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Design of an Energy Sharing System for a Smart Mircogrid Application: New Concept and Preliminary Study

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ABSTRACT: In the field of smart grids, many published studies investigate electrical energy management yielding to important findings. The overall objective has been to improve energy command and control during the production, distribution and consumption phases. Despite its lack of popularity, energy sharing is a crucial part of the energy management process. In this contribution, we explored energy sharing in a multi-source, multi-consumer installation. To ensure optimal sharing, we developed a modified "demand side management algorithm" introducing the various parameters that influence energy cost. Energy cost minimization was attained using several parameters and assigning optimal schedules to households. This application allowed a maximal reduction in smart microgrid energy cost and helped to avoid heavy bills and breakdowns and to lower the peak-to-average ratio. The utility company presents our conventional non-renewable source whereas the renewable power was harvested via photovoltaic panels coupled with wind turbines. It guarantees the optimal renewable installation that ensures always the minimal energy bill for the energy partners as one prosumer without harming the public utility company. Therefore, for a smart microgrid, we insure energy efficiency with lower cost. To achieve our goal, we counted on our own proposed stack that was mainly concerned with two layers: physical and protocol. Our proposed algorithm managed to decrease the total annual cost by almost 38% with the possibility of selling renewable energy, thereby guaranteeing an even greater reduction in the overall cost of electrical energy.

KEY WORDS: Demand-side management, energy consumption scheduler, energy cost function, energy cost reduction, energy sharing stack, renewable sources, smart microgrid.

I. INTRODUCTION

Several targeted developments require to streamline our consumption of electrical energy, especially in the economic field. For this reason, management of electrical energy is progressively important mainly in the case of multiple sources and limitation of electrical energy resources. Therefore, a management system which ensures a reasonable level of consumption and achieves balanced, consistent and harmonized energy distribution is an adequate and desirable solution while maintaining a reliable network. Without doubt, the management of energy is a very important domain in all fields and levels: economic, energetic, environmental, etc. Therefore, we usually find a lot of studies within this framework. Among those researches, we can cite algorithms that focus on smart pricing and programs based on agreements with conventional producers of electricity in order to load energy when the renewable production cannot cover the needs of consumers. In this context, the best-known examples are real-time pricing (RTP) [1], [2], [3], [4], [5], where the hourly electricity price varies enormously, depending on the season, the month and even the period of the day. This forms the main disadvantage of these algorithms, disturbing the comfort of customers who must follow the variation of the tariff. There is another drawback presented by the synchronization of loads which condenses and creates different peak hours of the first ones without, considerably, reducing the numbers and the values of the Peak-to-Average Ratio (PAR) [6], [7], [8], thus without solving the problem of the PARs. We cite also the time-of-use pricing (ToUP) [9], [10], [11], [12], and Critical Peak Pricing (CPP) [13], [14], [15], algorithms that are characterized by the same problem of PARs in addition of other shortcomings. Concerning the second type, these agreements come,

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essentially, from giving the company utility the freedom to control and command certain devices directly and remotely by changing their operating status from ON to OFF and conversely according to the available energy and their instantaneous corresponding price as the Direct Load Control (DLC) [16], [17], [18], [19], [20], algorithms.

Energy sharing is a fundamental new concept of energy management but, unfortunately, it is a little neglected as evidenced by the scarcity of work on this topic. For that, we concentrate on the level of sharing of electrical energy in a smart electrical network with a multi-source, multi-consumer installation. In this context, we have proposed in previous works [21], [22] a new protocol stack model created to manage an “energy sharing system”. Our proposed work aims to assign to every user the optimal planning over the year.

In this paper, with the intention of minimizing as much as possible the energy cost, we take into consideration several directions to explore and examine. In the first place, we focus our work on the optimization of the electrical energy production issue in order to find the optimal and best combination of renewable sources. Second, we are interested in consumption optimization by studying the cost function and also integrating the energy consumption scheduler (ECS). Finally, the simulation (MATLAB simulator) results present an evaluation of the optimality and convergence of the proposed algorithm. The rest of this paper is organized as follows. In Section II, we introduce the structure of energy sharing stack. The multi-source installation is presented in section III. Section IV explains the assumptions and discusses the production optimization. The proposed consumption optimization algorithm is detailed in Section V. Section VI illustrates the simulation results. Section VII concludes our proposed contribution.

II. THE PROPOSED ENERGY SHARING STACK STRUCTURE

Our proposed energy sharing stack [21], [22], illustrated in Fig. 1, is composed of two main layers. The first is the physical layer, which is essentially divided into two distinct parts: the communication and the power parts, responsible for the control of some devices by changing their states from ON to OFF and inversely. The second is the protocol layer which is engaged with management, i.e. it ensures the functionality and conditions the network performance. In a multi-source, multi-consumer installation, in order to efficiently share electrical energy, a process is needed that makes the appropriate decisions to ensure the optimal consumption and sharing, make the total price as low as possible and reduce PARs.

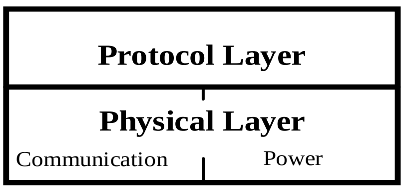

Fig. 1. The proposed energy sharing stack.

A. Physical Layer Part

The physical layer is basically related to the different devices in order to control and command them. It is also in charge of the communication part between all integrated elements of the smart microgrid.

