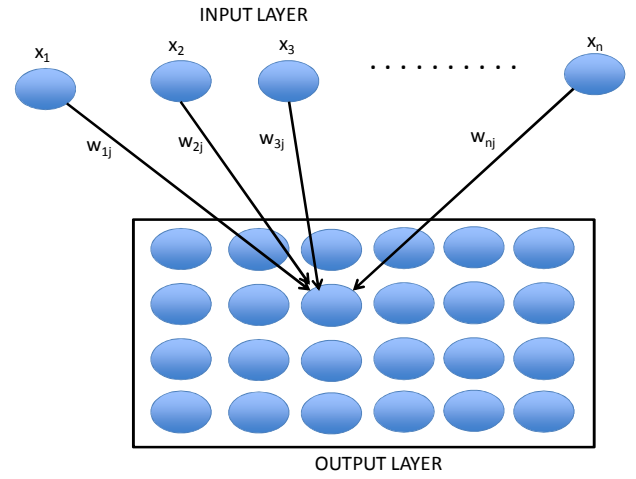


Fig. 1 Scheme of a Kohonen Neural Network.

The architecture of the SOM is a neural network with two layers. The input layer consists of n neurons one for each input variable. The neurons in the output layer are spatially distributed along a two-dimensional grid. Each input neuron i is connected to each output neuron j through a weight w_{ij} . Thus, the output neurons have a weight vector W_j called codebook which is a reference vector as it is the prototype (average) vector of the category represented by the output neuron j .

In the basic training algorithm of the SOM, first the weights of the network are initialized. Then, a new input vector \vec{x} is considered. After the activated neuron, whose weights are closest (in the Euclidean distance sense) to the vector \vec{x} is found, the weight vectors of the activated neuron and its neighboring neurons are modified using the following equation:

$$\vec{w}_j(t+1) = \vec{w}_j(t) + l_r h_{jv}(\vec{x} - \vec{w}_j(t)),$$

where \vec{x} is the input vector, \vec{w}_j is the weight vector of the neuron j , and $h_{jv}()$ is a neighboring function. Generally, the neighboring area is based on the dynamic learning rate l_r , which changes dynamically during the learning process according to the equation:

$$l_r(t) = \frac{l_{r0}}{\left(1 + \frac{ct}{nn}\right)}$$

where l_{r0} is a learning rate, c is constants (usually equals to 0.2), t is the current iteration and nn the number of neurons of the network [14].

Finally, the size of the neighborhood and the learning rate are continuously changing (or updated). This process is performed consecutively considering new input vectors \vec{x} until the training process is finished. To visualize the SOM is usually not an easy task, because the classification process can be performed in high dimension spaces. One of the most popular methods to visualize the proximity relations of the reference vectors in a SOM globally is through an unified distance matrix U [15].

B. A New Method for Load Profile Generation Based on SOM

In this paper, a new method to generate load profiles of residential electricity demand in isolated communities is proposed (see Fig. 2). In these communities, the energy supply is not available for the full 24 hour day. The main feature of the method is its capability of generating the electricity demand profiles by considering only the information obtained in a socio-economic survey conducted in the community, and without considering any measurement of the electricity demand in the past. The method is divided into three main components (see Fig. 2). In the first module of inputs, the information of each house in the community is obtained through surveys and site visits, which take place at each house. The information of the surveys is used in the second module of classification, where a SOM of Kohonen extracts the following information: classes, the elements of each class, and the features that differentiate each class. In the third module of search, a heuristic method is implemented. The characteristics of each class permit executing the search and assigning a profile that characterizes each class and then the total demand profile is obtained by multiplying by the number of the elements of each class. Each module is explained in details below.

