A Conceptual Microgrid Management Framework Based on Adaptive and Autonomous Multi-Agent Systems

Un Framework Conceptual para la Gestión de Microrredes Basado en Sistemas Multi-Agentes Adaptativos y Autónomos

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Abstract

The Smart Grids paradigm emerged as a response to the need to modernize the electric grid and address problems related to the demand for better energy quality. However, there are no fully developed and implemented smart grids. Centralized systems are still common, with a low granularity of control and reduced monitoring capacity, especially in low-voltage networks. In this work, we propose a framework for Microgrid Management, providing solutions for three main problems: Peak Shaving addressed with a distributed control algorithm based on Artificial Immune Systems for demand-side management; Transformer Lifespan Estimation using a thermal model adjusted by Genetic Algorithms; Short-Term Load Forecasting based on Artificial Neural Networks and Genetic Algorithms. Combining these solutions, we can reduce peak loads by controlling air conditioners without affecting user comfort, determine the negative effects of overloading on distribution transformers and provide demand forecasting. The proposed framework is based on autonomous and distributed systems, so the Organization Centered Multi-Agent Systems methodology was applied for modeling and development. The implemented solutions were applied in the Tucumán province, Argentina, exposing the system's benefits and the relevance of the information generated by the framework.

Keywords: Demand-Side Management, Distributed Systems, Lifespan Estimation, Load Forecasting, Organization Centered Multi-Agent System.

Resumen

Las Smart Grids surgieron como respuesta a la necesidad de modernizar la red eléctrica y abordar problemas relacionados con la demanda de energía de mejor calidad. Sin embargo, no existen Smart Grids totalmente desarrolladas e implementadas. Todavía son comunes los sistemas centralizados, con baja granularidad de control y reducida capacidad de monitorización, especialmente en redes de baja tensión. En este trabajo, proponemos un Framework para la gestión de Microgrids, resolviendo tres problemas principales: Peak Shaving abordado con un algoritmo de control distribuido basado en Sistemas Inmunológicos Artificiales para gestión de la demanda; Estimación de la vida útil del transformador mediante un modelo térmico ajustado con Algoritmos Genéticos; Predicción del consumo a corto plazo basado en Redes Neuronales Artificiales y Algoritmos Genéticos. Combinando estas soluciones, podemos reducir los picos de carga controlando equipos de aire acondicionado sin afectar al usuario, determinar el impacto de la sobrecarga en transformadores y proporcionar una predicción de la demanda. El Framework se basa en sistemas autónomos y distribuidos, por lo que se aplicó la metodología de Sistemas Multi-Agentes Organizacionales para modelarlo y desarrollarlo. Las soluciones implementadas se aplicaron en la provincia de Tucumán, Argentina, exponiendo sus beneficios y la relevancia de la información generada.

Palabras claves: Gestión de la demanda, Sistemas distribuidos, Estimación de la vida útil, Predicción del consumo eléctrico, Sistemas Multi-Agente Organizacionales.

1 Introduction

The energy consumption and the users' requirements have grown steadily over the last few years. This scenario exposes the need to incorporate new technology into the Power Distribution Systems, leading to the Smart Grids (SG) paradigm [1]. In this context, the electrical network is shown as a set of interconnected layers [2]: a physical grid, connected by conductors and several devices, but also by communication and autonomous control systems. In other words, the network can be seen as a set of interconnected layers. Also, the view of the network as a whole has changed, migrating to the concept of smaller networks or Microgrids (MG) [3], which are self-controlled, self-regulated, and produce their energy, among many other features.

Although this new paradigm has many advantages, such as increasing the quality of the electricity distribution service, it is difficult to find fully developed and implemented Smart Grids. Instead, it is common to find few field tests to prove concepts and new technologies on a small or medium scale. Moreover, the system developed to manage the energy network is focused on a centralized approach. Also, it is common to use SCADA Systems whose granularity of control is one of its significant issues. Although SG and MG are fully compatible with the distributed control approach, the current systems are not adequate to respond to this requirement properly.

The use of Smart Grids in developing countries such as Argentina is incipient [4]. The monitoring and control barely cover the middle level in the energy distribution system, leaving aside the last mile (the low-voltage network). The low penetration of the SG is due to different factors, mainly the lack of proper investment by companies and poor planning in the energy distribution context. For this situation, the margin between installed power and the consumers' demand is reduced year after year, resulting in a progressive decrease in service quality. Consequently, the electricity distribution system has a minimum reserve margin. As a result, the government of Argentina declared a state of energy emergency in 2015 [5].

The Energy Management System (EMS) for any MG needs to have a series of features that must be considered as part of the underlying implementation [3]. Among other things, the system must:

- Regulate its consumption and address different issues.
- Use distributed approach for the monitoring and control systems like the algorithm for Demand-Side Management (DSM) proposed in [1].
- Provide helpful information for the decision-making process implementing techniques like Load Forecasting and Transformer Lifespan Estimation.

All these features must be supported by a platform developed using an adequate paradigm. It must respond to the complexity of the monitoring and management system, providing adaptive, self-regulated capacities and a high level of fault tolerance. The Multi-Agent Systems (MAS) paradigm fits this class of problems due to all the features required by the Smart Grid, the Peak Shaving approach with DSM techniques, and the Cyber-Physical Systems.

Some models and systems were proposed by other authors, considering the MAS approach for power optimization and management problems [6, 7, 8, 9]. This work mainly focuses on the Peak Shaving techniques addressed with the Demand-Side Management approach [10, 11]. Several works and patents were presented considering this approach, but those systems have a common feature: a centralized control system.

This paper presents a conceptual framework for Microgrid Management. It mainly covers the Peak Load problem addressed with an autonomous and distributed control system based on the Artificial Immune Network for Demand-Side Management [12]. The modeling of the proposed solution is based on Organizational Centered Multi-Agent Systems (OCMAS) [13] developed under the ASPECS methodology [14]. There is a previous model focused only on the Peak Shaving problem [8]. The actual model aims to represent the control system behavior for Microgrid, which also implements some data analysis techniques to support decision-making: *i)* Transformer Lifespan Loss Estimation due to overload using a thermal model adjusted by Genetic Algorithms [15], and *ii)* Short-Term Load Forecasting using Artificial Neural Networks and Genetic Algorithms for variable selection [16].

