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An Artificial Immune Network for Distributed Demand-Side Management in Smart Grids

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ABSTRACT

In this work we present a Distributed Demand-Side Management system based on the Artificial Immune Network algorithm. It implements an intelligent, distributed and autonomous control of the customer's Air Conditioning devices in order to meet the desired demand. The system is particularly adapted to tackle the Peak Load problem that appears in Tropical and Subtropical climates due to the use of thousands of these devices at the same time. The design follows the guidelines set by the Smart Grid paradigm, in the sense that it is fault tolerant, distributed and self-controlled. It requires minimal communication infrastructure when compared to a centralized system.

The algorithm was evaluated using synthetic and real data. We define Maximal and Average Tolerance as performance metrics, and show that the system keeps the consumption within 1% of the given load limit in all 5 cases.

1. Introduction

Energy consumption, and in particular the electric energy consumption, has grown steadily over the last few years, due to the natural increase of the population and new technologies [29]. In this new scenario it is necessary to improve the features of the electrical grid, which brings about the Smart Grid paradigm [10,28]. This kind of electrical grid provides a set of characteristics that allow a better use of energy, an increased control, an improvement of management adding real-time monitoring. They also lower the maintenance costs, help in the decision-making process and providing a better electric service, among other aspects. Moreover, Smart Grids must be auto-regenerative, able to support different types of anomalies in the system, give a certain degree of reliability and efficiency, while always having control of the entire network stages (Generation, Transport, Distribution and Client stage).

Currently, one of the most influencing problem is the so-called Peak Demand or Peak Load Problem [27]. The Peak Demand Problem consists in an overload generated by the simultaneous energy consumption of several devices connected

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to the grid (in general Air Conditioning or Heating devices) in a relatively short period of time. This electric consumption reaches critical energy levels that severely affect distribution equipments. This problem causes different types of damages related to technical and operational issues, being sometimes irreversible or irreparable. The economic cost associated with repairing damages or replacing burnt or broken devices is high. Other collateral effects related to this problem are the inconveniences and discomfort caused to the consumers, gradually affecting the image of utility companies. Even in the case where no equipment is damaged, the difference between low and peak consumption forces utility companies to oversize several expensive aspects of the grid in order to cope with this demand.

The Peak Load problem is complex because it changes depending on the particular population and involves different kinds of actors and factors, and its effects cannot be entirely measured. To tackle this problem, some researches were conducted to avoid the peak using different viewpoints with techniques like Spinning Reserve [9] and Load Leveling [16], Peak Shaving [19,20] and Battery Storage [25]. Previous research related to the Peak Load Problem can be categorized in two approaches: top-down and bottom-up. The first mainly focuses on Generation and Transport stages, the second focuses on distribution and client stages. Our work is inspired by the second approach with the Demand-Side Management [23,30] and Demand Response techniques [21].

In this work, a heuristic algorithm based on the Artificial Immune System (AIS from now on) [14] is presented in order to address the peak demand problem. The proposed algorithm uses the dynamic and auto-regulation capacities of the AIS to control the energy consumption in a determined zone and time period. The algorithm controls the load in a determined spot in the grid called the Energy Supply Node (ESN), to avoid the possible damages of an overload. Moreover, the system provides a mechanism that allows the electric utility company to regulate and diminish the consumption in a given area, redirecting the energy to other uses or simply saving it. The algorithm features follow the guidelines set by the Smart Grid paradigm, in the sense that it is fault tolerant, distributed, autoregulated and self-controlled (features provided by AIS heuristic). Other algorithms found in the relevant literature are centralized, require human supervision, and/or require an expensive and complex communications infrastructure, but the proposed one requires minimal communication infrastructure when compared to a centralized system. This paper corresponds to a patent application, presented in No. 2016 (see Section 7).

The rest of the paper is organized as follows. In Section 2 the peak load problem is described followed by the mathematical formulation presented in Section 3. Section 4 describes the related works and the focus of this paper. Section 5 contains the main contribution of this article. In this section, the basic concepts of AIN are presented followed by the full description of the proposed AIN-PS Model. Finally, Section 6 contains the results and Section 7 presents our conclusions and future works.

2. Peak load problem

The electric emergency was declared as one of the major problems that should be addressed taking into account the efficiency and the environmental impact [33]. Also, most of the aspects that influence the energy consumption have regional validity, and the characteristics of the problem change depending on the scale, certain infrastructure, market conditions, or even political and socio-cultural aspects [3,15]. Additionally, thermo-controllable devices are commonly associated with the Peak Load problem, and its effects are more visible in countries with Tropical and Subtropical climates due to the utilization of a high number of air conditioning devices.

In the Tucumán province (Argentina), during the hot season, the average apparent temperature is about 35 °C with a maximum of 60 °C, and 40% of Humidity [18]. This scenario holds for over 80% of the time during this period. Consequently, the use of cooling devices is extremely high and their use increases every year. Furthermore, the houses and buildings in the province are usually not adequately insulated relying in a wide use of Air Conditioning devices to maintain a comfortable temperature. In fact, they are kept running for long periods of time for the heat does no drop considerably during the night. Peak hours or in our case “peak consumption hours” in the summer span up to four hours (from 1 p.m. to roughly to 5 p.m., o even more). It is a long period of time of high electric consumption in about two to four months a year.

As the installed capacity fails to meet the energy demand, there are periodical and partial denials of service, followed by blackouts covering large areas on extreme cases. This extreme peak consumption affects and reduces the lifespan of the nodes and equipments that provide the electric energy. In December 2015, the Argentine government in an official statement [7] decreed the energy emergency, highlighting that although the energy production is in good shape, but the distribution sector is severely affected by this situation.

This problem affects not only the social and economic aspects of several countries, but it also has an impact on global climate change: many works emphasize that Energy Management and Optimization are some of the most feasible and proactive approaches to climate change in the short and medium term according to section two of the Kyoto Protocol.[1] Even more, in the Paris Agreement[2] one of the main Energy Efficiency Targets is to achieve at least 27% increase in energy efficiency. Furthermore, the proposal of setting air conditioning devices to 25 °C (77° Fahrenheit) was evaluated by the ClimateLab,[3] and it estimates a global CO_2 emission saving of 194.16 Mt of CO_2. That amounts to an energy saving of about

[1] http://www.kyotoprotocol.com/.

[2] http://unfccc.int/paris_agreement/items/9485.php.