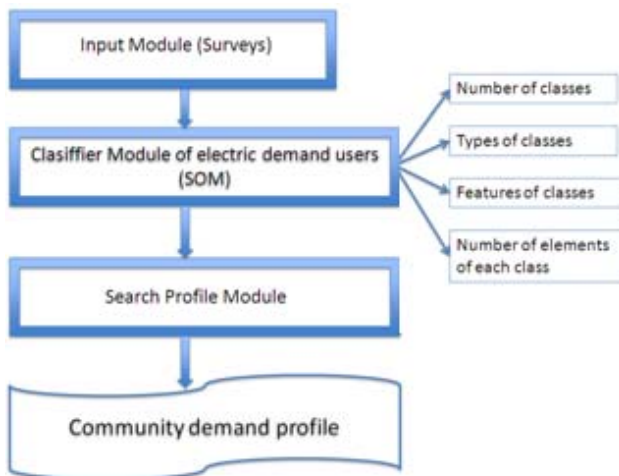


Fig. 2 Procedure for Load Profile Generation Based on SOM

Input Module. This consists of obtaining relevant information from the community through well-structured surveys. Two methods of collecting the information are used: one is through the analysis of magazines, documents, and statistical data from various sources such as population and housing censuses, websites, and review of reports in libraries or in publications of governmental organizations. The other method is by the interviews in the field with the representatives of the relevant institutions of the town and the community itself, [16].

The individual surveys carried out in each house of the community are focused on obtaining information such as: number of persons living in the house, ages and occupations, incomes, number and type of electrical appliances, and hours of use of each appliance. In this module it is also very important to perform data processing, elimination of erroneous data, estimation of the missing data, numerical assignment of

qualitative variables obtained from the surveys, and normalization of the data.

Classifier module. The main objective in this module is to obtain a classification of the different kinds of houses in the community in an unsupervised way, considering some criteria known a priori such as the number of family members, occupation of each of them, income, number of electrical appliances, and so on. The module will also provide information on the number of families in each class using an automated classifier. The classification of the houses is obtained by a self-organization, by making the neighbor neurons react more strongly to similar input patterns. In our case, as a measure of similarity we have chosen the Euclidean distance. The SOM does not require labels for each class; however, in order to reduce the complexity in the visualization process, the data could be labeled with for example the names of the family members, so that the results are visually easier to understand.

Search Profile Module. For the searching process, a heuristic selection technique was used. The classifier considers the characteristics of all the classes and then in order to classify an input, it searches for the class with very similar characteristics in the database.

The database is where demand profiles that define the classes are stored. The proposed method is suitable for communities that do not have a 24-hour energy supply, and thus, first, a data-base from another community with a 24-hour energy supply is required. Then, a metering system is installed at some houses and by using a survey, the characteristics of each house is obtained assigning a type of house. Then, the profiles of each type of house are stored.

Initially, the database includes a certain number of pre-defined profiles; however, the database is flexible in the sense that it is possible to consider more and diverse profiles. The groups included in the database are: elderly couple, elderly person alone, elderly person and adult, adult alone, adult couple, couple with a child, adult couple with a teenager, couple with two young children, adult couple with two teenagers, couples with more than three children, and a profile assigned to those that do not correspond with any of the mentioned groups.

Community demand profile. Finally, the total residential demand is obtained by summing the product of the number of elements in each class by the profile assigned to the class:

$$d_r = \sum_{c=1}^c p(c) * ne(c)$$

where d_r is the total residential demand, c is the class, $p(c)$ is the profile assigned to the class and $ne(c)$ is the number of elements in the class. Note that this generated load profile is vital for sizing the microgrid distributed generation units during the microgrid project design stage.

III. LOAD FORECASTING USING A NEURAL NETWORK WITH ONLINE LEARNING

For the electricity demand prediction, we used a neural network trained on-line. In the Fig. 3, the main steps of the forecasting procedure are shown. First, the data acquisition is performed. Then, after a pre-processing of the data, the requirements for the predictions are defined, such as sampling time, prediction horizon, step prediction, etc. Finally, a neuronal network is identified and the load forecasting is obtained [17]. Each step is described below.

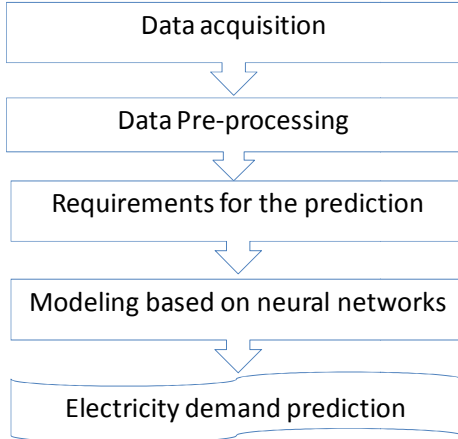


Fig. 3 Method for the Load Forecasting in the Microgrid

Data acquisition. First, the available measured variables are determined. In this work, on-line measurements of the electric demand are available. This data is used for the training of the neural network.

