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Load Estimation Based on Self-organizing Maps and Bayesian Networks for Microgrids Design in Rural Zones

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***Abstract*—Microgrids are suitable electrical solutions for providing energy in rural zones. However, it is challenging to propose in advance a good design of the microgrid because the electrical load is difficult to estimate due to its highly dependence of the residential consumption. In this paper, a novel estimation methodology for the residential load profiles is proposed. Socio-demographic data and electrical power consumption are used to generate significant knowledge about the load behavior. Socio-demographic data are used as input for a neural network called Self-Organizing Maps (SOM). The SOM proposes a way to group dwelling according to their different features. Moreover, a probabilistic model based on Bayesian networks incorporates daily variations of the electrical load, simulating the behavior of the electrical appliances. The methodology, as a whole, is applied to a case study in a rural community located in Chile. The methodology is easily adaptable to other rural communities.**

***Index Terms*-- Microgrids, residential load profiles, rural communities.**

I. INTRODUCTION

Rural communities are human settlements, where the residents are scattered and develop their daily activities in the countryside far from big cities. Microgrids provide power supply integrating different local sources of energy and they have proved to be suitable for isolated rural communities and remote areas. Thus, microgrids highly contribute to improve the quality of life of rural communities by providing a reliable electric service [1], [2], [3], [4].

For the design of microgrid projects, it is necessary to determine in advance the electrical load that will be required to satisfy the demand. This includes characteristics such as its behavior at different hours, the identification of load peaks, critical loads and others relevant aspects related to load dimensioning [1], [5]. The stage of design is very much more complex in the case of microgrids that depend on renewable energy sources due to its highly variability over time [3]. Moreover, in the rural communities context an important challenge is to estimate the electrical demand due to its highly dependence of the residential consumption behavior, which is variable along the year [6]. Different methodologies have been described in literature; however, they have been mainly applied to case studies in urban zones. The *top-down* approach is the most used [7], which allows to identify load patterns based on general information of a group of customers (aggregated information), defining global load profiles through statistics distributions, considering a high homogeneity in the load behavior of the end users. The disadvantage of this approach is the difficulty to generate individual load profiles and their specific variations [8]. A mechanism to estimate the load in a more detailed way is the *bottom-up* approach, where the information regarding the end users is collected, based on surveys and load measurements using smart meters [9]. For the identification of patterns, this approach requires an important quantity of data and a good knowledge related to the behavior of the customers, such as social and demographic data [10], [11].

From the literature, it is important to recognize the contribution from the computational intelligence field. Among these algorithms, the implementation of neural networks, such as Self-organizing Maps (SOM), has been able to ease the visualization of the data. Then, with a SOM is possible to create clusters of the data, so to group inputs that show a degree of similitude to each other [12]. SOM is recommended for clustering of survey data due its prominent visualization properties [13]. In the literature, SOM has been applied for the study of load and it has been employed to compare set of customers with similar features or attributes, analysis of data of infrastructure regarding electrical consumption, the identification of patterns associated to load, among others [14]. Furthermore, algorithms of Bayesian networks are used for prediction and estimation of residential load consumption, employing data about the behavior customers and personal data for the identification of probability of use of electric appliances [15], [16].

In this paper, a novel methodology for the estimation of residential load profiles is derived in order to design microgrids in rural communities. Socio-demographic information of a community together with consumption measurements obtained by smart meters are used. The methodology relies on the close relationship between the load behavior and the behavior of the customers [1], [6], [17], [18], [10]. A SOM is used for grouping households considering their particular features. In addition, a Bayesian network model is employed for the residential load profile generation, considering the daily variability of the load through the knowledge about the use of electric equipment in households. Finally, a case study is presented with real life data coming from a Mapuche rural community called Huanaco Huenchun, located in the south of Chile. The methodology is presented as a systematic tool to estimate residential load profiles, in order to ease the microgrid design stage based on local context of the different rural communities [3].

