# A Self-configurable Agent-Based System for Intelligent Storage in Smart Grid

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**Abstract.** Next generation of smart grid technologies demand intelligent capabilities for communication, interaction, monitoring, storage, and energy transmission. Multiagent systems are envisioned to provide autonomic and adaptability features to these systems in order to gain advantage in their current environments. In this paper we present a mechanism for providing distributed energy storage systems (DESSs) with intelligent capabilities. In more detail, we propose a self-configurable mechanism which allows a DESS to adapt itself according to the future environmental requirements. This mechanism is aimed at reducing the costs at which electricity is purchased from the market.

**Keywords:** smart grid, multiagent systems, storage.

## 1 Introduction

Smart grid technologies are positioned as one of the leading frameworks to build the next generation of systems and applications. Intelligent functions are expected to provide the smart grid with self-corrective and reconfiguration features, by creating a more complex interaction behavior among intelligent devices [1]. To address these issues, the multiagent system paradigm is widely agreed to be one challenging approach to build these systems [2, 3, 4, 5, 6].

In the last few years, agent-based technologies have been used to model smart grid systems, mostly focused on optimizing the system performance. In [7], agents represent customers which are faced with a multi-scale decision-making problem along temporal and contextual dimensions. The objective of these agents is to maximize the utility focused on these dimensions by learning the information of time-series. In [8], authors propose a model for dynamic coalition formation to approximate optimal micro-grid configurations.

The multiagent paradigm is envisioned as a strong solution to different approaches based on the smart grid, however, little work has been done focused on the use of agent-based techniques for storage management in these domains. Related to this issue, in [3] authors present an agent-based model for micro-storage management in the micro-grid. They propose a strategy based on game theory which reduces costs and carbon emission and converges to an efficient storage

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behavior. Their storage strategy proposed is focused on a learning mechanism that decides on when to store energy and when to use the stored energy in home devices. However, agents are self-interested with the aim of maximize their individual monetary profit. Therefore, conflicts that may arise depending on the distributed decision-making (e.g. a limited number of devices allowed to charge simultaneously at the same moment) are not considered.

The use of widely distributed energy storage systems (DESSs) with intelligent monitoring, communications, and control will enable the power grid of the future [9]. According to [10], the storage opportunity involves multiple interests with value propositions: (1) electric energy time-shift for purchasing electricity during periods when price is low to use the stored energy or to sell it when the price is high; (2) electric supply capacity for reducing the need to buy new central station generation capacity; (3) sub-station on-site power for managing equipments when the grid is not energized; (4) energy storage to provide highly reliable electric service; and so on. A DESS optimally located on the grid allows to maintain control over the grid and to the service reliability [9]. Storage can be applied at the energy production, at the transmission system, at the distribution system, and on the customer's side [11].

One of the benefits from storage that has been discussed in the literature long ago is referred to the use of storage systems for energy arbitrage. This involves purchasing electric energy during periods when the price is low, to charge the storage devices, so that the stored energy can be used or sold at a later time when the price is high [10]. This approach have been also studied in other works [12, 13, 14]. These decisions depend on different factors such as the market prices, the storage costs, the transmission costs, etc. In addition, depending on the storage device system, different parameters are associated to each one such as the efficiency, the charge rate, the storage response, the energy retention time.

To this respect, we focus on how intelligent storage systems can be build to achieve optimal configurations in the smart grid. We propose a self-configuration mechanism in order to provide a DESS with intelligent storage for improving the efficiency level. This mechanism uses an organizational representation of the DESS and focus on an adaptation of the roles played by agents. The objective of this process is aimed at scheduling the supplying and charging periods in order to reduce the electricity purchasing cost for supplying the system.

The rest of the paper is organized as follows. Section 2 presents the DESS model. Section 3 explains in detail the self-configuration mechanism. Section 4 shows the evaluation of the mechanism proposed. Finally, Section 5 presents some concluding remarks.

## 2 DESS Model

The DESS modeled in this work represents a group of storage devices which are geographically distributed (Figure 1). Each one of these devices is able to supply its stored electricity for a given area (e.g. a neighborhood, a town, etc.). The self-configuration mechanism is aimed at deciding for any storage device, when to store electricity by purchasing it from the market and when to use the stored electricity. Therefore, the optimal configuration is aimed at minimizing the cost of purchasing the electricity demanded by the areas during several periods of time (e.g. hourly, daily, etc.). The optimal configuration is dependent on the current and future electricity purchasing prices, and the current and future electricity demand. For reasons of clarity, in this work we assume an homogeneous system of storage devices in order to omit some of the parameters which could influence the optimal configuration, such as the standby losses or the transportation losses.