Data Pre-processing. Once data has been acquired, pre-processing must be performed: scaling, missing data estimation, data correction, normalization, etc.

Requirements for the prediction. The parameters needed to define the model and its future use are determined, such as the prediction horizon, the steps of prediction, and the sample time of measures. Based on the requirements, and considering all these parameters, the predictor is developed.

Modeling based on neural networks. Neural network identification is comprised of the following steps (see Fig 4).

Initial variable selection. This consists of detecting the most relevant variables. Correlation analysis of the candidate variables is done.

Data Selection. Once the variables of the model are obtained, the data is divided into three groups: training, test, and validation. The percentages 60%, 30%, and 10% are used respectively.

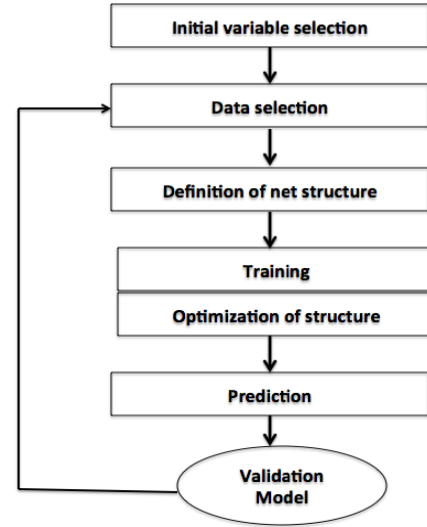


Fig 4 Neural Network Identification

Definition of the initial structure of the neural network.

The structure of the neural network includes: (1) number of neurons in the input layer, which corresponds to the number of inputs of the models obtained in the initial variable selection step (this number is modified later in an optimization-based procedure to obtain the optimal inputs). (2) Number of hidden layers. The number of neurons in the hidden layer (in the initial structure twice the number of the input layer is considered). (3) The nonlinear activation function (tansig is used). (4) One neuron in the output layer with linear activation (function purelin).

Training. On-line backpropagation training is used.

Optimization of structure. The neuronal structure optimization consists of determining the optimal inputs to obtain a predictor with minimal error, and to determine how many neurons are optimal in the hidden layer (keeping the balance of good prediction and complexity of the model). A sensitivity analysis is used for the selection of the relevant inputs. The derivative of the output with respect to each input is considered, and using a good threshold, the most important inputs are determined [17].

Prediction. The prediction model can predict within a horizon of two days or 192 periods of fifteen minutes.

Validation. Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and variance of the MSE are considered as the performance index.

$$MSE = \frac{1}{N} * \left(\sum_{i=1}^N (P_i - \hat{P}_i)^2 \right)$$

$$MAPE = \frac{1}{N} * \left(\sum_{i=1}^N \left(\frac{|P_i - \hat{P}_i|}{P_i} \right) \right) * 100$$

where P_i is real power, \hat{P}_i is the estimated power, N is the number of data points (one hour $N=4$; 12 hours $N=48$; 24 hours $N=96$; 48 hours $N=192$).

IV. CASE STUDY

The proposed methods are used for the load profile generator and forecasting in a microgrid located in a small isolated village in the Atacama Desert, in northern Chile called Huatacondo (20° 55' 36.37" S 69° 3' 8.71" W). Its electric network is isolated from the interconnected system and the energy is supplied only during 10 hours each day by a diesel generator. A renewable based microgrid that takes advantage of the location and the availability of distributed renewable resources in the area provides a 24-hour service to the village. Since the village experienced problems with the water supply system, an integrated management solution should be considered, including water consumption together with the energy needed. Additionally, a demand side option to compensate the generation fluctuations caused by the renewable sources is considered. Fig. 3 summarizes the key components of this microgrid, including photovoltaic panels, a wind turbine, a diesel generator (typically an existing unit in isolated locations), a battery bank, a water supply system and a demand side-management mechanism (loads) [18]. This renewable energy based microgrid project presents a novel way for integrating a community, through a SCADA system. The Social SCADA is developed with the aim that communities perform the microgrid managing, maintenance tasks, consumption and generation monitoring, and decision-making processes, among others [19].