The rest of this work is organized as follows: Section 2 presents a brief description of the addressed problems related to demand-side management, load forecasting, and transformers lifespan estimation; Section 3 describes how each solution has been modeled and implemented with the Organization Centered Multiagent System approach; Section 4 presents a brief description of the obtained results; Finally, the conclusions and future work are presented in Section 5.

2 Applications for Microgrid Management

2.1 Peak Load Problem

The increase in electricity demand that occurs in short periods generating electrical peaks for a few hours is one problem that significantly impacts the power system. It is known as Peak Load Problem [17]. The extreme consumption produced by these peaks causes damage or reduces the useful life of the devices involved in the distribution grid. In order to avoid these problems, power distribution companies need to oversize the installed power capacity, even if it is only needed for a few months of the year (generally in hot seasons for warmer subtropical and tropical climates, and cold season for colder climates). Also, a significant part of existing resources is used for maintenance tasks, reducing the investing capacity available to improve the grid.

Many approaches were developed to handle the Peak Load Problem, like Load Leveling [18], Battery Storage [19], or Spinning Reserves [20]. However, considering the SG principles, the bottom-up perspective proposed by the Demand-Side Management (DSM) [1] approach fits better. So, in this context, there is a solution based on Artificial Immune Network (AIN) [21] [22] called the AIN-DSM Algorithm [12]. This control algorithm exhibits self-regulated, adaptive, and autonomous capabilities that are desirable to address this complex problem. It consists of monitoring and controlling the power consumption at a specific point in the distribution network, called *Energy Source Node* (ESN). The control involves manipulating the normal operation of some power-shiftable and time-shiftable devices connected to the ESN. The AIN-DSM algorithm proposes a compromise between the distribution network (energy load) and the consumers (energy demand).

In this work, the implementation of the control system is composed of:

- The ESN represents a distribution transformer in the Low-Voltage network. It has sensors for reading the consumption level and a broadcast unit responsible for transmitting this value and other parameter values for the control algorithm to all the controlled devices. It is feasible to use currently available IoT technologies in order to support the communication requirements.

- The Controllable Devices are Air Conditioners (AC). They include a Smart Control Unit (SCU) with a communication module for receiving information from the ESN, a processing module for computing and determining the new state of the device, and implement a mechanism to change the operating mode of the AC device from cooling mode (consuming) to fan mode (not consuming) and vice versa.

Fig. 1 shows a diagram of the proposed implementation. As can be seen, the system requires a communication infrastructure, which must be adequate and provide the necessary services to ensure that all controllable devices receive the data sent by the ESN. It is important to note that the communication is unidirectional, since the control algorithm is executed in each SCU without any intervention of external elements. Each SCU is autonomous, taking its own decisions about its operation with local information. This feature allows the system to incorporate new devices at any time, resulting in easy scalability of the system.

The AIN-DSM algorithm tries to maintain the antibody concentration at a certain level as the immune

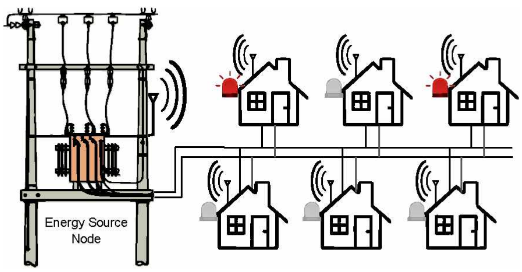


Figure 1: Representation of the Energy Source Node (the distribution transformer) feeding a set of customers and their respective devices.

system would do in nature. In our case, it means that the system maintains the energy load of a certain ESN below a prefixed limit. In this way, the algorithm can prevent cases when the consumption level exceeds the rated capacity of the transformer and damage begins. The following simplified equations rule its behavior:

$$\frac{dA_i(t)}{dt} = \left[a_{\mathrm{ESN}}(t) - k\right] a_i(t) \qquad (1)$$

$$a_{\mathrm{ESN}}(t) = \left[1 + e^{\mathrm{ESN}_{\mathrm{Energy}}(t) - \mathrm{ESN}_{\mathrm{Limit}}}\right]^{-1} \qquad (2)$$

$$a_i(t) = \left[1 + e^{\mathrm{Consumption}_i(t) - \mathrm{ESN}_{\mathrm{Available}}(t)}\right]^{-1} \qquad (3)$$

First, Eq. 1 presents the change of the antibody concentration. The first term within the brackets summarizes the stimulation among antibodies. This term represents the total energy that the ESN is providing. It is calculated using the squash function defined by Eq. 2, where:

- $\mathrm{ESN}_{\mathrm{Energy}}(t)$ is the total energy measured and provided by the ESN to all devices in a broadcast message at time t,

- $\mathrm{ESN}_{\mathrm{Limit}}$ is the maximum amount of energy that the ESN can handle at time t (i.e., the rated capacity of the transformer).

The second term in Eq. 1 is a constant value used to model the cell's natural death, equal to $k = 0.5$. Finally, the $a_i(t)$ represents the current antibody concentration related to the specific consumption of the device i. It is calculated using the squash function defined by Eq. 3, where:

- $\mathrm{Consumption}_i(t)$ is the energy consumption measured from the i device at time t.

- $\mathrm{ESN}_{\mathrm{Available}}(t)$ is the available energy, calculated as the difference between the limit value $\mathrm{ESN}_{\mathrm{Limit}}$ and the total energy consumed at time t, $\mathrm{ESN}_{\mathrm{Energy}}(t)$.

Finally, the AIN cloning process supports the mechanism for granting permission to consume energy. Using the concentration change previously calculated (Eq. 1), each controlled device decides if it must remain in the current consumption state or change it (from waiting to consuming or vice versa).

The AIN-DSM algorithm was tested with theoretical and real data to analyze its behavior in several scenarios [12]. The energy consumption was restrained to 75% or 80% of the maximum value. The algorithm controls the energy consumption in all cases, maintaining the load closer to the limit with a small deviation. Some results for the AIN-DSM algorithm can be seen in Section 4.