1) Power Sub-layer: The power sub-layer is mainly concerned with the various smart devices. In other words, this sub-layer allows and controls the supply of energy to multiple appliances from various sources. Our microgrid contains renewable and non-renewable sources to cover the electricity needs of consumers. It provides the required power for each user according to the renewable production and a planning that is well-defined from a prior agreement with the public company of electricity (PC). The PC is considered as an infinite conventional non-renewable source of energy whereas the photovoltaic (PV) panels and wind turbines afford the renewable power. Users can be households, industries or anything that needs to manage electrical energy. In our application, the users are households which share common sources and demand to manage ideally a set of appliances to guarantee the energy efficiency and reduce electricity cost.

2) Communication Sub-layer: The communication sub-layer establishes the link for the exchange of data between sources and consumers. It is concerned with error detection and possible correction. It is essentially dedicated to

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ensuring the safe distribution of data to the various participants. These data include the variable tariffs and the published messages about optimal schedule of each user.

B. Protocol Layer Part

To make suitable decisions and ensure optimal sharing, we need a satisfactory energy sharing process. Therefore, our proposed algorithm assigns to each user the suitable planning that automatically guarantees cost decrease. Fig. 2 exhibits the synoptic schema of a demand-side management strategy for smart grid [22] which puts in evidence the interactions both among customers and between users and sources.

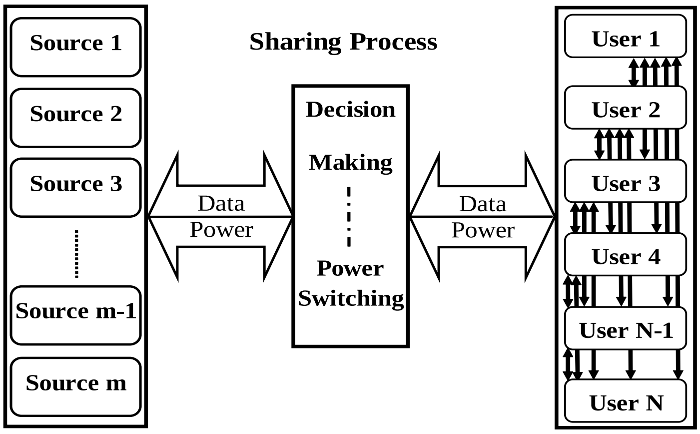

Fig. 2. A demand-side management strategy for the smart grid.

1) The Sharing System: In our application, the algorithm will provide the optimal amount of PV and number of wind stations to be installed by users, the optimum cost function form and its best coefficients and, finally, assign to each user the appropriate planning to decrease the total energy bill as low as possible and guarantee the minimization of PARs number and the diminution of their values during the year.
2) The Criteria of Energy Sharing: In general, there are several sharing criteria but, in the context of our application, we limit them to the following: first, the presence of users in their houses and, second, the consumption profile and the usual need for power of each one which defines and presents the predefined energy.
3) The Circumstances of Energy Sharing: It is obligatory to respect a set of conditions in order to improve the energy management and ensure an ideal sharing. First, all users share the same common sources. Then, our approach is based on an agreement between users and PC, so they have to respect the entire regulations and every rule of PC. Then, their households must be equipped with smart meters that can manage customer energy requests by limiting power consumption or remotely connecting and disconnecting some devices.

C. Goal and Hypothesis

In this paper, we propose an ECS algorithm that aims to minimize the total cost of electric energy and also the PARs. To achieve both objectives, the priority is given to renewable sources as long as they can provide energy. If there is a production excess, we stock it to the next hour and repeat doing that until we have no more renewable energy. If we have no renewable energy, we resort to the non-renewable. In which case, users have to pay for it, and the cost function intervenes. In general, the cost is lower when renewable production is supposedly greater (the afternoon, the hot days in summer and days with considerable wind power in autumn and winter). It is assumed, in our application, that there are two renewable sources: PV and wind turbines, a single non-renewable source: PC and N consumers (N = 6, in our case).

1) Types of Users: Our users can be everyone who has the need and the desire to efficiently manage a set of appliances. They are usually household, industries and all others who want to minimize their electrical loss/waste, reduce considerably their electricity bills and also avoid the breakdowns produced by load peaks. Our goal is to primarily manage an electrical network containing devices characterized by soft energy consumption constraints.

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2) Shiftable and Nonshiftable Devices: There are two types of devices and it depends on the method of controlling them according to the ability to advance or to delay their operations: appliances with shiftable and nonshiftable operations. We are interested in shiftable ones that are the most considered in our application because of their flexible management so there are no severe constraints. Therefore, we can easily choose their operating times and change their states from ON to OFF and conversely. Then we can shift their uses from hours of peaks to others with lower load. In our application, 10 devices are assigned to each user, 5 of each type. The nonshiftable appliances include electric stoves (daily usage: 2.01 kWh for regular and 1.89 kWh for self-cleaning), heating (daily usage: 7.1 kWh), lighting (daily usage for 10 standard bulbs: 1.00 kWh) and refrigerator-freezer (daily usage: 1.32 kWh) [23]. These are characterized by nonshiftable operation, which presents exact and severe energy consumption scheduling constraints. Hence, we have no right to command them. We also integrate 5 appliances with shiftable operation for each user that we can automatically command by the smart meter with ECS capacity. They comprise washing machines (daily usage: 1.49 kWh for energy-star, 1.94 kWh for regular), clothes dryers (daily usage: 2.50 kWh), dishwashers (daily usage: 1.44 kWh) and plug-in hybrid electric vehicles (PHEV) (daily usage: 9.9 kWh) [23]. We admit that the load demand is lower during the night contrary to the evening. In addition, we presume that our users have electric cars that can be charged mostly between the afternoon hours on each day and the early morning hours on the next day. 170.18 kWh is the average of the daily consumption across all users with an average almost equal to 28.36 kWh for each one.