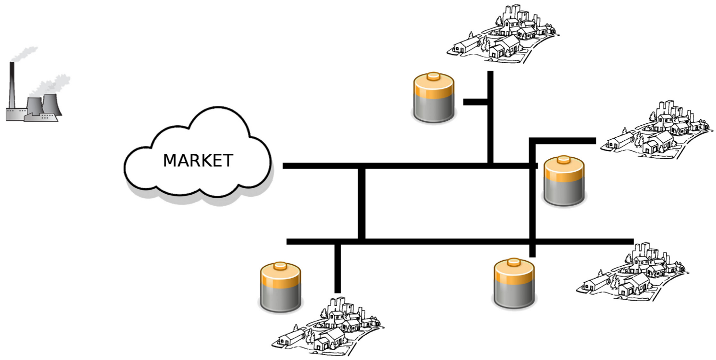



**Fig. 1.** Representation of the DESS

The optimal configuration that is obtained, represents a decision-making problem that determines the state of each storage device. Similar to other real-life problems, a conflict may emerge in this problem when different and autonomous decisions are taken distributively. As an example, if all storage devices decide to charge simultaneously, this could cause to exceed the generation or the transportation capacity. In order to solve this conflict, our approach selects the most optimal configuration according to the domain restrictions and not only by considering the individual preferences of the storage devices.

Since this problem determines a distributed scenario, we represent the group of storage devices as autonomous agents with organizational capabilities, in order to configure them according to the organizational constraints that must be fulfilled. These constraints are referred to the limited capacity of the transportation system, which determines the maximum number of storage devices that can be charged simultaneously. Based on our previous definition of dynamic organization [15], we model the DESS as a multiagent system $G^t = \langle \mathcal{A}^t, \mathcal{R}, \mathcal{P}^t, \Lambda^t, \Delta_i^t, \Phi \rangle$, where:

- $\mathcal{A}^t = \{a_1 \dots a_n\}$ denotes the set of agents that are associated to the storage devices. Each agent $a_x$ is able to supply electricity to its specific area $x$ and has associated different parameters for a given moment $t$: $L(a_x)^t$ represents the electricity load; $Q(a_x)^t$ represents the electricity supplied to the area; and $P(a_x)^t$ represents the electricity purchased from the market.

- $\mathcal{R} = \{supplier, charge, idle\}$ denotes the set of roles which agents can play. We define three possible roles that agents can play (but not simultaneously) depending on the state of the storage device. An agent $a_x$ playing the *supplier* role refers that the electricity demanded by the area $x$ is supplied from the storage device; an agent playing the *charge* role refers that the storage device is being charged by purchasing electricity from the market, and the electricity demanded by the area is also directly supplied from the market; finally, an agent playing the *idle* role is neither charging its storage device nor supplying electricity to its corresponding area.
- $\mathcal{P}^t = \{\mathcal{S}^t, \mathcal{C}^t, \mathcal{I}^t\}$ denotes the three subsets of agents depending on the roles that they are playing at the moment $t$. We define $\mathcal{S}^t \subseteq \mathcal{A}^t$ as the subset of agents that are playing the *supplier* role at the moment $t$. We define $\mathcal{C}^t \subseteq \mathcal{A}^t$ as the subset of agents that are playing the *charge* role at the moment $t$. Finally, we define $\mathcal{I}^t \subseteq \mathcal{A}^t$ as the subset of agents that are playing the *idle* role at the moment $t$.
- $\Lambda^t = \lambda^{t+1} \dots \lambda^m$ denotes the sequence of electricity purchasing price estimations for the following moments. A given electricity purchasing price $\lambda^y$ represents the estimated price at which the electricity can be purchased from the market at the moment $y$. For reasons of simplicity, this estimation is the same for every storage device.
- $\Delta_i^t = \delta_i^{t+1} \dots \delta_i^m$ denotes the sequence of forecast demand of electricity associated to each area for the following moments. A given demand $\delta_i^y$ represents the forecast demand of electricity for the area $i$ at the moment $y$.
- $\Phi$ denotes the set of constraints that must be fulfilled at each moment. As we stated above, we enforce that the number of storage devices that can be simultaneously charged at the same time does not exceed a predefined value $Nmax$, which corresponds to the limit capacity of the transportation system: $\phi_1 :\mid \mathcal{S}^t \mid \leq Nmax$.