II. METHODOLOGY

The methodology is based on four steps, as shown in Fig. 1. In step A) socio-demographic data of the households (dwellings) are obtained and processed to provide the inputs needed for the clustering algorithm based on SOM. As output, each dwelling of the community is sorted in different clusters (groups). Based on the main features of each group, one reference dwelling (d_R) is selected per group. In step B) for each reference dwelling d_R, an electric consumption meter is installed for obtaining measurements of load. In this way, characteristic daily average load profiles are determined for each group. These load profiles are named "base load profiles". In step C), data regarding the electrical appliances used in the dwellings is used as input for a Bayesian network, which provides the probability of use of the electric appliances (loads) in each dwelling. From this information, variations of the load profiles are generated for each dwelling (d_1, d_2, d_3…, d_i). Finally, in step D) a modeled load profile is generated adding the base load profile of d_R with the variation load profile for each dwelling (d_i).

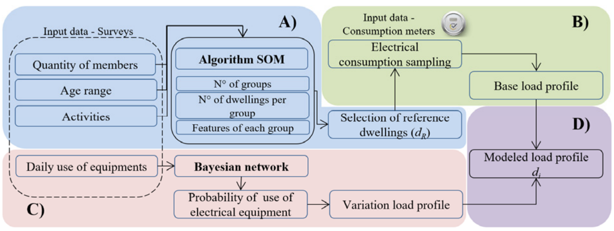

Figure 1. Flow diagram of the methodology.

A. Dwelling clustering according to features associated to the electricity demand

This section describes the SOM clustering algorithm and its inputs. The residential electricity demand is associated to the consumption behavior and their particular patterns. All these aspects are very important to identify the main features in order to perform the clustering process in a community. In the literature, the features are usually related to electricity demand, number of people that live in the dwelling and their behavior during a typical day [10], [15], [17], [18]. In this paper the features used in the SOM clustering process are:

Number of members: in [17] and [19], the number of members are considered in order to predict the residential electricity demand. The demand tends to increase with the number of members; nevertheless, the increase is a nonlinear function because the electricity consumption depends of the electrical home appliances (lighting, TV, refrigerator, among others). Moreover, the electricity consumption is different for each family member.

Age range of members: in [10] and [19], the age of the members is included because the behavior seems to be age dependent. For example: elderly people tends to remain in their dwelling for a longer time during the day and night, while young people develop more activities outside.

Activities (occupation): the people behavior in a typical day is an aspect that affects significantly the electricity consumption. The main activities related to the people behavior in a community are: attend to school, work full day, moving from a place to another, etc. These activities are related to the time that people spend doing dwelling activities, and they are considered potential electricity consumers [17], [20].

The information of the dwellings is obtained from the surveys, which are based on a participatory model proposed in [4]. The topics considered in this work are: family composition, productivity activities of their members, number and kind of home appliances and the current situation of the power system. Table I shows the main features used for the clustering process. The main features were selected based on general information from rural areas, such as the activities of the community which have the tendency to be quite different between different communities.

TABLE I. FEATURES ASSOCIATED WITH ELECTRICAL DEMAND

Aspect	Feature	Description
Members	Number of members	People living in the dwelling
Age range	Number of young	Members under 18 years old
	Number of adults	Members aged over 18 and under 60
	Number of adults older	Members over 60 years old
Activities	Number of farmers	Members who practice family farming or subsistence
	Number of house owner	House owners that at a time practice family farm activities
	Number of students	Students who attend to school regularly
	Number of full-time worker	Members who practice full-time or similar working day.

The features were obtained from surveys applied to each dwelling of the community and used as inputs of the SOM. The aim of SOM is to identify similarities among dwellings in the community, using the features or inputs in order to get clusters. The SOM uses a nonsupervised training, and generates groups based on the similarity of the input data [21]. Figure 2 shows a scheme of a SOM, the input layer has the attributes of each element (dwelling). In this paper, the input layer has eight neurons (attributes in Table I). Dwelling clusters (C_1, C_2, C_3…, C_u) are obtained according to the similarity between its features.