2.2 Lifespan Estimation of Distribution Transformers

One of the most important capacities of the SGs is the possibility to measure, monitor, and control anything happening in the network. It allows improving the management and the quality of the service. In this sense, estimating the lifespan of the distribution transformers helps to take the necessary actions for resource management on time [23]. These actions include replacing the transformer with another with higher capacity, distributing the electricity consumption to nearby transformers, and expanding the electrical system with a new transformer whenever possible. However, the accumulative effects of the transformer deterioration are difficult to determine, so estimating its expected lifespan is a challenging task, even under strictly controlled conditions [24]. For this reason, in this work, we limit the causes of deterioration to temperature increase due to overloading.

The most commonly used method to estimate the effects of the temperature inside the transformer is based on thermal models proposed in loading guides. The IEC 60076-7 [25] provides a thermal model that calculates the hot-spot temperature in the winding using the load and ambient temperature measurements. From this hot-spot temperature, the lifespan of the winding is estimated based on expected values obtained from tests performed on transformers with different construction characteristics.

Based on the loading guides, [15] proposed a method to adjust the parameters involved in thermal models using Genetic Algorithms (GA). It aims to adapt and validate the thermal models to local conditions and equipment, comparing the estimated values of top-oil temperature with real measurements from 315 kVA distribution transformers. In short, the authors used the Deterministic Crowding algorithm, a Niching Genetic Algorithm, to determine the possible combinations to fit the parameters of the thermal model with real data.

A general scheme of the lifespan estimation process is shown in Fig. 2. The inputs are the load factor K and the ambient temperature $\theta_a [^\circ C]$, and the outputs are the lifespan loss rate V and the accumulated lifespan loss L. The first step is to calculate the temperature of the cooling oil. Eq. 4 describes the dynamics of the oil temperature change on the upper level of the container. This equation is used to estimate the top-oil temperature rise. Then, the top-oil temperature θ_o is obtained by solving the differential equation with traditional numerical methods. Table 1 describes all the parameters involved and their values adjusted using Genetic Algorithms and real top-oil temperature measurements [15].

$$\frac{d\theta_o}{dt} = \frac{1}{k_{11}\ \tau_o}\left[\left(\frac{1+K^2R}{1+R}\right)^x \Delta\theta_{or} - \theta_o + \theta_a\right] \quad (4)$$

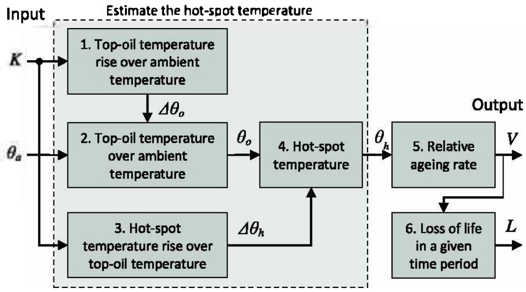


Figure 2: Block diagram of the procedure for estimating the relative aging rate V and accumulated loss of life estimation L, based on the load factor K and ambient temperature θ_a [15].

Next, we calculate the hot-spot temperature rise above the top-oil temperature $\Delta\theta_h$. For modeling the thermal behavior of the winding hot-spot, the mentioned loading guides propose Eq. 5 and 6.

$$\frac{d\Delta\theta_{h1}}{dt} = \frac{1}{k_{22}\tau_w}[k_{21}\ K^y\ \Delta\theta_{hr} - \Delta\theta_{h1}] \quad (5)$$

$$\frac{d\Delta\theta_{h2}}{dt} = \frac{k_{22}}{\tau_o}[(k_{21}-1)K^y\ \Delta\theta_{hr} - \Delta\theta_{h2}] \quad (6)$$

The hot-spot temperature θ_h is calculated by Eq. 7, combining the previous equations. Solving these equations corresponds to steps 1 to 4 in the block diagram shown in Fig. 2.

$$\theta_h = \theta_o + (\Delta\theta_{h1} - \Delta\theta_{h2}) \quad (7)$$

Once the hot-spot temperature has been calculated over a given period, the transformer insulation's degradation rate V is calculated using Eq. 8. Finally, the total lifespan L from that period is obtained, integrating the relative aging rate over time (steps 5 and 6 in the scheme in Fig. 2).

$$V = \exp\left[\frac{15000}{110+273} - \frac{15000}{\theta_h + 273}\right] \quad (8)$$

Table 1: Parameters involved in the equations for estimating the lifespan loss of 315 kVA transformers with the ONAN cooling system, located in Tucumán, Argentina.

Parameter	*Symbol*	*Value*
Oil exponent	x	0.94
Oil time constant	τ_o	106
Top-oil temperature rise	$\Delta\theta_{or}$	40.6
Hot-spot to top-oil gradient	$\Delta\theta_{hr}$	35.0
Loss ratio	R	5.31
Winding exponent	y	1.6
Winding time constant	τ_w	4.0
Thermal constant	k_{11}	1.0
Thermal constant	k_{21}	1.0
Thermal constant	k_{22}	2.0

The main input variables for calculating the lifespan loss are the load rate and ambient temperature. There are more complex models that use other expensive variables such as solar radiation, but it can be estimated from other weather variables simpler to measure [26]. The calculation can be performed near the transformer location if each transformer has the appropriate sensors. This interesting possibility would improve response times and save bandwidth. In this way, there is no need for a central system to collect and process the data. This paradigm is known as edge computing [27].

Results showed that the parameters obtained by the GA were similar to the values recommended by the loading guide (Table 1 shows these parameter values). However, the error in estimating the oil-top temperature was reduced by 63.7% in validation data. So, the proposed model provides more accurate temperature estimation and more accurate lifespan estimation in distribution transformers used in Argentina. Section 4 details the temperature curves and lifespan loss estimates when the distributed control algorithm for demand-side management is applied using real data.