[3] http://climatecolab.org/contests/2016/industry/c/proposal/1329804.

327 [TWh/year] and a cost savings of 29,500 million [USD/year] with an estimated average energy cost of 90 USD/MWh, among other benefits.

3. Mathematical formulation

As a viable solution for these problems, we propose in this work a distributed control system which manages the running periods of the Air Conditioner (AC) devices. This involves working with smart ACs, or Installing appropriate control devices. In this case, the system decides the energy consumption state of each controlled AC in order to avoid the peak load generated in the Energy Supply Node (ESN) by their simultaneous use. So, the problem was classified as a constrained Job Scheduling problem. These constraints are related to the state of consumption of each cooling device connected to the electric energy provider node or ESN, and to technical characteristics of the devices.

We restrict ourselves to the most common Air Conditioning devices in our country, but it can be easily extended to freezers, refrigerators, and other appliances depending on the consumption characteristics. ACs present two energy consumption states: *Consuming* or *High* state and *Waiting* or *Low* state. In the High state, the device freely consumes the amount of energy that is needed (refrigeration mode). In Low mode, the energy consumed is restricted to a minimum value, usually close to zero (Ventilation Mode).

Another critical factor is the time during which a device remains in low mode because it is inversely related to the user's comfort and the peak load. Therefore, it is desirable for a device to allow a high consumption mode for as long as possible. The system is designed to maintain a total load consumption below a predefined level. What is more, the ESN has a maximum physical amount of energy it can provide. Beyond this limit the ESN lifespan will be affected and significantly reduced, resulting in the partial or total damage of the equipment [5].

The optimization function for this problem is not clearly known and depends on a large number of factors, which could even be random. Moreover, the function is geographically distributed, and the interaction among the related actors presents a highly complex communication problem. Then, we define the problem as: let $AC_i, i = 1 \ldots n,$ be a cooling or heating device connected to a particular ESN, i.e. air conditioners, freezers, refrigerators or any device feasible to be controlled, attached to an ESN, which could be a transformer, the electric supply entrance of a home, the primary supply of a building or any point within a power conductor where the consumption must be controlled. The defined function is shown in Eq. (1).

$$TT_{LOW} = \min\left(\frac{1}{N}\sum_{i=1}^{N}(TTLM_i)^2\right) \tag{1}$$

subject to the following constraints:

$$\begin{cases} \min(CTHM_i(t)) \geq MTHM, & \forall\ i = 1, \ldots, N \\ \max(CTLM_i(t)) \leq MTLM, & \forall\ i = 1, \ldots, N, \ \forall\ t \\ ESN_{LOAD}(t) \leq ESN_{LIM}(t) \leq ESN_{MAX}, & \forall\ t \end{cases}$$

where:

- TT_{LOW} is the average total time in low mode for all appliances connected to the supply node.
- $TTLM_i$ is the total time that an appliance i was in low mode during one hour.
- $CTLM_i(t)$ is equal to 0 if the appliance is On at time t. Otherwise, its value is equal to the time lapse that the device remains unchanged in low mode and contains the t time.
- $CTHM_i(t)$ is equal to 0 if the appliance is Off at time t. Otherwise, its value is equal to the time lapse that the device remains unchanged in high mode and contains the t time.
- *MTLM* is the maximum time that an appliance should be waiting until it changes its state to high.
- *MTHM* is the minimum time that an appliance should remain in the high state until it changes (or not) its state to low.
- $ESN_{LOAD}(t)$ is the ESN's consumption in [kWh] at time t. This term could be depicted as the sum of the non-controlled consumption or BaseLoad, and the controlled ACs consumption. To clarify, the BaseLoad is the consumption generated by devices that are not controlled or limited.
- $ESN_{LIM}(t)$ is the maximum predefined energy consumption allowed to be provided by the ESN at time t.
- ESN_{MAX} is the ESN's maximum amount of electric energy that it can physically provide.

and

$$ESN_{LOAD} = Base_{LOAD}(t) + \sum_{i=1}^{N} AC\_State_i(t) * AC\_Consumption_i(t) \tag{2}$$

where:

- $AC\_State_i(t)$ is the state of the AC_i at time t. The states is 1 if the AC is in *Consuming* state, otherwise is zero.
- $AC\_Consumption_i(t)$ is the energy consumption of AC_i at time t.
- $Base_{LOAD}(t)$ is the consumption of non-controlled devices at time t.

To summarize, the problem was described in terms of controlled devices connected to an ESN, the running behavior of the controlled devices, the ESN consumption and its main restrictions.

4. Related works

The Peak Load problem is a complex one, because it changes depending on the particular population and involves different kinds of actors and factors, and its effects could not be entirely measured. To tackle this problem, some researches were conducted to avoid the peak using different viewpoints. In the generation and transport stages, the Spinning Reserve [9] and Load Leveling [16] techniques are commonly used, whereas in the distribution stage Peak Shaving [19,20] and Battery Storage [25] are the most usually applied. Additionally, some approaches combine two or more of the previously mentioned techniques, like Peak Shaving with Battery Storage [25].

However, all the mentioned methods and works are based on the management of suppliers and the time when these provide energy. On the other hand, the Demand-Side Management [13] approach extends the control concept and tries to solve the problem by introducing changes on the demand itself. Indeed, with the ability to control the consumption or redistribute the way energy is consumed, a new view point was established. The purpose of this approach consists in influencing or trying to affect the consumption using methods like the Demand Response or the Dynamic Response [2,24]. Sometimes, this mechanism is applied by governments or utility companies through social policies like time restrictions or shorter periods of device use in exchange for electric bills reductions.

In [34], the authors present a metaheuristic algorithm based on the Cooperative Particle Swarm Optimization to optimize scheduling and operation of time-shiftable and power-shiftable devices in a set of smart homes of a district. The dynamics of this approach consist in having each home (represented by a “Home Agent”) propose a schedule of running time of its own devices and send it to the “Grid Agent”. This agent makes modifications taking into account a fitness function using the Cooperative PSO algorithm, and it returns the fixed schedule to each home agent. Its main aim consists in making a local optimization and through it, a global optimization depending on the aggregation of controlled zones. The only disadvantage is that the proposed algorithm needs a central computing node that decides how to fix the proposed schedules. The communication between the nodes and the central node plays a key role. In a similar way [21] introduces a distributed algorithm for sparse load shifting in demand-side management with a focus on the scheduling problem of residential smart appliances. A Newton method is employed to accelerate the centralized coordination of demand side management strategies that super-linearly converge to a better Nash equilibrium minimizing the peak-to-average ratio. But, a centralized unit collects and processes data from customers’ demand to decide the optimal appliances scheduling, being necessary a bidirectional communication infrastructure.