3) Renewable and Non-renewable Sources: In general, renewable sources are the least polished and less expensive. Non-renewable sources, unlike renewables which are affected by the weather and environment circumstances such as solar radiation and wind speed, present a source that still exists. Therefore, to secure reliable use of some nonshiftable devices and ensure energy efficiency, it is crucial to marry both types.

4) Planning: For each user, we propose three different schedules (plans, Table 1) according to energy needs while respecting their usual consumption profile. Planning defines the daily partition of load presented by a matrix: we hourly declare the available consumption and also specify the status of appliances (ON/OFF) for that hour $h \in H = \{1... 24\}$. The columns of matrices present the 24 hours of a day and the lines are corresponding consumption of devices. Otherwise, the given value declares possible consumption at this hour. The differences between the associated schedules are manifested basically in the partition of the operating hours of the electrical devices and also the corresponding quantities of consumed energy. Plannings are actually the sum of matrices of shiftable and nonshiftable appliances of each user. The nonshiftable matrices are very similar, so the difference between plannings is practically in the other matrices. In Fig. 3 and 4 [21], examples of nonshiftable and shiftable matrices associated with planning A of user 1(X1Ans and X1AsA) are shown.

Table 1.The different scenarios of each user

Scenario	**Plannings of users**					
	User 1	**User 2**	**User 3**	**User 4**	**User 5**	**User 6**
1	1A	2A	3A	4A	5A	6A
2	1B	2B	3B	4B	5B	6B
3	1C	2C	3C	4C	5C	6C

```
ref_freez1A=[0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055
0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055 0.055];
heating1A=[0.71 0.71 0.71 0.71 0.71 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.71 0.71 0.71 0.71 0.71];
lighting1A=[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.1 0.1 0.1 0.1 0.06 0.04 0.01 0];
self_cleaning1A=[0 0 0 0 0 0.63 0.63 0 0 0 0 0 0 0 0 0 0.63 0 0 0 0 0 0 0];
regular1A=[0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375
0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375 0.08375];
X1AnsA=[ref_freez1A; heating1A; lighting1A; self_cleaning1A; regular1A ];
```

Fig. 3. The matrix of nonshiftable appliances X1Ans.

```
dishwasher1A=[0 0 0 0 0 0 0 0.48 0 0 0 0 0.48 0 0 0 0 0 0.48 0 0 0 0 0 ];
washing_machine_ES1A=[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.745 0.745 0 0 0 0 0 0 0 0];
washing_machine_REG1A=[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0];
clothes_dryer1A=[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.25 1.25 0 0 0 0 0];
PHEV1A=[1.98 1.98 1.98 1.98 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.98];
X1AsA=[dishwasher1A; washing_machine_ES1A; washing_machine_REG1A; clothes_dryer1A;
```

Fig. 4. The matrix of shiftable appliances X1AsA.

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III. THE MULTI-SOURCE STATION AND MODELING

In our case, the microgrid is a multi-source, multi-consumer installation where consumers share common renewable (PV, wind) and non-renewable (PC) sources. Finding the optimal combination between renewable sources is also one of our objectives. In this part, we will compute the optimal number of wind turbines and the best surface to be covered by PV while respecting the ratio of renewable production quality and the renewable installation cost. By adding the PC, we constitute our shared sources. The distribution of PV and wind turbine production has always priority by contribution to PC. As renewable production is available, users can load it in real time or from the previous hour storage while respecting assigned schedules.

A. Public Company of Electricity Source

The public company of electricity represents the non-renewable source whose load amount should be minimized. Since users will, eventually, pay for it, the PC is related to all that concerns the cost function (form, coefficient type, etc ...).

1) Public Company Source Modelling: The production of PC is consumed as an infinite source since it is always available. It is a paying one, hence our objective is to reduce this source's load, especially at peak load times, which are accompanied by high tariff and can cause breakdowns.

2) Energy Cost Function: The energy cost function is a very important formula to define since it encompasses the set of parameters that condition the cost of electricity. We propose a second order function [23]:

$$C_h(L_h) = a_h \times L^2{}_h + b_h \times L_h + c_h \qquad (1)$$

where a_h , $c_h \geq 0$ and $b_h > 0$ are the cost function coefficients and L_h presents the load across all users at an hour $h \in H=\{1,...,24\}$ of a day. It is calculated as:

$$L_h = \sum_{n \in N} l^h{}_n \qquad (2)$$

with N presenting the set of users and $l^h{}_n$ the load of user n ϵ N at the hour $h \in H$ of the day.

B. Photovoltaic Panels Production model

The PV production is unpredictable. For this reason, it is difficult to find a 100% reliable model. Despite that, we follow a real model of PV installation located near Lyon. It provides a whole year production in terms of surface covered by PV with different inclinations (0°, 30°, 60°, 90°) of the PV modules. Fig. 5 presents it in kWh/m^2 [24]. In our application, we have used the curve without inclination. The algorithm multiplies the daily value extracted from this curve by the covered surface of the photovoltaic panels.