2.3 Short-Term Load Forecasting

The data availability provided by SGs allows the implementation of many data analysis techniques to support decision-making for planning tasks like energy allocation and maintenance schedules. Load forecasting is one of the most widely used approaches among these techniques, although electricity demand prediction is a complex problem. It is a non-stationary process that depends on many conditions and factors, such as climatic, economic, cultural, random correlated, and uncorrelated effects [16]. The degree of randomness in the power consumption also varies according to the scale, being smoother as the aggregation level rises [28]. Load forecasting can be separated into three categories depending on the period under consideration. In the Long and Intermediate terms (weeks, months, or years), forecasting allows long-range planning, and it can be used to purchase energy in a city or state. On the other hand, *Short-Term Load Forecasting* (STLF) comprises a range from a few minutes up to 7 days ahead. It allows scheduling optimization of shorter-range planning like maintenance and human resources management.

Many machine learning models have been developed to forecast electricity consumption [29] and the model selection depends on each particular scenario. For example, there is a linear relationship between temperature and electricity consumption in some locations, while this relationship has a significant nonlinear component in other locations. In this work, we use the model and methodology proposed in [16] since it produced accurate results when applied in the northwestern region of Argentina.

A general scheme of this methodology is shown in

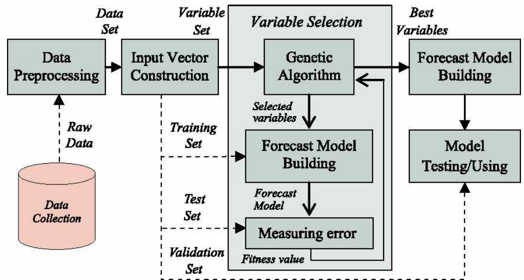


Figure 3: General scheme of the Short-Term Load Forecasting method [16].

Fig. 3. First, data are collected and pre-processed, preparing it for use in a machine learning model. The input includes variables derived from the electricity consumption, weather, information about the day type, and time (temporal variables). Lag variables were also added, obtained from the main variables considering three different points in the time series (2 backward and 1 forward). Thus, after the *Input Vector Construction* step in the forecasting methodology, there are 101 variables in total.

Then, noisy or redundant variables are removed in the *Variable Selection* process. A combination of a Simple Genetic Algorithm with Multi-Linear Regression (GA-MLR) is used in this step. The candidate solutions for the variable selection problem are encoded in a binary vector, indicating which variables will be used. Eq. 9 defines the fitness function used by the GA. It combines the Root Mean Squared Error (RMSE) with the Pearson's Correlation Coefficient (R) between real and predicted data. Also, it adds a penalization factor to force the GA to select the solutions (S) that provide fewer variables, avoiding complex forecasting models. That is, solutions with a high number of variables are penalized by reducing their fitness value. The parameter α controls the effect of the penalty. An appropriate compromise between solutions with few variables and low error is archived with $\alpha = 0.1$. This value reduces the size of the input vector to approximately 20% of the total variables.

$$f(S) = 1 - \frac{RMSE}{R}\left[1 + \alpha \frac{1}{N}\sum_{i}^{N} S_i\right] \tag{9}$$

Once the appropriate variables are ready, the prediction model is built from the data in a training process. Finally, the generated model is tested using a portion of the data not used for training. The methodology was tested using three models in the forecasting process: Multi-Linear Regression (MLR), Feed-forward Backpropagation Neural Networks (FFNNs), and Radial Basis Function Neural Network (RBFNN), but the last one provides more accurate predictions in our case.

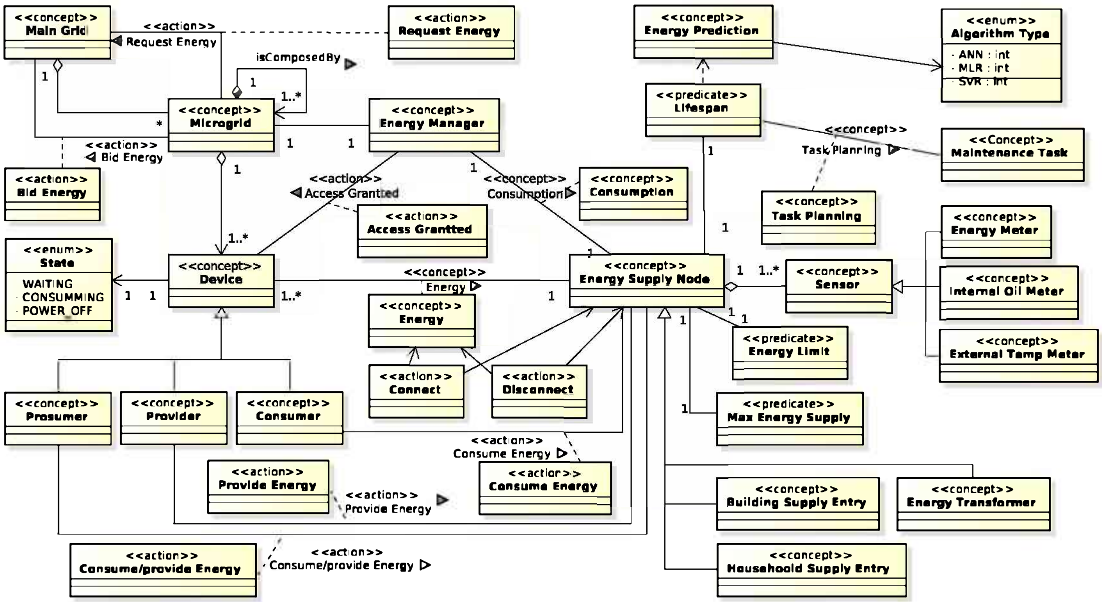


Figure 4: Ontology Diagram. It provides a general overview of the context of the application for our problem. This diagram shows the main concepts that describe certain aspects of Microgrid management and the relationships among these concepts, which were previously expressed in the system's requirements by the stakeholders.

3 OCMAS Modeling for Microgrid Management

The Multi-Agent Systems (MAS) paradigm [30] is a relatively novel approach that has dramatically grown over the last decades. It is a methodological framework that is well-adapted for analyzing and modeling complex, distributed, and open systems (open refers to the property of allowing the dynamic integration of new agents into an existing system). It regards systems as societies consisting of independent and autonomous entities, called *agents*, which interact to solve problems. The MAS has been successfully used in a wide range of domains, including the management and distribution of energy. Several works deal with different areas of the electric grid (production, transmission, and distribution) [31, 9].