Another remarkable work is the one presented in [32] where a hierarchical and distributed control strategy for thermostatically controlled applications (TCAs) is proposed. This work is focused on DSM and the Demand Response (DR) strategy. The authors combine a model based prediction strategy and a customer responsive behavior model into an Improved Original Optimal Temperature Regulation (OTR-I). In particular, they proposed the concept of Virtual Power Plant (VPP) which is the representation of the aggregation of all the participants that are geographically close in a given region. The VPP is connected with the upstream power system reducing the amount of information exchange, being the total power the only data that should be sent to VPP. The authors said “It (the algorithm) is nearly a center-free algorithm and there is no need to collect information of the DR devices or send a control signal to them”. But apparently, there is some data flow within the VPP among system actors, and among VPPs which could mean that the system needs a certain degree of complex communication. However, it is true that the amount of information exchanged in comparison with a centralized system is considerably reduced.

An organizational model of the proposed system can be found in [22]. It presents some agent models of the initial modeling phase of the ASPECS methodology to implement the AIN-PS algorithm proposed in this paper.

As explained before, previous research related to the Peak Load Problem can be categorized in two approaches: top-down and bottom-up. The first mainly focuses on Generation and Transport stages, the second focuses on distribution and client stages. Our work is inspired by the second approach with the Demand-Side Management and Demand Response techniques.

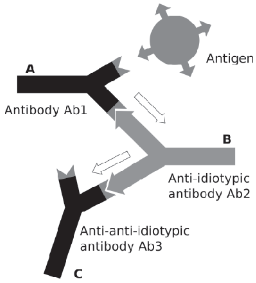
5. AIN model for Peak Shaving

In this section, a brief description of the basic concepts and the dynamics of the Artificial Immune Network (AIN) is presented. The model and adaptation of the AIN developed to address the Peak Shaving Problem is fully described in Section 5.2.

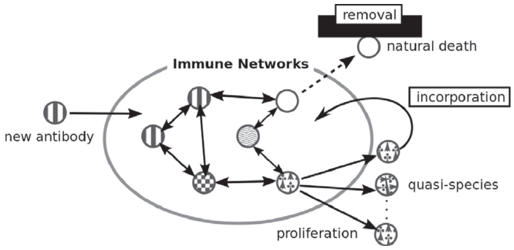
5.1. AIN model

In the literature, several works have been inspired by nature and biology. One of the relatively new models developed taking the human immune system as a model, which was widely applied, is the well-known Artificial Immune System (AIS) [14]. Of the different models developed, the most relevant are the Negative Selection mechanism, Clonal Selection, Danger Theory and the Immune Network Theory [1,6,11,26].

The biological immune system is mainly composed of macrophages, antibodies, and lymphocytes. These lymphocytes can be classified into B-lymphocytes and T-lymphocytes. The first cells type is created and released by the bone marrow, containing “Y” antibodies shape on their surface. Those antibodies are capable of recognizing specific antigens (foreign substances, cells, viruses and so on). The portion of the antigen recognized by an antibody receives the name of the epitope,



(a) Antigen-Antibody interaction.



(b) Dynamics of the AIN.

Fig. 1. Artificial Immune Network [31].

and the part of the antibody which recognizes the antigen is called paratope (see Fig. 1(a)). The T-lymphocyte cells, maturing in thymus, have the task of regulating the concentration of antibodies from B-lymphocytes and killing infected cells. This behavior was the base to the idiotypic network stated by Jerne [17].

The idiotypic theory stated that there is not only interaction between antibodies and antigens, but also among antibodies. So, taking this hypothesis, this kind of interaction in a large scale could be depicted as a network of interactions which includes stimulations and suppressions. In few words, when an antibody paratope matches an epitope of the antigen, the antigen stimulates the B-Cell and the antibody suppresses the antigen. Similarly, when an antibody recognizes another antibody, the first one suppresses the second, and the second stimulates the first one.

So, to resume, the bone marrow creates new antibodies that are incorporated into the immune system. The antibodies generate interactions in the network, whose outcome is the Proliferation of those types of antibodies or their removal from the system by their natural death. The Proliferation creates quasi-species that are mutations of the original clone antibodies, which are inserted in the immune system (see Fig. 1(b)).

The Immune Network Theory was proposed by Jerne and adopted by Farmer and Varela [12] who stated its meta-dynamics ruled by the differential Eq. (3).

$$\frac{dA_i(t)}{dt} = \left(\alpha \frac{1}{N} \sum_{j=1}^{N} m_{ij} a_j(t) - \alpha \frac{1}{M} \sum_{k=1}^{M} m_{ik} a_k(t) + \beta m_i - k_i\right) a_i(t) \tag{3}$$

In this equation, the interaction (stimulation/suppression) among the antibodies is represented by the two first terms in the brackets. The m_{ij} and the m_{ik} can be interpreted as an analogy of the grade of similarity or affinity between two antibodies. The βm_i depicts the affinity between the antibody i and the antigen. The k_i is known as the death or dissipation factor of the antibody cell. Finally, the a_i represents the concentration that can be calculated using Eq. (4).

$$a_i(t) = 1/(1 + e^{0.5 - A_i(t)}) \tag{4}$$

This function receives the name of Squash Function, and its aim is to maintain the stability of the system concentration. Thanks to the interaction between antigens–antibodies and antibody–antibody the system can be shaped as a network with relations or connections.

Many computational models have been developed since the Immune Network Theory was created. Those models received the collective name of Artificial Immune Network, AIN from now on. Due to its properties and features, a wide range of literature of application of AIN in different problems and areas can be found [6]. For example, some common uses are data classification, pattern recognition, weather forecasting, problem optimization, among others.

5.2. AIN model adaptation for Peak Shaving problem

In the previous section, the basic concept of the AIN model was described to state the theoretical context. First of all, some considerations should be taken into account in order to properly describe the AIN model for the Peak Shaving problem.