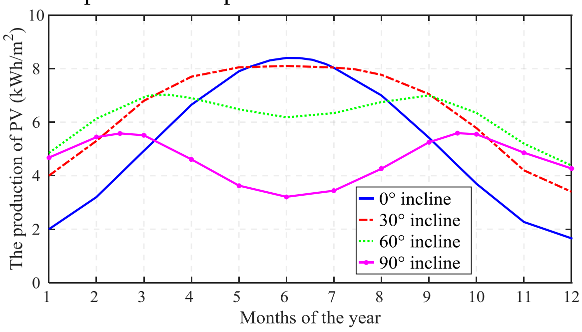

Fig. 5. The production of PV for different inclinations.

C. Wind Turbines Station Production model

The wind station is based on an m number of turbines which mainly have the following characteristics: a nominal output power of 400W and a nominal rotation speed of 900 rpm with a nominal wind speed-ref 12.5 m/s (45 Km/H) [25]. Fig. 6 illustrates the model of the energy production of a wind turbine station. The curve offers the average value of production during each month of the year. It presents the different monthly values that vary between 0 kWh (May) and 12.45 kWh (June) [25].

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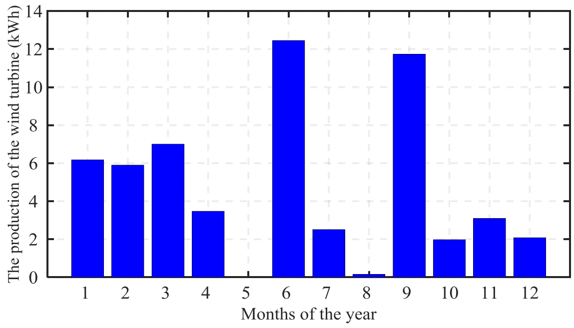

Fig. 6. The model of a wind turbine production.

IV. ASSUMPTIONS AND PRODUCTION OPTIMIZATION GOAL

In this section, we expose a set of assumptions while aiming to optimize both production and consumption. The cost function is crucial because it conditions the mathematical relation between electrical energy loading and pricing. It integrates the variable L_h which is influenced by the renewable production: as the latter increases, the load from PC decreases or stops altogether. In this section, we test the different assumptions by using our algorithm.

A. Energy Cost Function

Our cost function is defined by using equation (1). It is based on the total load of all users for each hour (L_h). It integrates three coefficients which can take constant or variable values. It presents the cost to pay to PC for the hourly load.

1) Linear function: For a_h=0, the cost function becomes:

$$C_h(L_h) = b_h \times L_h + c_h \qquad (3)$$

This linear form (3) patently gives a lower final cost which is good for customers, but it cannot suit the PC. It does not distinguish consumers according to their consumption profiles; thus, it can be unfair to some users.

2) Polynomial function of second degree: Equation (1) is more suitable, although it generates a higher cost than (3). The first term a_h designates a penalty for users when they exceed certain threshold of consumption at the hour $h \epsilon H$. It guarantees the benefits for both producer and consumers while choosing the appropriate type and the adequate values of coefficients. The different cost function forms and the threshold projection are presented in Fig.7 [21]. We consider that the values of the coefficients a_h, b_h and c_h are 0.003, 0.25 and 0.00625, respectively. Thanks to this projection, we define and adjust the threshold value.

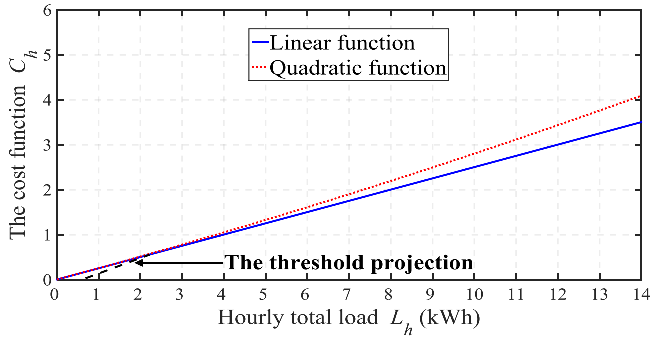

Fig. 7. The different forms of the cost function.

In this part and for the whole paper, the cost value is given before multiplying it by the price unit (which can be 1 Tunisian dinar (TD) or 1 US Dollar (USD) or 1 Euro). Fig. 8 illustrates the curves of the daily cost of all users for a year corresponding to the linear and quadratic forms of the cost function.

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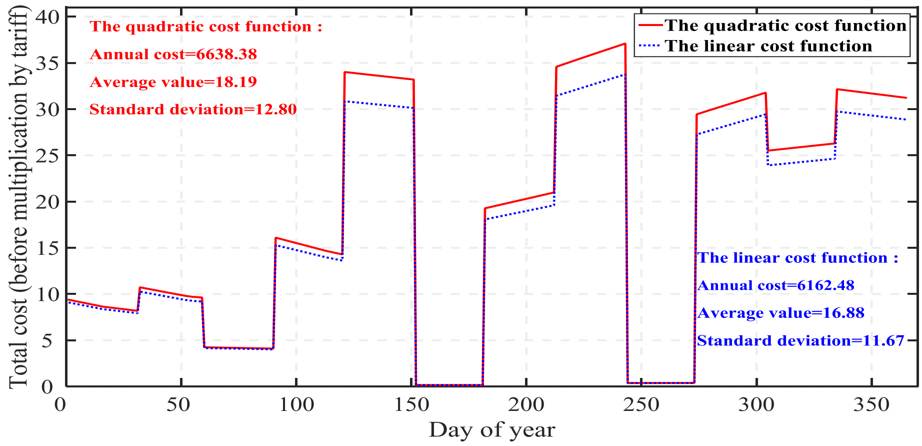

Fig. 8. The cost functions corresponding to the two forms.