As mentioned above, our proposal comprises many and varied aspects of the Microgrid administration. Some examples are the assessment of energy consumption, prediction, interaction with existing external systems (useful for collecting data that allow better internal control of the grid), device monitoring, and control interfaces. The design of our solution was done using the ASPECS methodology [32, 14]. As in any software development process, the first step of ASPECS is to carry out surveys of the requirements to define the system's scope and establish a reference language, unifying terms and concepts. In this first step, the diagrams of *Domain Requirement Description*, similar to the UML Use Case Diagrams and *Problem Ontology Description* are defined (Fig. 4). The latter, the only one we will illustrate due to the document length restrictions, highlights the most relevant concepts of the problem and its relationships. Each concept can be stereotyped according to the three available types: $<< concept >>$, $<< action >>$, and $<< predicate >>$. The diagram was designed based on the concept of Microgrid, which, by definition, is composed of a group of interconnected heterogeneous devices representing the sources and electric loads. The diagram expands/grows until it represents the concept of Energy Supply Node (ESN), the concepts related to the lifespan of the transformers, load forecasting, and sensors, among others.

Fig. 5 shows the organizations identified from the requirements. Here is a brief description of each of them:

- Peak Shaving: provides answers to the requirement of keeping the level of energy consumption below a set threshold.
- Artificial Immune Network (AIN) implements the bio-inspired algorithm adapted to the context of energy demand management to determine the device's state (demand control).
- Lifespan Estimation: determines the lifespan of an energy distribution device (e.g., transformer) using thermal models and genetic algorithms.
- Energy Forecasting: generates estimation models and predicts energy consumption.
- Sensor System: provides information from the database and other external devices that capture

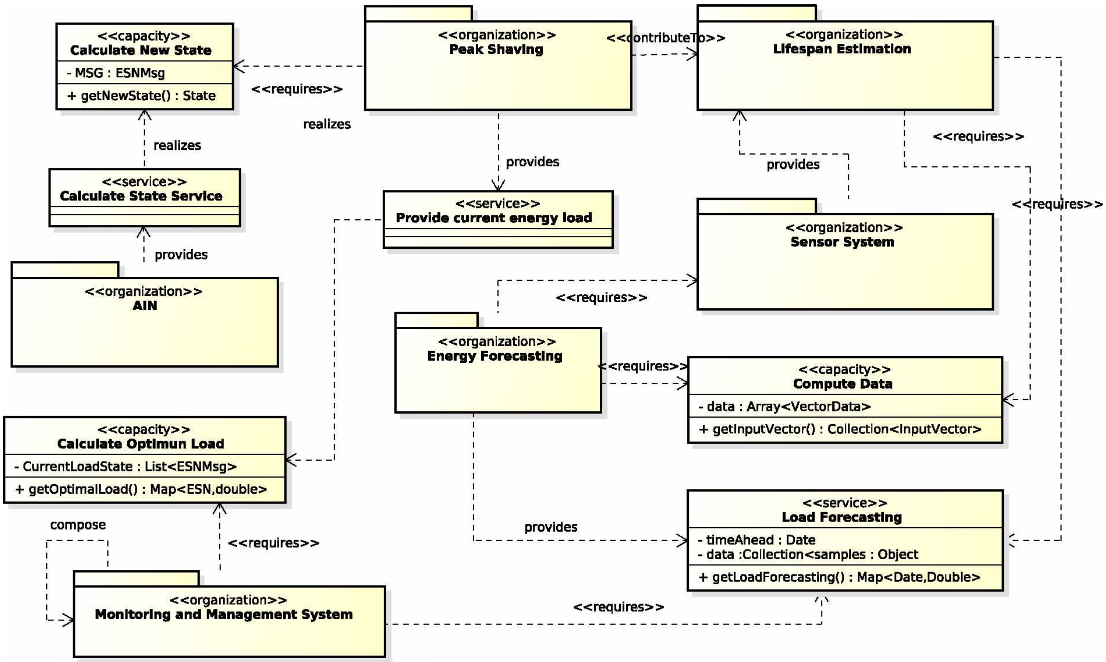


Figure 5: Organizational Diagram (partial). The global objectives of the system, arising from the requirements, are defined in this diagram. In order to solve the energy management problems described in this work, different technologies are used, most of which are bio-inspired algorithms, such as Artificial Immune Systems and Genetic Algorithms, among others.

data (SCADA and legacy systems) necessary for decision making.

- Monitoring and Management System: continuously tracks the electric grid producing relevant information, like consumption limits, for decision-making. It also acts as an interface between the system and the users.

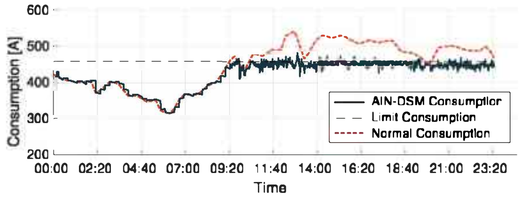
The system dynamics implies the performance of activities within each organization and an interchange of data among organizations through the different elements provided by the methodology. For example, to achieve its purpose of maintaining the consumption level, the Peak Shaving organization needs the results of the AIN and Energy Forecasting organizations. These also serve to estimate the reduction of the ESN lifespan using the Lifespan Estimation organization. The Sensor System organization provides all the data used for the different organizations. Finally, the Monitoring and Management System organization establishes the high standard working parameters for the complex system. It provides the necessary means for monitoring and controlling the resident module in the Microgrid.

The organizational approach allows us to address the modeling of a complex system through a series of characteristics such as *(i)* the possibility of using different languages in each interaction group, *(ii)* modularity in order to separate the behaviors embodied in organizations, necessary to achieve the objectives of the system, *(iii)* the possibility of defining multiple agent architectures and, finally, *(iv)* the elimination of centralized global control by allowing each group/organization to define its admission policies and/or control. It is correct to consider organizations as "blueprints" that can be easily reused in future developments. From a user and maintenance viewpoint, the use of MAS allows the user simpler and clearer maintenance, automated testing, easier and higher level introduction of changes, among other advantages.