As it is well known, the Peak Shaving Problem consists in reducing the load and reaching a safe and stable level of energy. There are some physical restrictions imposed by the power node, devices and the elements that form the electrical grid. Additionally, those constraints change from one level of the grid to another. Then, a multilevel control system is preferred rather than a complex one, conceived with the aim of controlling the whole grid as an entire entity. This approach is compatible with the concept of “Microgrid” [8] and the principle of controlling small parts of the electrical grid rather than the whole one. Fig. 2 shows a multi-level network being administrated by microgrids (MG) in the lowest levels and an upper system controlling other aspects of the Main Grid (MMS). In our approach, we considered that a distributed control system based on AIN could handle this problem appropriately, where each microgrid has an AIN-PS algorithm running and managing it in an autonomous and independent manner. On the upper level, another optimization control system (possibly another AIS with a different internal architecture) should be running. In this work, we are focus in the control system that should be implemented by each MG.

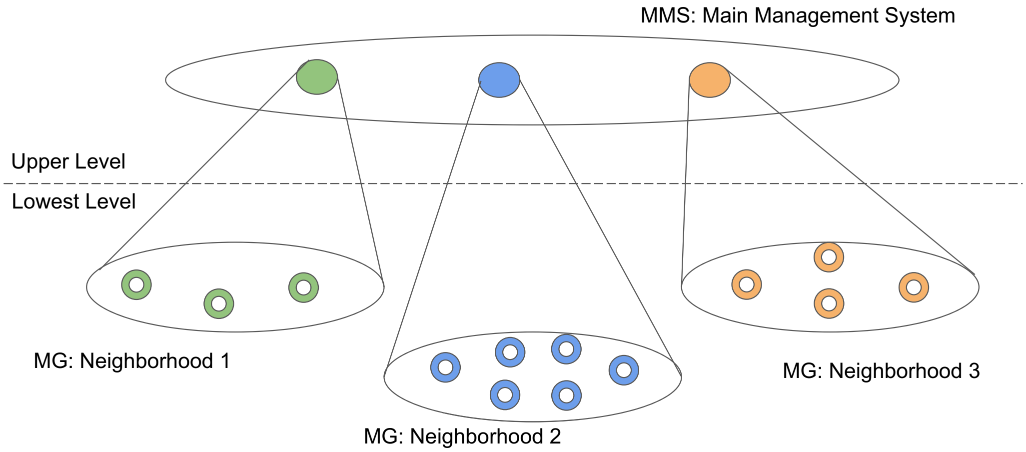


Fig. 2. Multi-level control system for Smart Grids.

The AIN model uses a set of antibodies, maybe of different types, which interact with each other and with the antigens. In our model, an antibody means a particular device that is currently *On* and consuming energy. In other words, the antibody points out an access granted by the proposed algorithm to a device at a particular moment for a configurable period. A new access requested by a device that needs to be turned on is represented by an antigen that appears in the AIN system. If the request is accepted, then an antibody is cloned.

In this first approach, we focus our attention on ACs, but this algorithm could be applied to any device susceptible to changing its state of consumption. For now, the only controlled apparatus that will be taken into account in the model (antibodies) are ACs, due to the fact that they can be easily modified in their consumption regime without seriously affecting the behavior from the client's viewpoint (preserving Human Thermal Comfort – HTC).[4] Even more, we consider that the energy consumption of an AC is equivalent to a single unit of energy in order to simplify the AIN Peak Shaving model (AIN-PSM) complexity. An *EnergyUnit* is a representative unit of the consumption measurement, and can be current [A], power [kW], or another unit. The general case (different consumptions) is also addressed later. In this context, some simplifications to Eq. (3) were performed.

$$\frac{dA_i(t)}{dt} = \left(\alpha \frac{1}{N} \sum_{j=1}^{N} a_j(t) + \beta m_i - k_i\right) a_i(t) \tag{5}$$

In Eq. (5), in comparison with Eq. (3), the term that represents the suppression of antibodies was deleted because there is only one type of antibody, so the difference between them is equal to zero. The term that depicts the antibodies stimulation is the m_{ij} value. It establishes the affinity/similarity between the antibody i and the antibody j, but in this case it becomes one since we are talking about of the same type of antibody. The first term represents the energy consumption in the ESN, the βm_i still represents the presence of an access request, and the k_i depicts the natural death of cells. Finally, $a_i(t)$ is related to the specific consumption of the device i.

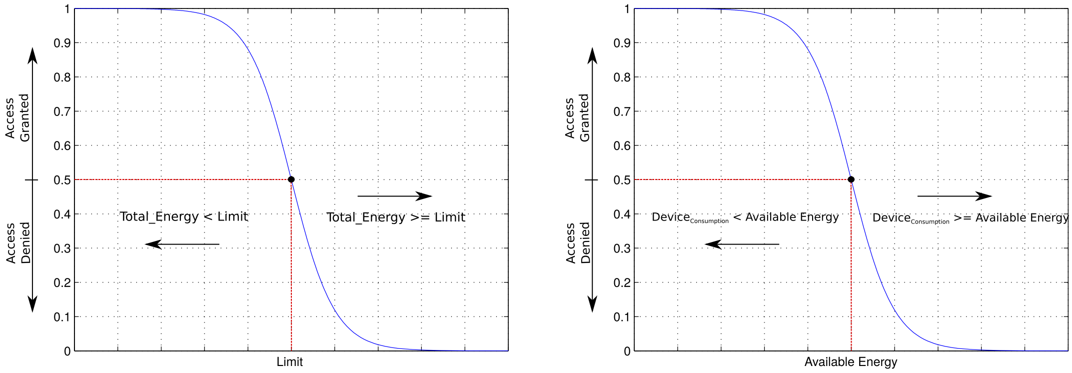
In our case, we consider that the electrical grid can be shaped like a directed rooted tree with nodes and connections, where a node supplies energy to a set of nodes or power devices. In order to fulfill the energy level restriction introduced by the ESN (see Section 3), some modifications to Eq. (4) were necessary.

$$a_i(t) = 1/(1 + e^{ESN_{LOAD}(t) - ESN_{LIM}(t)}) \tag{6}$$

- $ESN_{LOAD}(t)$ is the energy load in the ESN at time t.
- $ESN_{LIM}(t)$ is the max amount of energy that a particular level or ESN can handle at time t. It is the limit constraint of the energy source.