We simulate the final costs, while assuming that a_h = 0.003, c_h = 0.00625 and b_h = 0.25 and adopting a 6 m^2 PV area and 20 wind stations. We can see that the linear model gives a lower cost throughout the year (6162.48 < 6638.38). The form effect will be studied later.

B. Production Optimization goal

To optimize the energy cost, we propose an algorithm that mainly maximizes the use of renewable energy. It gives priority to renewable sources because they do not contribute to the cost function. Actually, the renewable installation costs money, it is not free, but it will be compensated in a few years incomparable with its productive period, especially for wind stations.

1) The Photovoltaic Station Size: In the case where only the PVs are considered as a renewable source, we have varied its surface to simulate the annual electricity cost for all users (see Fig. 9). While the PV surface increases, the cost decreases, it starts to stabilize at 3222 when the surface is equal to 1225 m^2. Besides, it continues to decrease slightly until it remains constant at 3096 with a surface equivalent to 5041 m^2, i.e. when the width or length value increases, it no longer diminishes. Since our main objective is to minimize cost, it is essential to reduce the load from the PC. However, it should be noted that 5041 m^2 is a very vast surface, which makes this solution impractical. Considering that PV and wind productions are practically complementary, it is then necessary to introduce wind turbine.

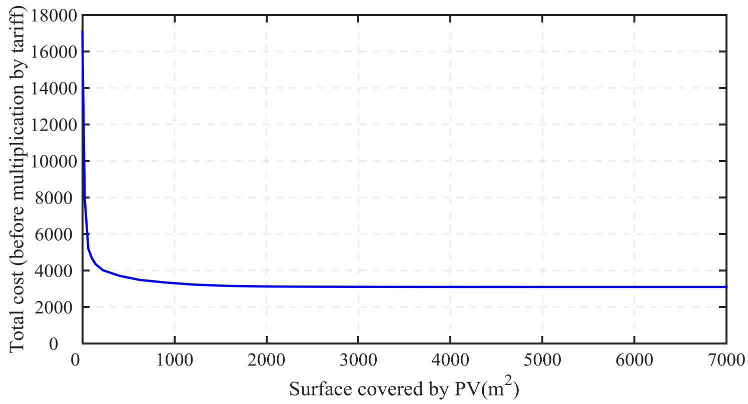

Fig. 9. The variation of the cost in terms of surface to be covered with PV.

2) The Wind Station Size: Fig. 10 illustrates the variation of the annual total cost in terms of the number of wind stations to be installed, when only the wind turbine is considered as a renewable source. We can see that when the number of wind stations increases, the cost decreases but for a number equal to 1482 stations the cost remains constant. It is a very huge amount. In fact, it reduces the load arriving from the PC, subsequently, it accomplishes our objective, but the station number remains very high, which is unrealizable for our microgrid. Then, it is essential to combine those renewable sources to reduce not only the number of wind stations, but also the PV surface.

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In the simulation results and discussion part, we detail the simulation of different combinations of renewable sources to be installed to single out the best one for our application.

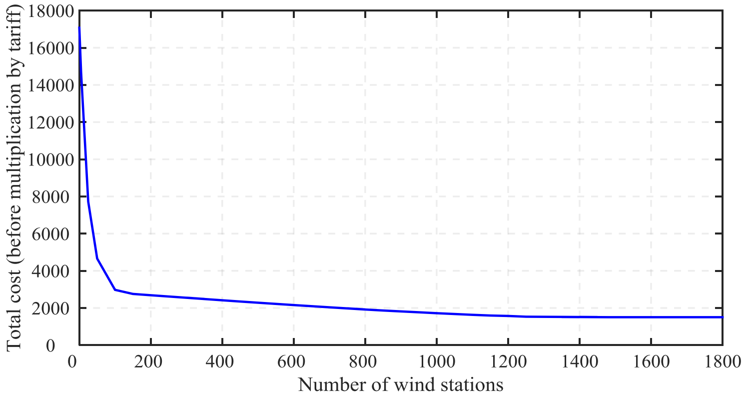

Fig. 10. The variation of the cost in terms of the number of wind stations.

V. THE PROPOSED CONSUMPTION OPTIMIZATION ALGORITHM

Our algorithm lowers maximally the electricity cost while keeping the profit of the PC. It also reduces the number and even the values of consumption peaks since it shifts the load from peaks. In addition, it shifts the load from the intervals when the tariffs are higher. Therefore, it solves the big bills problem by assigning adequate schedules to users.

A. The Sharing Process

In the context of our application, the process is summarized as follows: firstly, the algorithm randomly assigns to each user one of its associated schedules. Secondly, it chooses a random user and keeps varying their schedule until finding the lowest total cost of the set of users. The planning is next assigned to the random user. Then, we pass to the next user and redo the same work until we assign to each user the optimal planning.

B. Plannings and Organizational Chart

To achieve the main goal, i.e. a minimum total annual cost, our energy sharing algorithm follows the steps described just above in the sharing process part. The organizational chart in Fig. 11 represents them.