## 3 Self-configuration Mechanism

The self-configuration mechanism is intended at providing the decision-making process which determines the state of each storage device at any moment. This mechanism provides a general vision of the whole system and allows to determine the specific consequences of each change of state in the rest of the system.

This mechanism is based on our previous work about role reallocation for organizational adaptation in agent societies [16]. This work obtains the adaptation with the highest potential for improvement in utility based on the costs of adaptation. Similarly, the self-configuration mechanism presented in this paper, obtains the roles configuration of the storage devices which minimizes the electricity purchasing costs, depending on the electricity purchasing price and the electricity demand for the forthcoming moments. The problem of predicting future electricity purchasing prices is widely studied in other works such as [17, 18, 19], and is out of the scope of this work.

In order to determine the state of the storage device for the following moment, we define the concept of impact associated to each possible role that can be played by each agent. This impact represents the measurement of the effects of playing a role in terms of system utility based on the costs for carrying out each this action. This impact measures the different alternatives that can be chosen from the current storage devices configuration in order to adapt it, based on the benefits and costs of each alternative. Computing the impact becomes essential in order to empirically specify the value of each possible configuration before changing the state of the storage devices. Given the DESS model presented in Section 2, following we define the notation for obtaining the impact measurements for playing each possible role allocation.

First, each area can be supplied by its corresponding storage device, or directly by the market at the current electricity purchasing price. In this last case, considering $\delta_x^{t+1}$ as the forecast demand of electricity for the next moment $t+1$ associated with the area $x$, if this demand is supplied from the market, this will be purchased at the price $\lambda^{t+1}$, which defines the following cost for supplying the area $x$ from the market:

$$S(x,m)^{t+1} = \delta_x^{t+1} \times \lambda^{t+1}$$

Otherwise, if this demand is supplied from the storage device, this will be supplied at the following supplying cost:

$$S(x,a_x)^{t+1} = \delta_x^{t+1} \times \bar{p}^{\,t+1}$$

being $\bar{p}^{\,t+1}$ the average price of the stored electricity in $a_x$, according to the prices at which this stored electricity was previously purchased from the market:

$$\bar{p}^{\,t+1} = \begin{cases} \lambda^{t+1} & \text{for } t = 0 \\ \frac{(L(a_x)^t \times \bar{p}^{\,t}) + (P(a_x)^t \times \lambda^t) - (Q(a_x)^t \times \bar{p}^{\,t})}{L(a_x)^t + P(a_x)^t - Q(a_x)^t} & \text{for } t > 0 \end{cases}$$

In the above equation, the variables $L(a_x)^t$, $Q(a_x)^t$ and $P(a_x)^t$ represent the electricity load, the electricity supplied, and the electricity purchased as denoted in Section 2. In this case, the electricity supplied to the area by the agent $a_x$ for the next moment $t+1$ corresponds to $Q(a_x)^{t+1} = \lambda^{t+1}$. Otherwise, if the electricity is supplied from the market, this value is null: $Q(a_x)^{t+1} = 0$. Hence, the cost for supplying a given area $x$ can be calculated depending on which source supplies the electricity.

When the electricity is supplied from the storage device, the load of this device will be reduced to: $L(a_x)^{t+1} = L(a_x)^t - \delta_x^{t+1}$. This causes that each storage device needs to be charged eventually from the market. In case that the storage device is charged at the moment $t+1$, the cost associated to this charge is calculated as the amount of electricity purchased according to the electricity purchasing price at this moment:

$$C(a_x)^{t+1} = N(a_x) \times \lambda^{t+1}$$

being $N(a_x)$ the predefined amount of electricity that this storage device can charge (it could be related to the charge rate of each device). In this case, the electricity purchased from the market will be: $P(a_x)^{t+1} = N(a_x)$. Otherwise, $P(a_x)^{t+1} = 0$.