Each output neuron has a weight (w), this represents the effect of each neuron in the model. The output layer is defined by a set of neurons (m neurons). SOM process information building a layer, which can be rectangular or hexagonal. The main advantages of SOM corresponds to the ability to represent in an easy and intuitive way the clusters generated and the features that defined each cluster [10]. Another important aspect of SOM is the capacity to maintain the topology of the input space. The output of SOM shows the clustering of all elements. After clustering, the most relevant features of the dwellings in each group are identified.

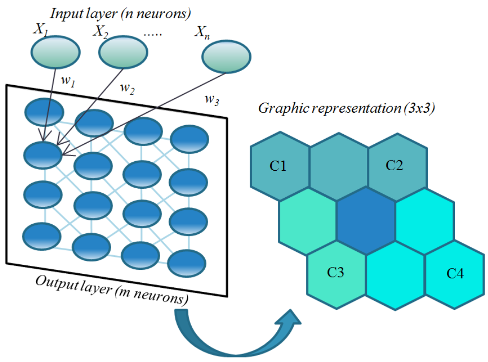

Figure 2. Scheme of a neural network SOM.

The number of clusters (u) depends of the input data and parameters defined by the user. In this work, the dimension of the grid is $x = 3$ and $y = 3$. Thus, it is possible to identify a maximum of nine clusters in the community. The basic training algorithm of SOM initializes the weights network (w) by random numbers, and updates them, moving the order of the output neurons, generating the clusters. From the numerical results, the most common clusters in a community are: houses composed by elderly couples, retired old single person, couple of adults practicing family farming, family of two adults and two young people, among others. Other groups are also presented in the data as each community can present different groups or number of groups, according to the features of the dwellings that compose it. What is the most important is on how the features of these clusters relate to electricity consumption patterns [10].

B. Base load profile generation

Afterwards clustering, a reference dwelling for each cluster is identified, d_R. This reference has an average behavior respect of observed features per cluster. For each dwelling, an electric consumption meter is installed, allowing to record instant power measurements every 5 minutes. This sampling facilitates the load profile generation for each reference dwelling (d_{R1}, d_{R2}, d_{R3}, …, d_{Ru}) with a high resolution level, including even small variations of the load.

In the real-life experiments, it was established a minimum measurement period of two months. The aim is to recognize a regular pattern of the electrical demand for each one of these dwellings. Based on the collected data, an average load profile for weekday and weekend are generated. These profiles are named base load profiles.

C. Generation of variation demand profiles based on Bayesian networks

The daily use data of the residential loads for each dwelling in the community are used to adjust a Bayesian network (*BN*) to generate variability in the loads utilization. With the characteristic base consumption and the generated variations over it, the daily demand profiles are estimated for each dwelling.

First, the surveys incorporate questions about quantity, type and typical scheduling of use for the dwelling loads to estimate their characteristic consumption. Table II presents an example of the requested data with 14 basic domestic loads considered, with the possibility to incorporate more if needed.

TABLE II. USE AND QUANTITY OF LOADS

Load	Fridge	TV	Microwave	…
Power (W) / *Hour (h)*	350	165	650	…
0:00	1	0	0	…
1:00	1	0	0	…
2:00	1	1	0	…
…	…	…	…	…
22:00	1	2	1	…
23:00	1	1	0	…

The survey includes information for a typical day, distinguishing weekdays and weekends, and indicating the number of loads working at a certain hour (h). Each load has a typical nominal power (Pn) and a use factor (fu), derived from [17] and [22], where fu is the proportion of time (per hour) that the load actually works.

Given that the survey only contains information for typical days, a probabilistic approach based on *BN* is applied to include variability in the load profiles of the dwellings, in respect to a base consumption of their membership group. Variables are represented by *nodes* and, given the relations between variables, these nodes are connected to each other, with associated probabilities of occurrence. These probabilities are obtained via an inference process, in which the evidence (previous knowledge) is propagated through the network, updating the knowledge about the unseen variables [23]. In this way, *BN* can be used to explain a variety of phenomena by making use of the interdependence of a series of variables, in a cause-and-consequence relationship.