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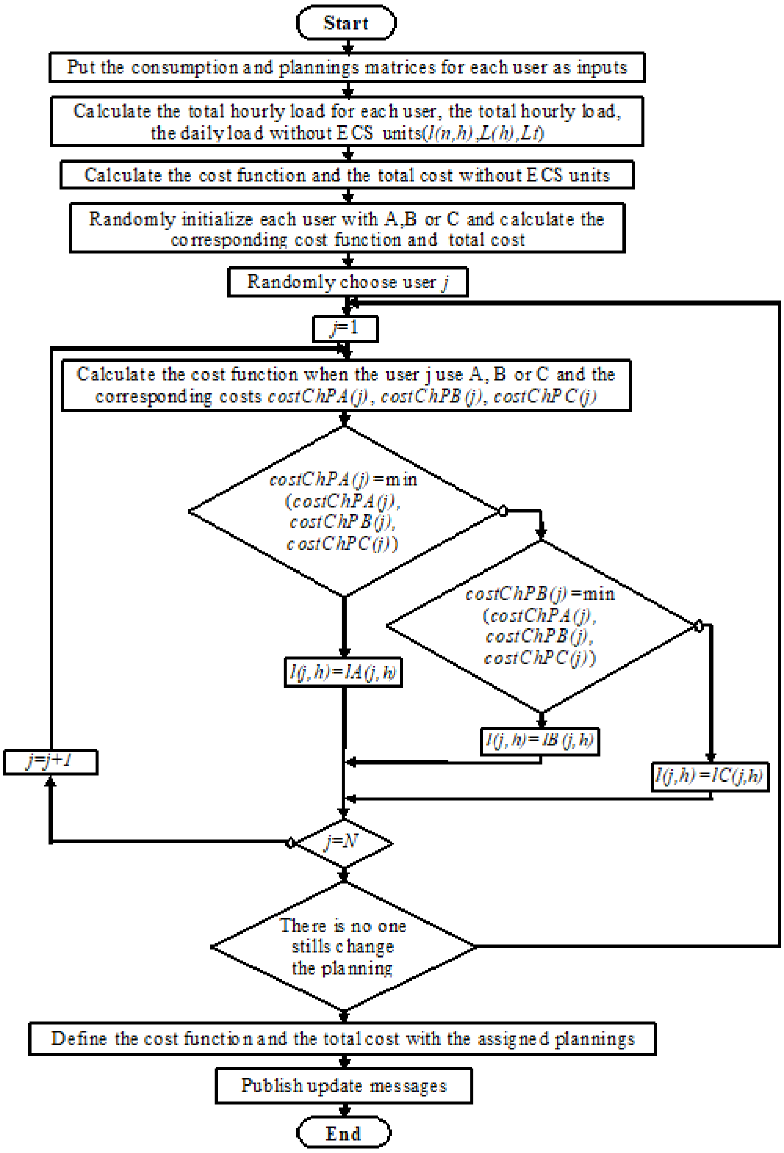

Fig. 11. Organizational chart of the proposed sharing algorithm.

First, we associate for each user its own three plannings A, B and C and define them as inputs. Second, our proposed algorithm calculates the hourly load for each user $n \in N$, the total hourly load, the daily total load without ECS units ($l(n,h)$, $L(h)$, Lt). Then, it illustrates the cost function and calculates the total cost without using ECS units. After that, it randomly initializes each user planning (A, B or C), adjusts the cost function and calculates the corresponding total cost. In the next step, our algorithm randomly chooses one user $j \in N$, determines the cost function when it uses A, B and C while adopting the randomly assigned plannings to the other users, calculates the corresponding total costs (*costChPA(j)*, *costChPB(j)* and *costChPC(j)*), finds the minimum of them and considers the corresponding planning as this user j optimal schedule. After that, it passes to the next user and repeats the same work until each one is assigned by the suitable schedule (there is no user stills change the schedule). Then, it defines the cost function and total cost using the assigned plannings. Finally, it publishes the update messages. All these steps are repeated every day of the year.

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VI. SIMULATION RESULTS AND DISCUSSION

In this Section, we suggest the optimal application parameters and the best combination of renewable sources to install. This combination produces a renewable production almost equal to the consumption average of all users. But users still need to load from the PC because renewable energy is highly volatile. Therefore, our sharing algorithm guarantees energy reliability with the lowest cost.

A. The optimal cost function

We have already proposed two forms given by equations (1) and (3). The corresponding cost functions are shown in Fig. 8. The linear one is, generally, inferior to the other except in the two following intervals of days [152 175] and [245 270] (and almost equal in [60 90]) when the total load does not exceed the threshold, hence no need for penalty. But at the end, we choose to adopt the quadratic form because it encourages users to minimize their load in certain periods of the day and ensures benefits for users and PC together.

We report above that a_h and c_h are constants. As for the coefficient b_h, we assign a dynamic value in [0.1 0.4] that varies hourly depending on the renewable production and the consumption required at this hour [21]. It gives a better result, i.e. the variable b_h generates an annual total cost significantly less than the other case (b_h=0.25). By using the quadratic function given by equation (1) and considering 6 m^2 as the surface covered by PV and 20 as the number of wind stations, the annual total cost decreases from 6638.38 to 4454.59. It is reduced by more than 32% which is a crucial result that shows the importance of considering a dynamic coefficient of the cost function. For that we select a variable value for b_h.

B. The Optimal Combination of Renewable Sources

We tested several combinations of different dimensions of PV and number of wind stations to find the optimal which generates the daily closest total renewable production to the average of the total consumption and a lower final cost. In our application, the predetermined consumption average of all users for 24 hours is equal to 170.18 kWh. In our simulation, we vary the surface (in m^2) covered by PV in the range [5 15] and the number of wind stations in {25, 26, 27}.We adopted them because they produce the closest daily values to the consumption with also lower standard deviations. The curves, illustrated in Fig. 12, reflect the daily average of the renewable production and the total microgrid consumption in terms of renewable sources. Their intersections present the optimal renewable production which calibrates the renewable installation size. Less than this production quantity, users will be obliged to load more paid energy from PC. More than that, the installed quantities of renewable sources are greater than the required, which means a waste of energy.