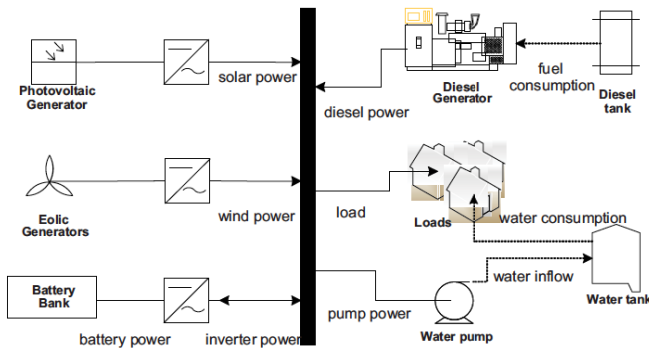


Fig. 5 Renewable-based Microgrid Diagram

A. Results for the Load Profile Generation Based on an SOM

As explained in Section II, the proposal consists of three stages as detailed below. First, is the input module obtained from the surveys in situ. There are 31 houses, the number of inhabitants is 72, and there is one school in the village. The individual survey provides the following information: number of family members, age and occupation of each member, family earnings, and domestic electrical appliances. In the Fig. 6, the number of domestic electrical appliances in the community of Huatacondo is shown.

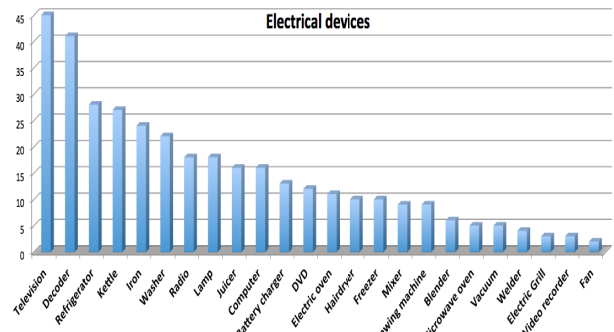


Fig 6 Electrical Appliances of Huatacondo

In the second module, the input data has 14 attributes (dimensions), so we will have 14 neurons in the input layer, and in total 24 houses were surveyed. To determine the prototype vectors an SOM is used, and for the visualization, a two-dimensional matrix-U. The output layer has 25 neurons (in a grid of Nx=3 by Ny=3. In Table 1 the parameters of the SOM are presented.

Initialization	Linear
Size of map	Dimension Nx=3, Ny=3.
Neighboring function	A Gaussian function
Shape of the map	Hexagonal
Coarse adjustment	Allows to modify the activated neuron, a value of 3000 was used
Detailed adjustment	Allows to modify the neighboring and the activated neurons, a value of 1000 was used

Table 1 Parameters of the SOM

The survey results are classified identifying 7 types of families, as shown in Fig. 7. The hexagonal mesh with different colors represents the distance. The groups were verified through a manual classification due to the small number of inhabitants. Figure 7 allows checking and verifying the coherence in the classification process.

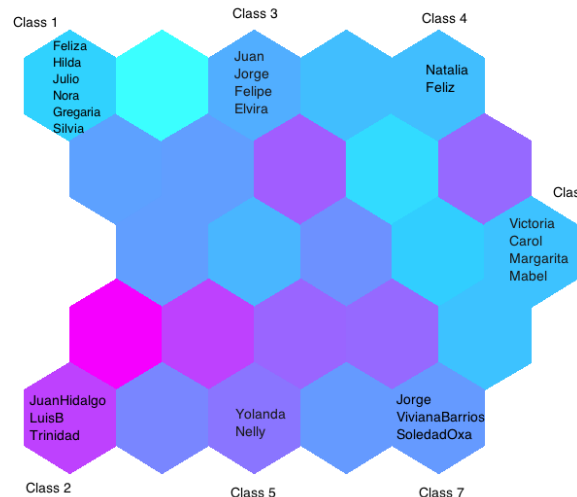


Fig. 7 Classification of Huatacondo House Types.

The classification provides a class number, characteristics of each class, and number of elements belonging to each class. That information is very important in the search stage, where the profiles are assigned according to the class to which they belong.