Fig. 3 shows the topology of two nodes *BN* utilized, in which the causes are the evidences (Hour), and the network generates the consequences or effects (Load State). The Load State (*LS*) is conditioned by the Hour of the Day (h), having probabilities associated to three possible states of *LS*: increase$P_{(I)}$, decrease$P_{(D)}$, and maintain$P_{(M)}$. These states correspond to the probability that, for the dwelling v_i, the use of a specific load e at a specific hour h respect to the reference dwelling d_R increases, decreases or maintains it value, respectively. In each group, the quantity of loads that variate over the dwelling d_R (states of *LS*), is adjusted to the standard deviation of the load considered in the group.

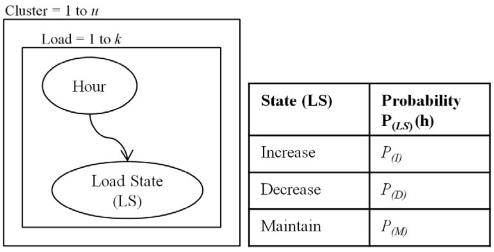

Figure 3. Topology of the *BN* utilized for the demand variation profiles model

With the survey information (Table II), and considering as database the whole community, the *BN* parameters are estimated using the Expectation Maximation (EM) algorithm. Thus, for each identified group, and for each load, one *BN* is obtained. Each *BN* generates variations in the consumption as the change in the use of a load in a specific dwelling i (d_i) respect to a reference dwelling for a certain group, at a certain time.

Thus, for each of the u groups, and k loads, a realization of the *BN* is performed to obtain demand variation profiles for each dwelling. Considering [17], the dwellings in each group are assumed to have a similar consumption behavior. The demand variation profiles are generated as follows:

$$p\emptyset_i\,(t) = \sum_{e=1}^{k}\left(R\big(P_{(LS)}(h)\big)_e \cdot Pn_e \cdot fu_e\right) \quad (1)$$

Where $p\emptyset_i(t)$ corresponds to the estimation of the variation in power at instant t in a dwelling d_i with respect to d_R, and $R\big(P_{(LS)}(h)\big)$ is the response at time h of the state LS for each load. This value is multiplied by the nominal power Pn_e and use factor fu_e for the load e. The sampling time t is 5 minutes, and it is considered the behavior of loads that have short periods of use, as kettles among others [17].

D. Residential load profile generation

Finally, the residential load profile for each dwelling d_i is created aggregating the base load profile for the membership group (average load profile of d_R, define in the Section II.B) and the load variation profile (as in Section II.C). For each event (a day), a different load profile is created, reflecting the variability of the residential electrical consumption day to day (2).

$$p_i(t) = p_{dR}(t) + p\emptyset_i(t) \quad (2)$$
$$p_i(t) \geq 0$$

where $p_i(t)$ corresponds to the consumed power at instant t for d_i, $p_{dR}(t)$ represent the power value metered in the reference dwelling (d_R) at time t. In the case that p_i is negative, the value is adjusted to zero, taking over that in those situations the consumed power is null or nearby to zero.

III. CASE STUDY

The methodology is implemented in the Huanaco Huenchun community, which is composed by 68 dwellings and currently has electrical supply from a utility. Below, the main results regarding the study are shown.

A. Dwelling clustering according to features associated to the electrical demand

Sixteen electrical appliances were identified that are used in the dwellings in a regular way. In Fig. 4 the average quantity of the appliances in the community and the standard deviation of the loads is presented. The main appliances correspond to refrigerators, TVs, electrical kettles and lighting, presenting a homogeneity regarding the possession of equipment inside the community.

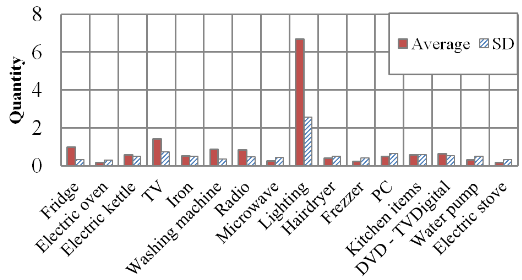

Figure 4. Average quantity of electrical appliances within community.