If the storage device is not charged in the next moment $t+1$, it will be able to supply electricity until its reserves are running out (denoted as the moment $t+n$). Being $L(a_x)^{t+1} = L(a_x)^t$, the charge could be postponed to a future moment $t'$, which is comprised in the period of time up to $t+n$, at which the electricity purchasing price is the cheapest one, formally:

$$(t+2 \leq t' \leq t+n) \wedge \left(\delta_x^{t'} = \underset{i \in [t+2, t+n]}{\operatorname{argmin}} (\delta_x^i)\right) \wedge \left(\sum_{i=t+2}^{i=t+n} \delta_x^i \leq L(a_x)^t\right) \wedge \left(\sum_{i=t+2}^{i=t+n+1} \delta_x^i > L(a_x)^t\right)$$

According to the above notation, the impact for an agent $a_x$ for playing the *supplier* role at the moment $t+1$ is measured as: (1) the cost required for supplying the electricity demanded from the storage device; (2) the benefits for not supplying this electricity from the market at the next moment; (3) the cost for charging the storage device in the future moment $t'$ (the best case); and (4) the benefits for not charging the storage device at the next moment:

$$I(a_x, supplier)^{t+1} = S(x, a_x)^{t+1} - S(x, m)^{t+1} + C(a_x)^{t'} - C(a_x)^{t+1}$$

We must note that in order to an agent $a_x$ being able to play the *supplier* role, it must maintain the supply availability, i.e. the current load of the storage device must be higher than the expected demand for the next moment, otherwise, this storage device cannot be a supplier:

$$\phi_2 : L(a_x)^t < \delta_x^{t+1} \rightarrow I(a_x, supplier)^{t+1} = \infty$$

The impact for an agent $a_x$ for playing the *charge* role at the moment $t+1$ is measured as: (1) the cost required for supplying the electricity demanded from the market at the next moment; (2) the benefits for not supplying this electricity from the storage device; (3) the cost for charging the storage device at the next moment; and (4) the benefits for not charging the storage device in the future moment $t'$ (the best case):

$$I(a_x, charge)^{t+1} = S(x, m)^{t+1} - S(x, a_x)^{t+1} + C(a_x)^{t+1} - C(a_x)^{t'}$$

The impact for an agent $a_x$ for playing the *idle* role at the moment $t+1$ is measured as: (1) the cost required for supplying the electricity demanded from the market at the next moment; (2) the benefits for not supplying this electricity from the storage device; (3) the cost for charging the storage device in the future moment $t'$ (the best case); and (4) the benefits for not charging the storage device at the next moment:

$$I(a_x, idle)^{t+1} = S(x, g)^{t+1} - S(x, a_x)^{t+1} + C(a_x)^{t'} - C(a_x)^{t+1}$$

Finally, we measure the impact of a whole self-configuration of the system as the aggregation of the impact of each role allocation:

$$I(\mathcal{P}^{t+1}) = \sum_{a \in \mathcal{S}^{t+1}} I(a, supplier)^{t+1} + \sum_{a \in \mathcal{C}^{t+1}} I(a, charge)^{t+1} + \sum_{a \in \mathcal{I}^{t}} I(a, idle)^{t+1}$$

Given the state of the system defined as $G^t = \langle \mathcal{A}^t, \mathcal{R}, \mathcal{P}^t, \Lambda^t, \Delta_i^t, \Phi \rangle$, some agents could be reallocated to play other roles in the future moment $t + 1$. A role reallocation process entails transforming the current set of role allocations $\mathcal{P}^t$ into $\mathcal{P}^{t+1}$. Each one of the possible role allocations determines a different $G^{t+1}$ with an associated impact $I(\mathcal{P}^{t+1})$.

Let $\Theta$ denote the set of all the possible different role allocation that can be obtained from the current configuration. The challenge of the self-configuration mechanism is to find the specific role allocation $\widehat{\mathcal{P}}^{t+1}$ that minimizes the role allocation impact:

$$I(\widehat{\mathcal{P}}^{t+1}) = \operatorname*{argmin}_{\mathcal{P}^{t+1} \in \Theta} I(\mathcal{P}^{t+1})$$