In the AIN model, the squash equation has the aim of controlling and maintaining the antibody concentration level. In a similar way, the proposed Eq. (6) is used to define the maximum energy level allowed by the source node. Fig. 3(a) shows shape of the modified Squash function. As a result of the exchange of the terms in the exponential function, the form of the squash function was inverted. It was done because it is desirable to reduce the energy consumption as the current level approaches to the ESN_{LIM} value. Then, as long as the load stays below the power limit, the system provides access to any request (left side of the figure), otherwise the access is denied (right side). Although it is a fact that the algorithm requires the ESN_{LOAD} to make decisions, it does not imply that this is a centralized approach. The measurement taken in the ESN and

[4] ANSI/ASHRAE Standard 55 (Thermal Environmental Conditions for Human Occupancy).



(a) Squash for ESN. (b) Squash for Device.

Fig. 3. Squash representative shape for the ESN and the device behavior.

broadcasted to the nodes (controlled devices) is all the information each node requires to make an adequate decision and regulate its own behavior without commands from a central control.

Following the idea that the source node has a maximum level of energy it can provide, and the current consumption (ESN_{LOAD}) is the sum of each antibody consumption in a particular moment and the summed consumption of all the non-controlled devices, Eq. (5) has to be adapted once again.

$$\frac{dA_i(t)}{dt} = \left(a_{totalEnergy}(t) - k_i\right)a_i(t) \tag{7}$$

where

$$a_{totalEnergy}(t) = 1/(1 + e^{totalEnergy(t) - ESN_{LIM}}) \tag{8}$$

and

$$totalEnergy(t) = NCC(t) + \sum_{p=1}^{Q} AbConsumption_p(t) \tag{9}$$

In Eq. (9) the *totalEnergy*(t) represents the total energy that is being provided by the ESN. In other words, it is the energy that both antibodies ($AbConsumption_p$) and all other non-controlled devices ($NCC(t)$) are consuming at time t. The variable $Q(t)$ is the total number of antibodies being currently in the system or the controlled devices in *consuming* mode.

The simplification on Eq. (7) corresponds to the fact that the set of antibodies and other consumptions are translated to only one load or antibody that consumes the entire energy. That is, it represents the consumption in the ESN. Under this hypothesis, the summation operator and the normalized parameter $1/N$ are eliminated. The α value is only used to increase or reduce the effect/speed of the immune response (since it directly affects the derivative of the response).

All the adaptations, the analogies assumed, and the simplifications were done based on the features of the immune systems, the problem specification and the control possibilities given by Smart Grids technologies. The algorithm has the capability of managing the access of the devices, and it depends on the global state of the ESN related to the current consumption of both the controlled and the non-controlled devices.

However, in the present condition of the system, it only gives good results if the energy consumption of each device is equivalent to a single unit of energy. In real cases, the consumption is related to the device features, and it varies in a wide range. Furthermore, in some cases, the devices have the capability to autoregulate their consumption. In those situations, the algorithm can have some problems upholding the constraint that the energy provided stays below a given threshold. An example of this scenario is when the current consumption (*totalEnergy*(t)) is less than the *Limit* by a single unit, and a device with energy consumption equal to two EnergyUnits requests access to the system. The behavior of the algorithm will grant access to this device even though the ESN limit is overloaded, leading to an imminent crash. So, to deal with this problem, the specific consumption of the device which is trying to get an access permission was introduced into the concentration Eq. (7), more precisely modifying the $a_i(t)$ multiplication term.

$$a_i(t) = 1/(1 + e^{AbConsumption_i(t) - AvailableEnergy(t)}) \tag{10}$$

where

$$AvailiableEnergy(t) = ESN_{LIM}(t) - totalEnergy(t) \tag{11}$$

Eq. (11) shows the current energy that the ESN could provide without achieving a critical or dangerous energy level. So, in Eq. (10) the algorithm tries to evaluate what happens within the system if the particular device i with a non-unitary

Table 1
Set of cases used in the performance analysis of the AIN-PS Algorithm.

Case	Total Energy	Limit [%]	#AC's	Consumption [EnergyUnit]	Waiting Time [min]	Consuming Time [min]
1	100	75	100	1	3	3
2		80	100	1	3	3
3	446	75	100	3.7; 4.5; 5	3	3
4		80	100	3.7; 4.5; 5	3	3

consumption request access. Fig. 3(b) is shown as an illustration of the behavior of this equation, and its shape is essentially the same as the theoretical Squash in Fig. 3(a). The important changes are the parameters that will be compared, the device consumption and the energy available. The other aspects as regards the access actions (grant/deny) are the same.

The presented AIN-PS algorithm has two dimensions: global and particular state. The first one corresponds to the vision of the global consumption on the ESN taking into account all the devices connected and the current energy consumption. With this first dimension, we ensure that globally the system controls the total energy provided by the ESN and the level of energy remains below the stated limit. The second aspect is related to the particular device that tries to get access, and in this dimension, the focus is put on the consumption of the device and whether this consumption is greater than the currently available energy or not.

The last part of the algorithm is the clonal process of the cells, that is how the access is managed. Some models of artificial immune systems do not define this process, reducing the process to only copying one selected cell through a determined criterion. In our case, we are particularly interested in this step, so the mechanism described in [4] was adopted.

$$nC_t^i = \lceil C_t^i \cdot (nC^{max} - nC^{min}) + nC^{min} \rceil \tag{12}$$

In Eq. (12), the nC^{min} and the nC^{max} are the minimum and maximum cloning number of cells allowed to be cloned for each selected antibody. The C_t^i is the current change of concentration calculated by each cell with the Eq. (7). Depending on the nC^{min} value, the result could be negative, which represents the need of eliminating cells and the number of them that must be suppressed in that time step. That is due to the natural behavior of the AIN, which has the property of maintaining the concentration at a particular level. In our case, the minimum and maximum values were set to zero and one, respectively, because this equation is the one that defines if the access will be granted or denied. We do not use negative values in the cloning equation because we considered that if the system allowed access to a device, it must not be revoked until the time of the access is over. A negative value would represent the need to revoke access.