As a result, there are three best renewable combinations provided in Table 2. Fig. 13 depicts curves in the space which illustrate the renewable production average and the corresponding annual total cost. Ultimately, we head toward the combination that generates the lowest cost which is 10.5 m^2 of PV and 25 wind turbine stations. It generates an average value equal to 170.4 kWh that produces 3087 as final total cost.

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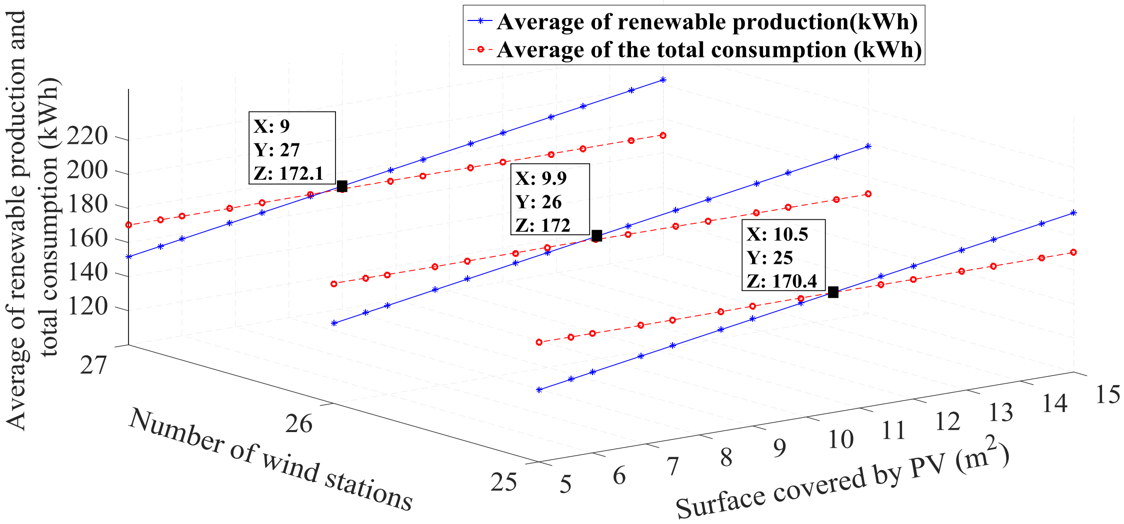

Fig. 12. The daily average of renewable production and total consumption.

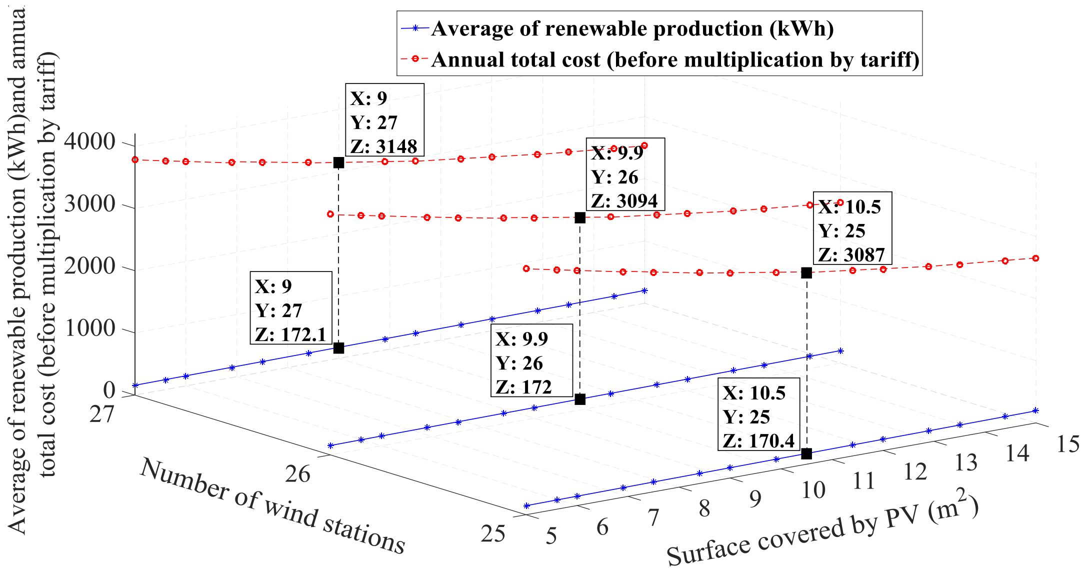

Fig. 13. The annual total cost and the daily average of renewable production.

Table 2. The illustration of best combinations

The intersection combinations		Average renewable production (kWh)	Annual microgrid cost (before multiplication by tariff)
PV surface (m^2)	Number of wind turbine stations		
9	27	172.1	3148
9.9	26	172	3094
10.5	25	170.4	3087

C. The Optimal Cost reduction

Over a year, our proposed algorithm daily assigns to each user one of his own plannings (A, B or C). In order to test the optimality of our algorithm, we simulate the cases when ECS units are used or not, while adopting the optimal parameters (10.5 m^2 of PV, 25 wind turbine stations, quadratic cost function and dynamic coefficient b_h). We calculate their corresponding annual costs and compare the results. Our proposed algorithm (ECS units are used) provides a cost reduction of almost 38% (4969.22 from to 3087) as presented in Fig. 14, which obviously shows its optimality and

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efficiency. As part of our application, we have proposed 6 as the number of users, 3 schedules for each one, 10 devices for each household etc ...These assumptions can be improved in order to generate more optimal results, particularly by increasing the number of the proposed schedules.