The third stage corresponds to the search module that assigns a profile to each identified class in Huatacondo. The construction of the data base for Huatacondo is the following: two assigned profiles corresponding to two classes were obtained using real data of two types of houses from the rural community, Santa Rosa, Ecuador where there is 24-hour energy supply. The resting profiles were reconstructed from these real profiles, and by using the survey information that projects the future for the use of the domestic electrical appliances. Figure 8 shows the assigned profiles of each class.

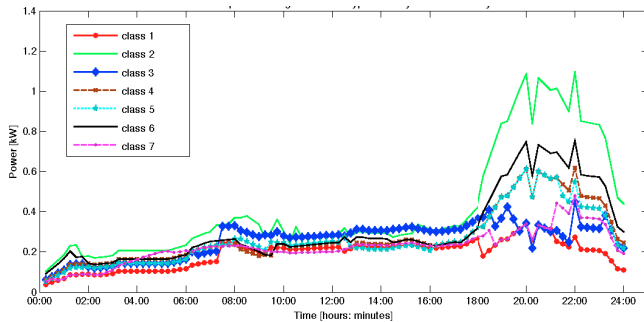


Fig. 8 Electricity Demand Profiles of each Type of Family in the Community of Huatacondo.

The profiles are multiplied by the number of families in each class, and then, the sum of the results represents the residential total demand in the Huatacondo community. Figure 9 shows the load profile generated with the SOM and the real Huatacondo load profile with uninterrupted supply, when the ESUSCON project was launched. In this figure, the errors of each class and the high stochasticity features of the microgrid have an effect on the prediction of the total consumption; however, the trends are very similar and useful as they generate a daily electricity demand profile of a community without measures of the consumption of electricity. The profiles were successfully used as a reference in the planning stage, as the signal obtained was similar to the real electricity demand. This demand profile could be used to design electrification projects in communities, including the renewable resources.

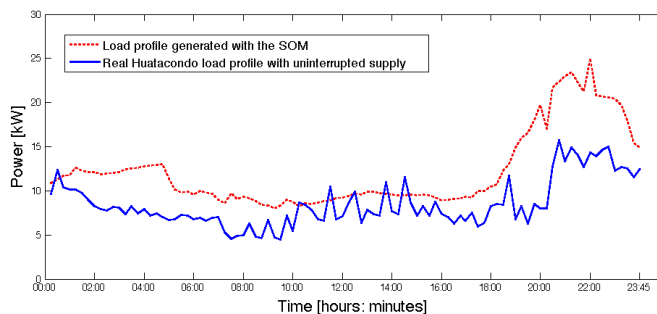


Fig. 9 Residential Daily Load Profile Generated by SOM Method versus Huatacondo Actual Load Profile.

B. Results of Load Forecasting on-line Learning based on Neural Network

The available data for the neuronal model is the electricity demand in the period from 02/12/2010 to 07/05/2011. This information is used for the neural network identification as presented in Section III, including the structural optimization of the network. The identification data was divided into: training, test, and validation.

The predictions of the demand in the micro-network are used as input in the Energy Management System (EMS), in a rolling horizon procedure, with a sampling time of the optimizer of 15 minutes, and a control horizon of 2 days [18]. The sampling time of the measurements is 15 minutes, and there are 192 prediction steps, equivalent to the two days of prediction.

For determining the structure of the neural networks, we use a correlation analysis between the electricity demand of Huatacondo and solar power, speed of wind, temperature, moisture, and solar radiation, from December, 2010 to July, 2011. The results are shown in Fig. 10. These variables do not have a higher correlation coefficient; therefore the model uses only the historical demand. Thus, the inputs for the neural network are the demand of the previous day with a sampling time of 15 minutes (96 inputs). The Table 2 shows the characteristics of the neural network used, after the optimization stage.