The data of each survey were entered to SOM clustering algorithm based on the features defined in Table I. The 68 dwellings were clustered in four groups, from where the main characteristics of the dwellings of each group were analyzed in Table III. From the identified characteristics, it is not possible to appreciate a correlation between the behaviors of the groups. Therefore, each group presents a particular behavior, different to other group.

TABLE III. GROUPS AND THEIR MAIN CHARACTERISTICS

Group	N° of dwellings	Observed features		
		Members	*Age range*	*Activities*
1	33	1 to 2	Only adults and elderly people	Mostly are farmers. Do not have full time employment.
2	11	3	Only adults and elderly people	Some members practice the agriculture and other full time employment.
3	5	2 to 3	Couple of adults	Only house owner and farmers.
4	19	≥ 5	Young people and adults	Farmers, house owner, students and full time employment.

B. Base load profile generation

Four reference dwellings are selected that show an average behavior per cluster. For each dwelling, a consumption electric meter was implemented, obtaining power data for a period of three months (Jul to Sep, 2015). In Fig. 5, base load profiles of each d_R are presented. Similar profiles for weekday and weekend were obtained. This is because the community has similar activities all the days of the week. These activities like familiar agriculture are regularly performed along the week, without high variations. Additionally, in most of the dwellings, a similar use of electric appliances for each type of day was declared in the surveys.

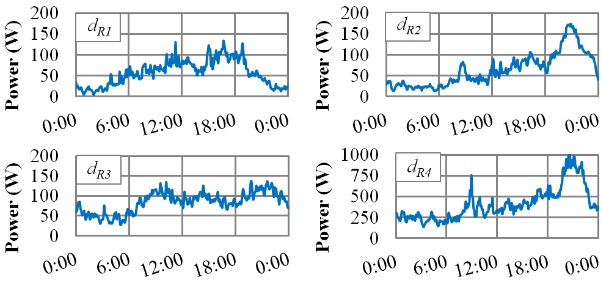

Figure 5. Daily base load profiles.

From the power data and surveys, it is clear that the consumptions within the community has predominantly low values, reflecting mainly the use of refrigerator (cooling cycle) and lightings [23]. Each one of the d_R has a similar load, however d_{R4} presents a higher consumption level that is explained as this dwelling belongs to the group with a higher number of members.

C. Load variation profile based on Bayesian networks

After the identification of reference dwellings, the information regarding to the daily use of electrical appliances is used by the Bayesian network model (Section II.C) to generate the state probabilities of *LS* for each cluster. In the Table IV, the values of nominal power *Pn* and use factor *fu* used in the generation of the load variation profile are shown [18], [23]. In Fig. 6, three load variation profiles for the same dwelling (d_i) are presented. The profiles are generated with a 5 minutes of resolution.

TABLE IV. ELECTRICAL APPLIANCES PARAMETERS

Load	Nominal power (W)	Use factor	Load	Nominal power (W)	Use factor
Fridge	195	0.7	Lighting	23 – 50	1
Electric oven	1300	1	Hairdryer	500	0.15
Electric kettle	1500	0.08	Freezer	180	1
TV	150	1	PC	300	1
Iron	1000	0.5	Kitchen items	500	0.5
Washing machine	520	1	DVD – TV Digital	150	1
Radio	60	1	Water pump	350	1
Microwave	800	0.25	Electric stove	550	1

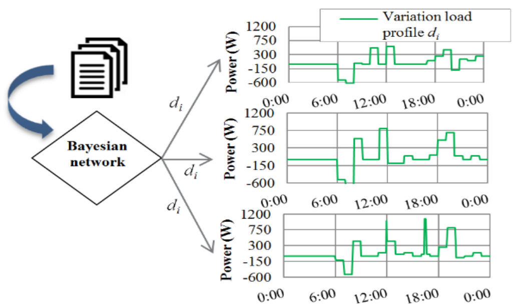

Figure 6. Load variation profile generation.

At each event, a different load profile is modeled, depicting a similar behavior with respect to each other, with local minor variations. This is due to the use of a probabilistic approach.