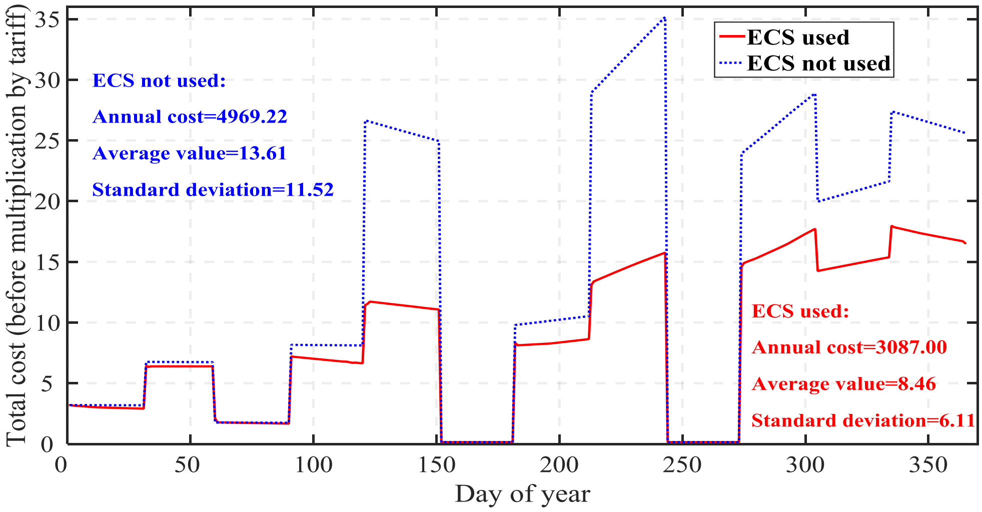

Fig.14. The illustration of the cost reduction.

In the case where it is assumed that users sell the excess of renewable energy to PC at the end of each day for a whole year, the cost of sale is calculated by the same cost function (given by equation (1)): same dynamic value of b_h and $a_h = c_h$=0. Fig. 15 indicates the different costs in the case where they sell the surplus of the renewable energy and in the opposite case. We observe that the annual total electricity cost takes a negative value (-3364.31) which means that the total sum of the daily renewable production is, practically, greater than the daily renewable consumption during the year. In the first case (sell of excesses), the daily average cost is equal to -9.22, i.e. users earn this money instead of paying. Consequently, users will pay less money than the income from the energy sale.

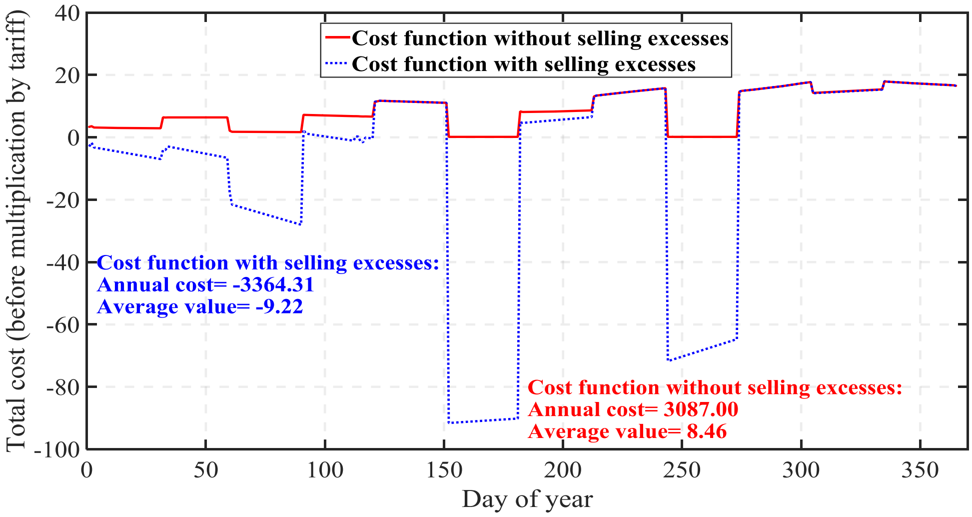

Fig.15. The costs when users sell renewable energy or not.

VII. CONCLUSION AND FUTURE WORK

In this paper, we proposed an unconventional, beneficial, optimal and incentive-based energy consumption scheduling algorithm conducive to the reduction of the total cost of electrical energy for a smart microgrid. It also aims at minimizing PARs, ensuring restraint and even elimination of breakdowns and high bills, besides balancing and harmonizing the total residential load when multiple participants share common renewable and non-renewable sources

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(photovoltaic, wind, utility company). It improves energy efficiency and reaches equilibrium between sources, consumers and sources-consumers together. According to our proposed energy sharing stack and multi-source modelling, the suggested energy consumption scheduler makes the optimal decision to assign the suitable and adequate schedules. We keep the same daily total consumption, yet we adopt a different optimal distribution from the initial one that maintains a lower cost. This demand-side management program, optimally, shares the energy by using appropriate cost function parameters. All in all, the results prove our sharing algorithm efficiency, but there remains always room for further improvement especially in how we reinforce renewable production.

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