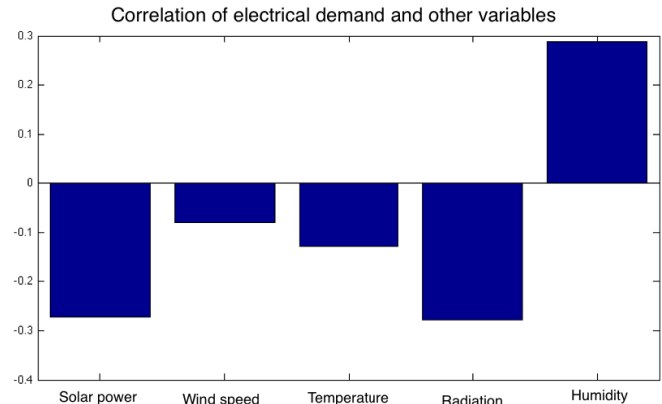


Fig. 10 Correlation of Electrical Demand and other Variables.

Neural Network Structure	
Number of layers	3
Number of hidden layers	1
Neurons of the input layer	96
Neurons of the hidden layer	8
Neurons of the output layer	1
Activation function of hidden layer	Tansig
Activation function of output layer	Purelin
Training online	Backpropagation
Kind of training	Supervised

Table 2 Neural Network Structure Used for Short-term Load Forecasting in Huatacondo

Table 3 shows the average forecast results of 20 days. The MAPE, MSE errors, and the variance are evaluated for different intervals: 1 hour, 12 hours, 1 day, and 2 days. The errors are increased when a longer step-ahead prediction is

considered. The errors obtained are not compared with other methods because most of the latter are applied in traditional power systems. Electricity demand is more stochastic in the microgrids than in the traditional power systems. Figure 11 shows the forecast for 2 days, MAPE 10%, MSE 1.382 kW and variance 1.2 kW. Note that when more data is included, the MAPE and MSE index errors decrease.

The real electricity demand is a stochastic signal that is followed by the forecast electricity demand. The signals have low power, which is a feature of this small-sized micro-grid, and the main difficulty in the prediction is that the energy demand of each house plays an important role in the total load profile. This is different from high scale power systems, in which the demand of each house has minimal impact on the total demand profile.

Step-ahead	Time	MAPE [%]	MSE [kW]	VAR [kW]
4	1 hour	12.851	1.811	1.379
48	12 hours	13.712	2.100	1.891
96	1 day	13.810	2.153	2.029
192	2 days	14.495	2.469	2.322

Table 3 Forecast Errors

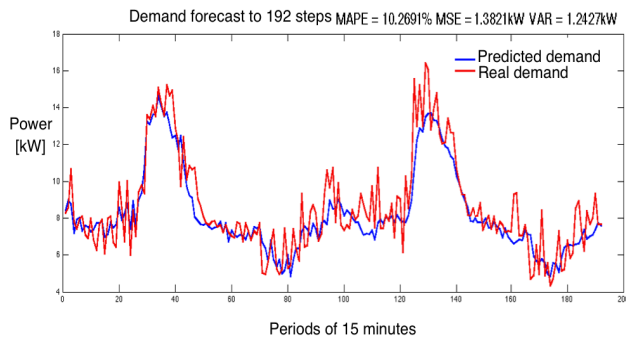


Fig 11 Forecasting of Electricity Demand versus Real Demand at Huatacondo

V. CONCLUSIONS

In this paper, computational intelligence techniques are used to solve real-life problems in the Energy Management Systems of microgrids in small and isolated communities. Kohonen self-organizing maps were implemented to generate demand profiles, used for classifying electricity demand of users; and neural networks perceptron multi-layers were implemented to forecast electricity demand in the microgrid.

A method based on an SOM for generating daily load profiles in isolated communities is presented. The community families are classified according to various aspects and then a load profile is assigned to each class by using an SOM classifier. This load profile generator can be used to design the unit size of the distributed generators of microgrid projects. The proposed load profile generator was tested using real data from the village called Huatacondo, obtaining a demand profile quite similar to the real one. It must be noted that the demand in the valley and the peak zones occurred during the

same hours of the real demand profile.

Also, in this paper, a neural network model with on-line learning for two days of load forecasting is presented. The model considers a two-day step-ahead prediction horizon updated every 15 minutes with on-line real measurements. This forecasting model is implemented as input for an Energy Management System of an isolated real microgrid located at Huatacondo.

ACKNOWLEDGMENTS

This work has been partially supported by the mining company Doña Inés de Collahuasi, the Millennium Institute “Complex Engineering Systems (ICM: P-05-004-F, CONICYT: FBO16, and FONDECYT project 1110047.

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