D. Residential load profile generation

Once obtained the base load profiles and load variation profiles, for each d_i, the corresponding load profile is modeled. In the Fig. 7, the load profile for a specific dwelling of the community is presented.

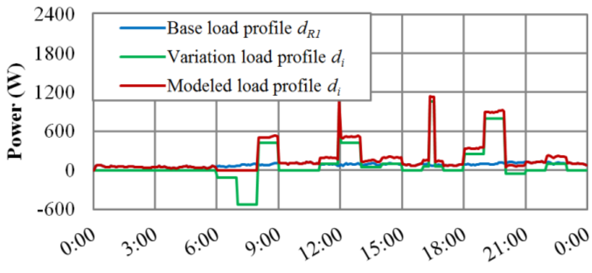

Figure 7. Modeled load profiled for one dwelling (d_i).

The modeled load profile for a dwelling d_i is obtained adding base and variation curves, keeping zero as minimum possible value. This procedure is replicated to all the dwellings and different days. In Fig. 8 three simulations of the community load profile are presented.

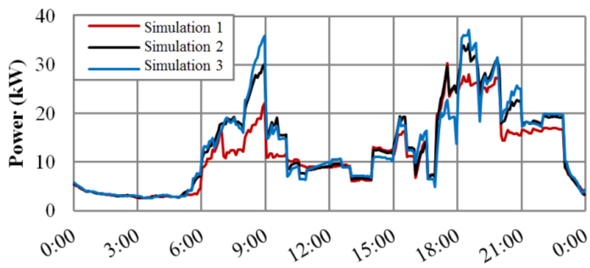

Figure 8. Simulations of the community load profile for one day.

Similarly to the individual case, aggregate load reflects the typical behavior of the residential load, depicting peaks at the morning hours (7:00 to 9:00 hrs) and at evening (18:00 to 21:00 hrs), which are periods with the most activities in the houses [20]. For the case of the community, based on the simulation of 60 days, a maximum power of 34.4 kW is registered. This value is presented during the evenings, while that of the minimum power is of 2.5 kW. The load factor is 0.38 and the daily consumption is of 315.6 kWh, which is considered representative for the sampling period.

E. Validation

For validation, a comparison with the monthly electrical consumption was performed. The electric company FRONTEL S.A. supplies energy to this community and a bimonthly rate is received for each customer. Since that there is not a complete base of the electrical consumption of all the dwellings of the community, a comparison with only 32 dwellings is carried out. For this, 60 simulations (60 days) were performed, to estimate the consumed energy for the period of two months for each one of the dwelling. After, a comparison was performed of the results with the actual records of the company for the same sampling period.

In the Table V, the aggregate comparison of each cluster is presented. The Table V shows a low relative error for each one of the clusters. The cluster 3 presents the higher error, being at same time the cluster with less dwellings in comparison with the others clusters.

TABLE V. ENERGY CONSUMPTION COMPARISON

Group or cluster	Compared dwellings	Registered consumption (kWh)	Modeled consumption (kWh)	Relative error (%)
Group 1	17	2459	2703	10.0
Group 2	4	677	725	7.1
Group 3	3	517	342	33.8
Group 4	8	1268	1645	29.7
General	32	4921	5415	20.1

Using more data from the meters installed, for different periods (for instance one year), it could be possible estimate the seasonal variations along of the year, including bimonthly average profile such as the base load profiles.

IV. CONCLUSION

A novel methodology based on SOM and Bayesian networks for load profile estimation is presented. The methodology can be applied for a whole community to generate load profiles for several days, taking into account the local variability of loads during short time intervals. We conclude that it is important the inclusion of socio-demographic data of the dwellings, since these allowed to identify particular features regarding electric power consumption. Besides, computational intelligence techniques, such as SOM and Bayesian networks, allowed capturing different behavior of the consumers and its variability.

The generated profiles provide relevant information for the design of microgrids; in particular, the installed capacity of each power generation unit based on the profiles that include the electric power consumption and power peaks over time, among others design variables needed. The methodology is successfully applied to a rural community and can be applied to others with partial or full power supply. Further research could include the social and cultural aspects in the methodology for improving the load profile estimation.

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