Until now, the full process to adapt the AIN to the Peak Shaving problem was presented, but a mechanism to measure the efficiency of the algorithm is necessary. So, two metrics of performance were proposed: $Tolerance_{MAX}$ and $Tolerance_{MEAN}$. Both of them try to express in percentage the amount of energy that is above or below the ESN_{LIM}.

$$Tolerance_{MAX} = \frac{max(ESN_{LOAD}) - ESN_{LIM}}{ESN_{LIM}} \tag{13}$$

$$Tolerance_{MEAN} = 1/T * \sum_{t=1}^{T} \frac{ESN_{LOAD}(t) - ESN_{LIM}(t)}{ESN_{LIM}(t)} \tag{14}$$

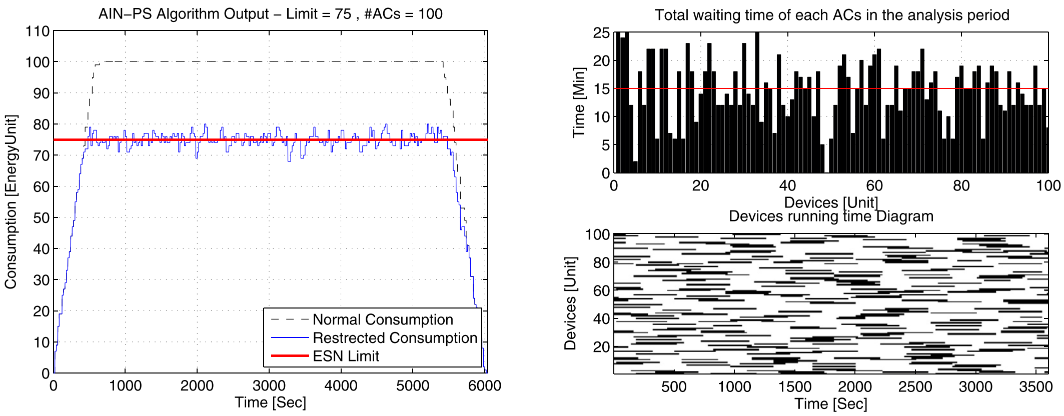
Eq. (13) calculates the max energy or peak load over the ESN_{LIM}. In our algorithm, this metric is important because this value must be zero or the most closely possible to the ESN_{LIM} value. Taking into account the constraints stated in Section 3 and depending on the available electric energy, in some cases the energy limit might be exceeded. On the other hand, Eq. (14) calculates the average of the difference between the ESN_{LOAD} and the ESN_{LIM} in the period, providing a more global efficiency measure.

6. Results

In this section, the experimental results and analysis of four theoretical cases and one real data case (provided by the electricity distribution company EDETsa) with *synthetic results* are presented, validating the performance of the proposed algorithm described in the previous section.

6.1. Experiments with theoretical data

Table 1 summarizes the features that describe each experiment. The presented cases correspond to four hypothetical scenarios. The devices considered by the system are only the controlled ACs, so it means that the Base Load was ignored. Those ACs have two states: *consuming* or *waiting*. In the first two cases the devices consume one unit of energy when they are in the consuming state (HighMode), while in the other cases, the consumption of the devices varies from 3.7 to 5 [EnergyUnit]. In all cases when the devices are in *LowMode*, their consumption is equal to zero. Moreover, after the start-up period the ACs are set to never achieve the temperature set point and continue running until the simulation stop.



(a) Peak Shaving Curve. (b) AC distribution of *waiting* time.

Fig. 4. AIN-PS system output experiment for case 1. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Fig. 4(a) shows in dotted line the sum of the ACs consumption without the AIN-PS algorithm control; the horizontal line marks the energy limit which was set to 75% (in this scenario equivalent to 75 units of energy); and finally, the solid line curve represents the ESN load generated by the controlled ACs with the proposed algorithm. In this test, the controlled consumption gets slightly above the limit line, because of the very strict time constraints set upon the algorithm. In other words, since we have 100 ACs requesting to consume and only 75 are allowed, the only way this can be achieved is with a perfect synchronization between devices. One of the most important constraints is that, after a certain configurable period, the AC will start even if the algorithm has not allowed it. This is done to ensure the HTC. There is an apparent inverse relationship between the amount of energy available and the number of ACs that are consuming energy in a time instance.

In order to analyze the system behavior, we have to look at the two graphics displayed in Fig. 4(b). On the upper one, we can see the *waiting* time of each device in a whole hour of analysis. The vertical bars represent the total Waiting time of a particular device. The horizontal line set in 15 [min] is related to the constraint the max *waiting* time that any device must respect in a centralized system to reduce exactly a 25% of the peak load using a fixed schedule. In this case, with the proposed distributed algorithm, this aim could not be fulfilled because some ACs did not get access to the system in many times compared with other ACs, e.g. one device just remained in low consumption state for five minutes in the whole hour. The graphic below shows the distribution of both states (HighMode in white, LowMode in black) by all the devices. The outcomes of the algorithm show a clear distribution of the access permissions.

In the second case, all the features remain unchanged, except for the *Limit* which was set to 80 [EnergyUnit]. As can be seen, the restriction of energy available is softer than the previous case resulting in a more efficient management of the access granting process. In this case, the consumption still gets slightly above the limit, without the peaks observed in the previous case.

Comparing Figs. 4(b) and 5(b), a difference becomes noticeable between the two time bars diagrams. Most of the ACs were in consuming mode for less than 15 [min] (since the bar is below the red line), while a few had to wait for over 20 min (bar ending way above the red line). This corresponds to the fact that being a distributed algorithm without transversal communication (which increases the complexity of the communications and hence was avoided in the design stage), it is impossible to coordinate for a more fair total time distribution.

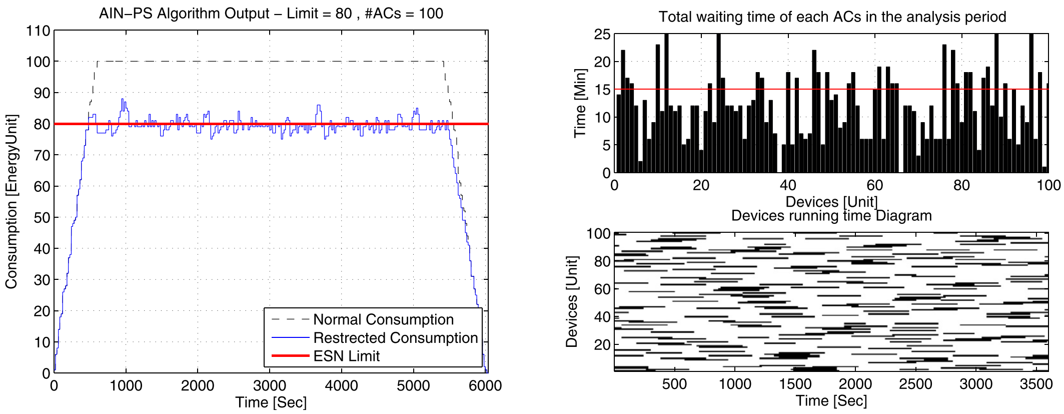
These two previous cases validate the behavior of the AIN-PS algorithm in controlled conditions and realistic features changing only the value of the limit. In the following two examples, we drop the hypothesis of unitary consumption of the ACs and proceed to consider devices with more than one level of consumption.