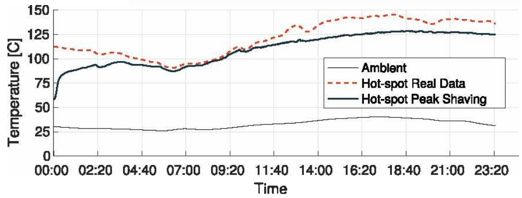
4 Experimental results

The two main aspects among the requirements and features provided by the proposed framework are the Demand-Side Management and the Transformer Lifespan Estimation. Regarding the first one, the AIN-DSM control algorithm was tested with hypothetical and real cases to prove its flexibility and capacity to adapt to different scenarios. This work reports only the results obtained with simulations using real data from a 315 kVA transformer installed in a residential neighborhood. The data correspond to the day with the highest electricity consumption register in 2013, provided by the local distribution company from Tucumán, Argentina.

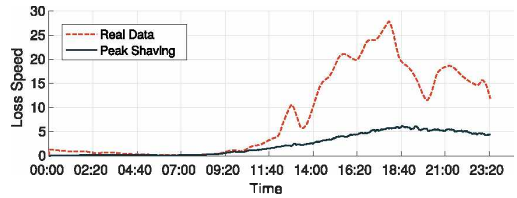
First, the AIN-DSM algorithm is analyzed from the viewpoint of consumption reduction at the transformer



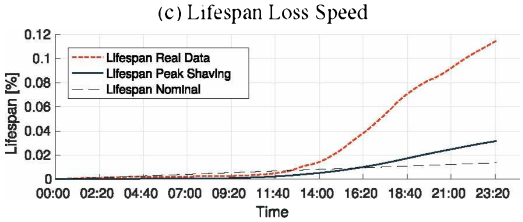
(a) Load curves



(b) Internal Temperature



(c) Lifespan Loss Speed



(d) Lifespan Estimation

Figure 6: Results for the distributed demand control with the AIN-DSM algorithm and the transformer lifespan estimation using real data from Tucumán.

substation. Fig. 6a shows the electricity consumption from the transformer with and without applying the control algorithm. Two different behaviors can be seen. In the first part of the day, where the consumption remains below the limit, both regular and controlled consumption by the AIN-DSM algorithm matches perfectly. In the second part, the demand level increases, where both curves exceed the prefixed power limit. However, the controlled consumption remains close enough to the limit. The average deviation is about 1% of the peak consumption most of the time.

Next, the method for transformer lifespan estimation described in Section 2.2 was applied to the same data used to test the AIN-DSM algorithm. Fig. 6b presents the temperature curves, including the ambient temperature and the two estimated temperatures from the top-oil and hot-spot in the transformer. These temperature curves correspond to real consumption data, with and without using the AIN-DSM control algorithm. Fig. 6c shows the calculated loss rate values, which indicates how fast the insulating material inside the transformer is degraded due to overload. Finally, Fig. 6d presents three curves for the accumulated lifespan loss: *(i)* the expected or nominal lifespan that is estimated to be 20 years for an ordinary distribution transformer (equivalent to approximately 0.014% in a day); *(ii)* the accumulated loss in the case without applying the control algorithm is 0.115% for all the analyzed period; *(iii)* the accumulated loss when the AIN-DSM algorithm is used. The value for the whole period is about 0.03%.

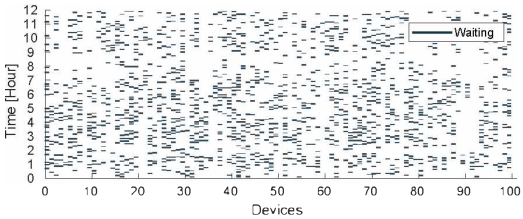
The proposed test scenario considers that the distribution transformer runs at full capacity the whole time, except for the peak days where the limit is exceeded. Furthermore, analyzing the available data, at least 30 days in the year present peak loads exceeding the maximum. The lifespan loss of the transformer without considering those 30 days is 4.59% in a year. Now, when considering those days into the calculation, the lifetime loss would be 8.04% in a year, reducing to 5.49% if the AIN-DSM algorithm is used. If the environment and consumption conditions are the same over time, the transformer's whole life will be about 12.44 years. In contrast, the total lifespan with the AIN-DSM algorithm is about 18.21 years. Table 2 summarizes the results described above.

This situation is hypothetical because, in real cases, the transformer is not working at 100% of its capacity all the time. The transformer lifespan may reach more than 20 years in many cases. However, the present analysis allows us to evaluate the impact of the AIN-DSM algorithm.

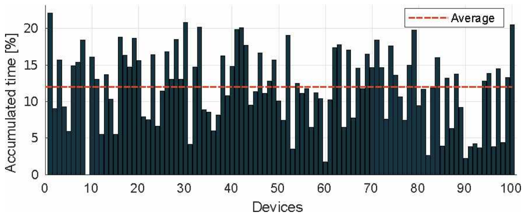
From the customer's viewpoint, it is important to analyze the periods when the AC's consumption is controlled by the AIN-DSM algorithm. Remember that this algorithm allows or denies the energy consumption of controlled devices. The period when the control algorithm denies the AC's consumption is called "waiting time". Fig. 7 shows the system behavior, considering only the part of the analyzed period when the control is active (12:00 to 23:59). First, the Gantt diagram in Fig. 7a shows the distribution of both states by

Table 2: Comparison using real data and the simulation results of the AIN-DSM algorithm to analyze the lifespan loss from a 315 kVA transformer.

Accumulated Lifespan Loss [%]	*Nominal*	*Real data*	*AIN-DSM data*
Day with high consumption	0.014	0.115	0.03
Month with high consumption	0.41	3.45	0.90
The rest of the year	4.59	4.59	4.59
A complete year	5.00	8.04	5.49
Ratio from nominal	1.00	1.61	1.10
Expected lifespan [year]	20.00	12.44	18.21



(a) Gantt Diagram of waiting times.



(b) Total waiting time of each AC device in the analysis period.