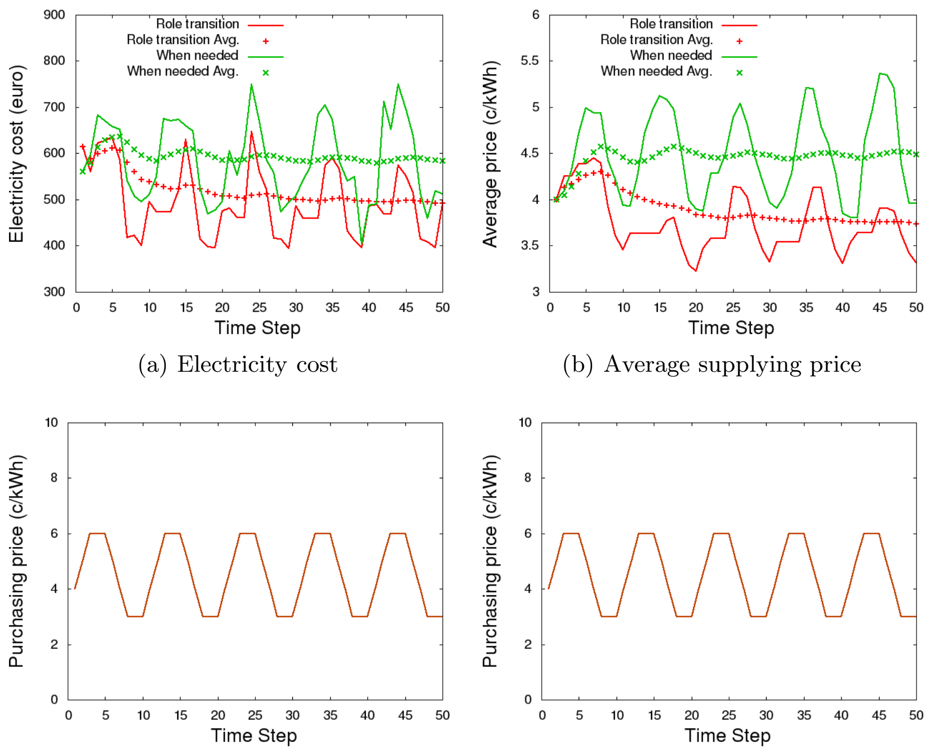
## 4 Evaluation

In this section we present some experiments for testing the performance of the self-configuration mechanism applied to the DESS model. For these experiments, the system is composed at any moment by a set of five agents $\mathcal{A}^t = \{a_1, a_2, a_3, a_4, a_5\}$ and the electricity demand and purchasing price is changing during 50 time-steps. Being $t$ the current time-step, the demand for a given area $x = [1..5]$ for the next time-step is calculated according to the following formula: $\delta_x^{t+1} = \delta_x^t \times random[0.95, 1.05]$. Due to the objective of the self-configuration mechanism is not focused on the price prediction but is focused on improving the performance of the system, we assume that the electricity purchasing price changes progressively by following a sequence from a lowest price of 3c/kWh up to a highest price 6c/kWh. In this experiment, the maximum number of devices that are allowed to charge simultaneously is defined as $Nmax = 3$.

In the first experiment (Figure 2) we test the performance of the DESS when the self-configuration mechanism is applied. Therefore, the configuration of the system at any moment reflects the role allocation which minimizes the impact.

In Figure 2(a) we show the aggregated cost for satisfying the demand of all the areas during the 50 time-steps. We compare the performance of the self-configuration mechanism with the performance of a static mechanism, in which the charge is carried out when it is needed, i.e. when the storage device has not enough electricity stored for supplying the following time-step. In Figures 2(c) and 2(d) we show the electricity purchasing price at any moment in order to compare it with the cost.

We can observe that the performance of the self-configuration mechanism is always better (the cost is lower) than the mechanism which charges the devices when it is needed. This is because the self-configuration mechanism changes the configuration of the storage devices by taking into consideration the forthcoming electricity demand and the purchasing price. Therefore, this mechanism configures the system for supplying the electricity in the following time-steps according to these parameters. It can also be observed that the average cost is decreasing on time when the self-configuration mechanism is used, while it is oscillating (as the electricity purchasing price oscillates) when the charges are carried out when they are needed. The average cost during the 50 time-steps is $492.54e\pm50.68$ with