In case three and four, the limit is once again set to 75% and 80%, respectively, of the total energy consumed by the 100 ACs, the Base Load is not considered, the time restrictions are the same as the previous cases, one hour of analysis, but the ACs consumption are evenly distributed between 3.7, 4.5 and 5 [EnergyUnits].

As the results are similar to cases one and two, only the graphics related to the limit set to 75% are showed in Fig. 6(a) and (b). In the first one, the total consumption depicted with the solid line overpasses the energy limit, but it is still close to it, as it is expected.

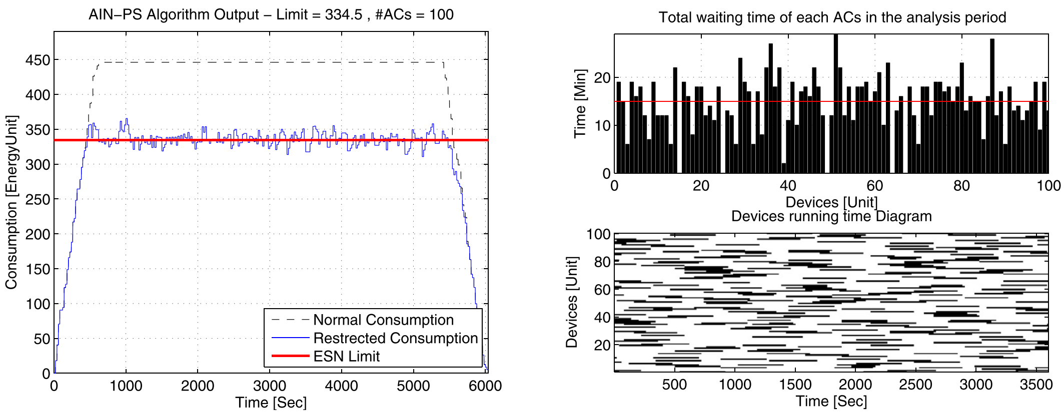
Table 2 presents the Max, Average and Min consumption Tolerance, following the Eqs. (13) and (14), as well as μ, σ and max value for each case. In this table we can see that the $Tolerance_{MAX}$ varies from 0.0679 (6.7%) to 0.0989 (9.8%), the $Tolerance_{mean}$ between −0.0062 and 0.0079, and the $Tolerance_{MIN}$ between −0.078 and 0.074. The negative sign means that the value is below the limit.

Statistical analysis of the results was carried out regarding 100 instances of each case over one hour periods. In this process, the initial 25 minutes were discarded to avoid the influence of the warm up time of the AIN-PS algorithm or any



(a) Peak Shaving Curve. (b) AC distribution of *waiting* time.

Fig. 5. AIN-PS system output experiment for case 2. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)



(a) Peak Shaving Curve. (b) AC distribution of waiting time.

Fig. 6. AIN-PS algorithm output for ACs with non-unitary consumption.

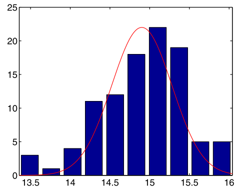
Table 2
AIN-PS algorithm – statistical results.

Case	Max tolerance	Average tolerance	Min tolerance	μ [min]	σ [min]	Max value [min]
1	0.0875	0.0022	−0.0760	14.9007	0.5374	22.00
2	0.0679	−0.0062	−0.0764	12.2953	0.6870	24.00
3	0.0989	0.0079	−0.0781	14.6445	0.9241	23.00
4	0.0780	−0.0003	−0.0740	12.0148	0.8703	23.00

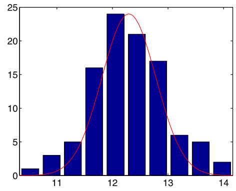
start-up effect. The μ value goes from 12.01 to 14.9, σ varies between 0.53 and 0.92 and the max value from 22 to 24. These results related to the total waiting time were fitted to a Gaussian distribution to analyze the dispersion of the system behavior.

In order to get a more graphical or intuitive presentation of the results for the four presented cases, we introduce Figs. 7 and 8. Both pictures show the results are statistically similar with a minimum difference in the dispersion. Even more, the histograms show a very close distribution between comparable cases (1 with 3 and 2 with 4). However, it is true that the access given to the devices is not equitably distributed. This behavior brings about cases where a device was only in waiting mode for almost three to five [min] in the whole hour, while others were in Low mode for about 20 and 25 [min]. This situation cannot be shown in these two figures because it only displays the average waiting time and its dispersion.

We can see in Fig. 9 a detail of the particular or typical time distribution. By sorting the max waiting time of each device of the 100 runs, we obtained Fig. 9(a) and (b). In both graphics, three plateaus are observed in 5, 10 and 20 [min]. In light

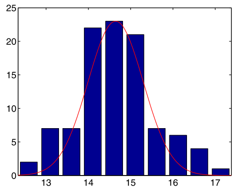


(a) Algorithm output with limit 75.

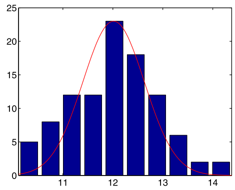


(b) Algorithm output with limit 80.

Fig. 7. Waiting time histogram and fitted Gaussian distribution for AIN-PS algorithm output with unitary consumption.