Figure 7: AC distribution of waiting times for each device.

all the controlled devices (normal consuming in white, waiting in black color). It shows a clear distribution of the consuming permissions determined by the control system. When AC devices are turned off (or placed in non-consumption mode), they remain in this state for no more than 6.6 minutes on average before returning to their normal operating mode (7.3 minutes in the worst case). This value ensures that the customer's thermal comfort is not affected. Fig. 7b shows the *accumulated* waiting time of each device, calculated over the last 12 hours of the test period. The horizontal line represents the average waiting time. This value indicates that the AC devices were forced to turn off 11.97% of the operating time.

Although the test case includes controlled A.C. devices and other non-controlled appliances, the system can adapt to any energy demand change. The distributed system requires a low level of interaction between the controlled devices, and yet the results are remarkable. The AIN-DSM algorithm implemented can adequately address the Peak Load Problem described in Section 2.1.

Regarding the STLF problem, the methodology described in Section 2.3 was tested using data from Tucumán in the interval between January 2014 and December 2015. The weather data are provided by a meteorological station located about 5 km from the distribution transformers selected to analyze. The forecasting variable is the phase current provided by a SCADA system. Its values were recorded from a three-phase transformer substation in the Low-Voltage distribution grid. The method was applied on 11 substations, predicting the current magnitude from one of its phases. Table 3 summarizes the average accuracy obtained using different error metrics on the validation dataset. One of the most commonly used metrics for

Table 3: One-Day-Ahead Load Forecasting results obtained with Radial Basis Function NN for the validation set.

Error Metric	*Average*	*Min.*	*Max.*	*Standar Desviation*
MBE	-0.49	-1.48	0.33	0.63
R	0.93	0.92	0.95	0.01
RMSE	16.14	9.84	21.03	3.74
MAPE [%]	**8.24**	6.89	10.10	0.94

error quantification is the average Mean Absolute Percentage Error (MAPE). In our case, its average value is 8.25%, similar to the results obtained with other methods applied in the same region [33]. Fig. 8 shows a comparison of the real data vs. the predicted values obtained using RBFNN as the prediction algorithm in the validation dataset (a week of data, between 12-13-2015 and 12-19-2015). Only one case is shown since the result is similar to the others. The curve profiles are consistent with the error level reported in Table 3.

5 Conclusions and Future Work

In this work, a conceptual framework for Microgrid Management was presented. Three problems and their possible solutions were identified, exposing its functionalities: *(i)* The Peak Load Problem was addressed with a distributed algorithm for demand-side management inspired on Artificial Immune System (AIN-DSM algorithm) that controls AC devices, *(ii)* Lifespan Loss Estimation of distribution transformers by using a model based on loading guides, adjusted using Genetic Algorithms (Deterministic Crowding), and *(iii)* Short-Term Load Forecasting addressed with Simple Genetic Algorithms and Multi-Linear Regression (GA-MLR). The proposed solutions and their main aspects were modeled based on the distributed paradigm of Organizational-Centered Multi-Agent Systems (OC-MAS).

Using the AIN-DSM algorithm prevents a premature reduction of the lifespan by around six years, indicating that the network is being protected. The savings generated by the use of the control algorithm could be invested in improvements and expansion of the current

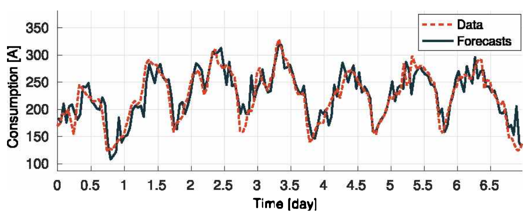


Figure 8: Load profile and one day-ahead forecasting from a Substation Transformer with residential consumption.

features of the distribution network instead of using the company resources in unnecessary repairing tasks. On the other hand, the estimation of the transformer lifetime loss allows us to evaluate the results of the previous approach. This feature, combined with the proposed method for load forecasting, provides helpful information about the transformer's condition. The proposed solutions provide remarkable results, promising the development of a whole system based on the presented approaches. They can provide essential information for the decision-making process and serve as input to other systems.

Future work will be on the same line, combining the Lifespan Estimation and the Short-Term Load Forecasting procedures. This combination would allow estimating when a given transformer will be affected and its lifespan shortened due to overloads, considering the uses and all the aspects proposed by the two mentioned methods. Also, we will implement the proposed framework using SARL, an Agent-Oriented Programming Language [34].

Competing interests

The authors have declared that no competing interests exist.

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Authors' contribution

VJ: software, validation, data curation, writing; DL: conceptualization, investigation, methodology, software, validation, writing - original draft; PA: formal analysis, validation; AW: supervision, project administration, funding acquisition, resources. All authors read and approved the final manuscript.

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References

[1] D. Lizondo, V. A. Jimenez, P. Araujo, A. Will, and S. Rodriguez, "Smart grid and demand-side management review," in *5to Congreso Nacional de Ingeniería Informática / Sistemas de Información (CoNaIISI 2017)*, (Santa Fe, Argentina), pp. 601–609, 2017.

[2] A. Nieße, M. Tröschel, and M. Sonnenschein, "Designing dependable and sustainable smart grids - how to apply algorithm engineering to distributed control in power systems," *Environmental Modelling & Software*, vol. 56, pp. 37–51, 2014.

[3] S. Monesha, S. G. Kumar, and M. Rivera, "Microgrid energy management and control: Technical review," in *2016 IEEE International Conference on Automatica (ICA-ACCA)*, pp. 1–7, 2016.

[4] P. G. Donato, I. Carugati, J. Strack, S. Maestri, C. Orallo, M. Hadad, and M. Funes, "Overview of the status of smart metering systems in Argentina and future perspectives," in *2018 IEEE Biennial Congress of Argentina (ARGENCON)*, pp. 1–7, June 2018. ISSN: null.

[5] "Decreto 134/2015 - Emergencia Energética," Dec. 2015.

[6] A. Pahwa, S. DeLoach, S. Das, B. Natarajan, D. Andresen, N. Schulz, and G. Singh, "Holonic Multi-agent Control of Power Distribution Systems of the Future," 2012.

[7] S. Frey, A. Diaconescu, D. Menga, and I. Demeure, "A Holonic Control Architecture for a Heterogeneous Multi-Objective Smart Micro-Grid," in *2013 IEEE 7th International Conference on Self-Adaptive and Self-Organizing Systems*, pp. 21–30, 2013.