(a) Electricity cost

(b) Average supplying price

(c) Purchasing price

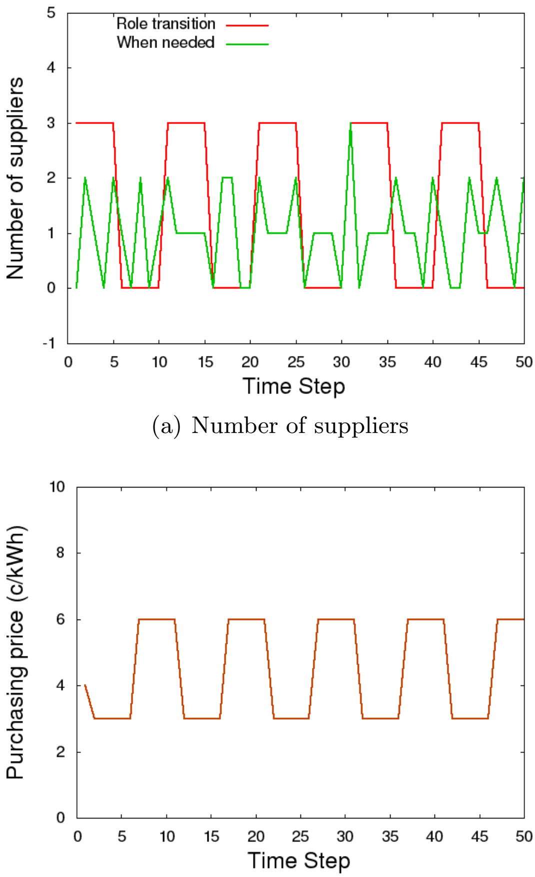
(d) Purchasing price

**Fig. 2.** Smart grid performance in a progressive electricity purchasing price scenario

a 95% confidence interval when using the self-configuration mechanism. In contrast, this cost is 584.33e±66.27 if the storage devices are charged when it is needed. This causes a whole economic difference between both approaches of 4579.63e during the 50 executions.

In Figure 2(b) we show the average price of all the storage devices at any time. Similar to the above figure, the average price is lower for the self-configuration mechanism. The average price for all the iterations is 3.74e when using the self-configuration mechanism and 4.49e when not, which represents an average price reduction of almost 17%.

In the second experiment we want to test the number of agents which are playing each role depending on the purchasing price changes. In order to observe more clearly the behavior of both strategies, we present an scenario in which the purchasing price changes from the lowest value to the highest one (Figure 3(b)). Thus, the differences between purchasing and supplying electricity may be quite different from one time-step to the following one. The objective of this experiment is to demonstrate how the self-configuration mechanism is able to adapt the role configuration according to the price is expected to abruptly




(a) Number of suppliers

(b) Purchasing price

**Fig. 3.** Smart grid performance in a progressive electricity purchasing price scenario

increase or decrease in the next few moments. In Figure 3(a) we show the number of storage devices which are simultaneously purchasing electricity (i.e. playing the *charge* role) at each time-step. We can observe that the self-configuration mechanism is able to configure the system in order to charge simultaneously the highest number of allowed devices (3) when the price is low and it is expected to increase in the next few moments. Similarly, the number of devices that are simultaneously charged is reduced to 0 when the price is the highest one and it is expected to decrease in the next few moments. We can observe that the storage devices are charging and the areas are supplied directly from the market when the price is low. This stored electricity is then supplied to the areas when the purchasing price remains high. In contrast, when the devices are charged when needed, the number of devices that are charged simultaneously do not follow any pattern. In this experiment, differences between both approaches are even higher than in the first experiment. The average cost during the 50 time-steps is 413.58$e\pm$1.03 with a 95% confidence interval for the self-configuration mechanism and 574.05$e$ $pm$86.77 if the storage devices are charged when it is needed. This causes a whole economic difference between both approaches of 8023.39$e$ during the 50 executions. The average price for all the iterations is 3.14$e$ when using the self-configuration mechanism and 4.07$e$ when not, which represents an average price reduction of almost 23%. Therefore, the self-configuration mechanism is able to reduce the cost for purchasing the energy demanded by the areas during a long-time period. This is caused because the role allocation adaptation allows to obtain the configuration with the highest potential for cost reduction, according to the future purchasing prices and demand.

## 5 Conclusions

We proposed a self-configuration mechanism which provide distributed storage in smart grids with intelligence. This mechanism is based on organizational adaptation by role reallocation. The representation of the DESS by means of a multiagent organization provides different future challenges such as including other organizational dimensions to be adapted (such as the agent population) and to improve the organizational interaction and cooperation among agents.

The decision-making process associated to the self-configuration mechanism, obtains the solution which minimizes the electricity supplying costs for satisfying the demand of the areas. As we observed in the experiments, these costs can be significantly reduced when taking into account the future prices and demand. In addition, since the objective is to maximize the utility of the whole system, conflicts that can emerge from individual utilities are solved due to the global view of the system. What is more, the configuration of the storage devices fits the current and future parameters of the environment by adjusting the number of devices that are charging and supplying energy at any moment.

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