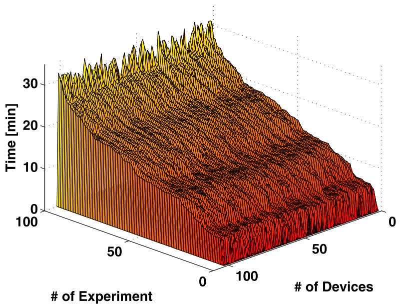


(a) Algorithm output with limit 334.5

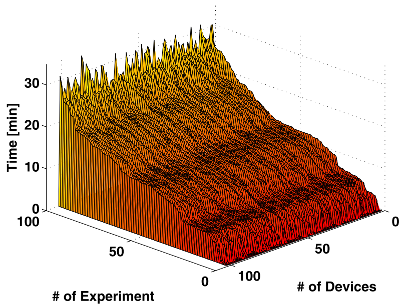


(b) Algorithm output with limit 356.8

Fig. 8. Waiting time histogram and fixed Gaussian distribution for AIN-PS algorithm output with variable consumption.



(a) Case with limit 75%.



(b) Case with limit 80%.

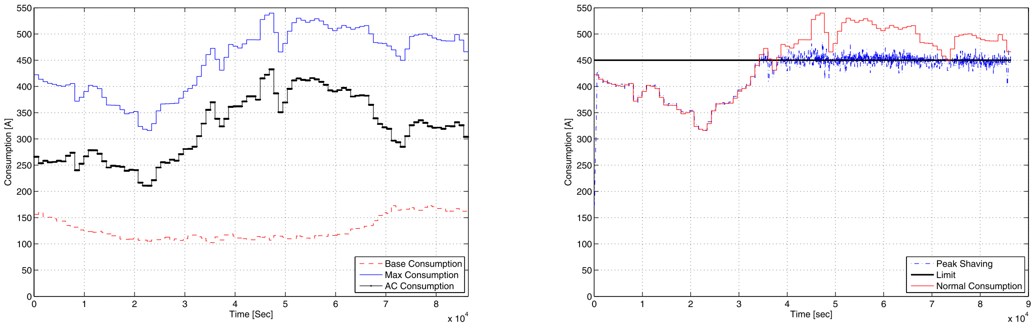
Fig. 9. Waiting time sorted for each AC in 100 experiments with limits 75% and 80%.

of this situation, it is clear that the system needs some mechanisms or modifications with the aim of providing a more equitable access distribution among the devices, avoiding scenarios where a particular device remains for a long period in waiting mode, while the average device waits a lot less.

6.2. Real case data experiment

In this section, we present a case based on a year of historical data of a particular transformer. This information was provided by he electrical Distribution company of Tucumán. The aim of these experiments is to show the AIN-PS System behavior in one day taken from real data (one Distribution SubStation Transformer's phase). The ESN device is a medium to low power transformer from 13.2 [kV] to 220 [V]. The power provided is 500 [kVA], so the nominal output is 710 [A]. The monthly average consumption is about 111.813 [kVA] and provides energy to 189 clients, which means (assuming all the 3 phases are adequately balanced) around 63 services connected to each phase. All the services attached to this transformer are either residential or household consumption, and a few small business, which means that AC commonly used are small split or windows type. Fig. 10 shows the typical power consumption of the selected transformer phase (left) and the DSM strategy applied by the proposed algorithm (right).

Fig. 10(a) was built considering a year of data of a particular transformer in Tucumán. The *Base Consumption* curve was calculated as the average daily consumption of the ten lowest curves in the year (that is, for the selected transformer we take daily average consumption, selected the ten lowest values, and with that we took the ten lowest curves). The *Max Consumption* is the curve that corresponds to the day with the highest energy load in the year, for that particular



(a) Normal consumption. (b) Applying Peak Shaving.

Fig. 10. AIN-PS system applied to one phase of a 13.2 [kV] transformer.

transformer. Finally, the *AC consumption* is the estimated load curve calculated as the difference between the Base Load and the Max Consumption. Using the average Base Load, we can estimate that the AC Consumption curve was generated only by AC devices. As can be appreciated, the *Base Curve* at the highest peak is about 107.09 [A], and the max consumption is almost 539.80 [A] which means that AC consumption is about 4.04 times greater than the normal consumption. Assuming all of this consumption corresponds to the most commonly used AC device in Tucumán, 3,500 frigories split and consumes 4.45 [A], we can further estimate that there are 97 ACs running simultaneously at that moment (an average of 1.5 AC per client). In this case, the *EnergyUnit* is given in Amperes.

On the other hand, Fig. 10(b) shows the response of the AIN-PS Algorithm to this scenario. The horizontal line is the ESN_{LIM} set to 450 [A] (corresponding to 83.3% of the highest load). The solid curve represents the regular consumption in the ESN, and the dotted line is the curve where the system is in control. The output behavior is similar to the one presented in Section 6.1, where the controlled consumption slightly overpasses the limit. We can also notice that in the first half of the day, during the morning, the consumption is the same as the original, what implies that all the devices freely consuming energy.

This shows that the utility company can protect its equipment and decrease the consumption to a desired level during peak consumption hours, with a minimal intervention to the users and certainly while every single customer enjoys full service in the rest of the house.

7. Conclusions and future work

In this work we presented an AIN-PS Algorithm designed to provide a Distributed Demand-Side Management based algorithm for the Peak Load problem. The algorithm was adapted to the peak load problem in Tucumán – Argentina during hot seasons, due to the use of thousands of Air Conditioners (AC). This algorithm uses the distributed, adaptive and auto-regulated capacity of the AIN techniques to regulate, in a distributed and autonomous way, the electric energy demand.

A mathematical formulation of the peak load problem generated by ACs was also stated, incorporating the constraints related to the Energy Supply Node (ESN) and the way ACs work. The mathematical description and modifications introduced in the algorithm as well as the influence of the different paramaters were also described in detail.

The algorithm performance was tested in four simulated cases and in one with real data provided by the Electric Distribution Company E.D.E.T.s.a. It showed good performance in all five cases, maintaining the load slightly above the ESN pre-established consumption limit. We understand that this effect is due to the strict problem restriction related to the HTC of the users, and the energy available.

The presented algorithm shows good results, but has to be improved to make the distribution of the consuming permissions more equitable, so that all the customers get similar consuming and waiting times.

It is important to notice that the only external information required by the system are changes in the consumption limit, since all other information is strictly local in nature. This means that the system requires minimal infrastructure and flow of data, as compared to centralized systems. It also means that it is very resilient to communication failures, since it can function in standalone mode for as long as the limit remains valid. Finally, one important feature is that the energy can be saved or redirected to other zones, by simply setting the limit to lower values.

For future works, we propose the development of hierarchical or composed Artificial Immune Systems to support the multi-level control for Smart Grids. Besides, an analysis focused on the HTC will be conducted.

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