[8] D. Lizondo, P. Araujo, A. Will, and S. Rodriguez, "Multiagent model for distributed peak shaving system with demand-side management approach," in *2017 First IEEE International Conference on Robotic Computing (IRC)*, pp. 352–357, 2017.

[9] A. Sujil, J. Verma, and R. Kumar, "Multi agent system: concepts, platforms and applications in power systems," *Artificial Intelligence Review*, vol. 49, no. 2, pp. 153–182, 2018. Publisher: Springer.

[10] L. J. Hill and E. Hirst, "Demand-side management: Research opportunities for electric utilities," *Electric power systems research*, vol. 8, no. 2, pp. 137–142, 1985. Publisher: Elsevier.

[11] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand Side Management in Smart Grid Using Heuristic Optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1244–1252, 2012.

[12] D. Lizondo, S. Rodriguez, A. Will, V. Jimenez, and J. Gotay, "An artificial immune network for distributed demand-side management in smart grids," *Information Sciences*, vol. 438, pp. 32–45, 2018.

[13] D. Isern, D. Sánchez, and A. Moreno, "Organizational structures supported by agent-oriented methodologies," *Journal of Systems and Software*, vol. 84, no. 2, pp. 169–184, 2011.

[14] M. Cossentino, N. Gaud, V. Hilaire, S. Galland, and A. Koukam, "Aspecs: an agent-oriented software process for engineering complex systems: How to design agent societies under a holonic perspective," *Autonomous Agents and Multi-Agent Systems*, vol. 20, no. 2, pp. 260–304, 2010.

[15] V. A. Jimenez, A. Will, J. Gotay, and S. Rodriguez, "Adjustment of model parameters to estimate distribution transformers remaining lifespan," *Smart Grid and Renewable Energy*, vol. 9, no. 9, pp. 151–170, 2018.

[16] V. A. Jimenez, D. Lizondo, A. Will, and S. Rodriguez, "Short-term load forecasting for low voltage distribution lines in tucumán, argentina," in *5to Congreso Nacional de Ingeniería Informática / Sistemas de Información (CoNaIISI 2017)*, pp. 940–949, 2017.

[17] A. Zhuk, Y. Zeigarnik, E. Buzoverov, and A. Sheindlin, "Managing peak loads in energy grids: Comparative economic analysis," *Energy Policy*, vol. 88, pp. 39–44, 2016.

[18] K. Okuyama, T. Kato, K. Wu, Y. Suzuoki, and T. Funabashi, "Load leveling of whole distribution system by autonomous output control of distributed generators," in *Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES*, vol. 3, pp. 2134–2138 vol.3, 2002.

[19] A. Oudalov, R. Cherkaoui, and A. Beguin, "Sizing and optimal operation of battery energy storage system for peak shaving application," in *Power Tech, 2007 IEEE Lausanne*, pp. 621 –625, 2007.

[20] M. Q. Wang and H. B. Gooi, "Spinning reserve estimation in microgrids," *Power Systems, IEEE Transactions on*, vol. 26, no. 3, pp. 1164–1174, 2011.

[21] D. Dasgupta, Z. Ji, F. A. González, *et al.*, "Artificial immune system (ais) research in the last five years.," in *IEEE Congress on Evolutionary Computation (1)*, pp. 123–130, 2003.

[22] X. Shen, X. Z. Gao, and R. Bie, "Artificial immune networks: Models and applications," *International Journal of Computational Intelligence Systems*, vol. 1, no. 2, pp. 168–176, 2008.

[23] L. Wang, X. Zhang, R. Villarroel, Q. Liu, Z. Wang, and L. Zhou, "Top-oil temperature modelling by calibrating oil time constant for an oil natural air natural distribution transformer," *IET Generation, Transmission & Distribution*, vol. 14, pp. 4452–4458, Oct. 2020.

[24] "IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators," *IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995)*, pp. 1–123, Mar. 2012.

[25] I. E. Commission, *Loading guide for oil-immersed power transformers (IEC 60076-7)*. Power transformers, IEC, 2005.

[26] V. A. Jimenez, A. Barrionuevo, A. Will, and S. Rodriguez, "Neural Network for Estimating Daily Global Solar Radiation Using Temperature, Humidity and Pressure as Unique Climatic Input Variables," *Smart Grid and Renewable Energy*, vol. 1, pp. 94–103, Mar. 2016.

[27] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637–646, 2016.

[28] R. Sevlian and R. Rajagopal, "Short term electricity load forecasting on varying levels of aggregation," *arXiv preprint arXiv:1404.0058*, 2014.

[29] A. Gonzalez-Briones, G. Hernandez, J. M. Corchado, S. Omatu, and M. S. Mohamad, "Machine Learning Models for Electricity Consumption Forecasting: A Review," in *2019 2nd International Conference on Computer Applications & Information Security (ICCAIS)*, (Riyadh, Saudi Arabia), pp. 1–6, IEEE, May 2019.

[30] M. Wooldridge, *An Introduction to MultiAgent Systems*. Chichester, U.K: Wiley, 2nd edition ed., 2009.

[31] R. Roche, B. Blunier, A. Miraoui, V. Hilaire, and A. Koukam, "Multi-agent systems for grid energy management: A short review," in *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, pp. 3341 –3346, 2010.

[32] M. Cossentino, V. Hilaire, N. Gaud, S. Galland, and A. Koukam, "The aspecs process," in *Handbook on Agent-Oriented Design Processes*, pp. 65–114, Springer, 2014.

[33] V. A. Jimenez, G. E. Lescano, and A. Will, "Regresión Simbólica aplicada a la Predicción del Consumo Eléctrico a Corto Plazo en el Nivel de Subestación," *Revista Tecnología y Ciencia*, pp. 85–102, Dec. 2020.

[34] S. Rodriguez, N. Gaud, and S. Galland, "SARL: a general-purpose agent-oriented programming language," in *The 2014 IEEE/WIC/ACM International Conference on Intelligent Agent Technology*, (Warsaw, Poland), IEEE Computer Society Press, 2014.

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