RESCoin to improve Prosumer Side Management into Smart City

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Abstract—*The transformation of a traditional city into a Smart City is not a simple task and requires necessarily start from a correct management of energy, which leads to energy efficiency through the sustainable behavior of prosumers. In fact, thanks to new technologies such as IoT and smart appliances, it is possible to induce in the consumer a new type of behavior, not only in energy consumption, but also in the exchange and sale of energy, assuming a fundamental role in Smart Grids . Prosumer Side Management appears as a way to manage micro smart grids in a much more complex, volatile and real-time energy market, control and management that are entrusted to Smart Agents and Blockchain to obtain a new model of management of the organs safely and reliably. This paper gives a micromesh model that includes within it a smart home, RES, Electric Vehicle, a control algorithm that leads to the management of the Virtual Power Plant in an adaptive and intelligent way and through the RESCoin (virtual currency linked to RES), so that prosumer facilitated by the process of exchange of energy and money can become the driving of energy transformation in future Smart Cities.*

Keywords- ***Demand Side Management; Smart city; Sustainable prosumer; IoT; Smart Agent; Smart Load; Virtual Power Plant; Blockchain; RESCoin.***

I. INTRODUCTION

Smart Cities puts people at the center of development, including the urban and environmental aspects, in order to improve the quality of life. The efficient management of resources through participatory processes, made possible by technological development, by ICT and by IoT, key factors for the creation of Smart cities, has led to a new design and planning of Smart Grids, in fact through elements of collaboration, participation and interaction of citizens, an integrated and sustainable development of resilient and innovative cities can be promoted.

Until today, an electric energy system is oriented unidirectional and from top to bottom, in which a balance must be maintained between supply and demand. This balance has become much more complex given the large penetration of renewable energy sources and the introduction of electric vehicles, requiring sophisticated control. [1] By this point of view it is fundamental that we need to move the city from the traditional management model for the Smart City management model, where the ability to plan and anticipate needs increases,actions are coordinated and integrated, resources are shared, investments can be scalable, and cost savings is enjoyed by all Real-time monitoring of environmental conditions and problems makes it possible to act promptly on solutions or avoid crises by anticipating possible contexts [2]. Demand Side Management (DSM) is a set of measures to improve the energy system on the consumption side. It goes by more smart energy tariffs with incentives for consumption patterns, up to the sophisticated real-time control of distributed energy resources. The energy effort becomes bi-directional, thanks to the intelligent loads are the EV or the smart appliances -Demand Shifting- that can be managed locally, in microgrid, to contain the transport losses. Each of these intelligent loads must have a digital identity, for a flexible use, and for the electric network, which works with great reliability, in order to be sure that they are collaborating and that the data cannot be manipulated. In reality, more than DSM seems more appropriate to talk about a Prosumer Side Management (PSM), because the behavior of intelligent consumers is fundamental, supported by user friendly platforms, they can interact autonomously in the energy market, without aggregators, in secure way. In fact several international committees are working on SG interoperability, smart measurement standards and energy management safety information [3], [4].

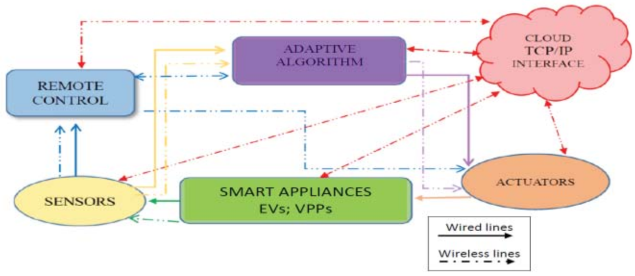

Fig. 1 Control scheme for Smart Home

Figure 1 shows the control scheme of a Smart Home, to manage through an adaptive algorithm, based on the Multi-agent system. Usually the control algorithms are based on procedures that consider the possibility of shifting the loads according to a pre - established order, often by the client, in this case the algorithm, through a Multi Agent System, will modify the order in relation to the behavior of the single Prosumer.

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II. PROSUMER SIDE MANAGEMENT OF SMART HOME: CASE STUDY

To obtain a Micro-Grid, a local controller must be inserted in each Smart Home to optimize the various decisions, taking into account the needs of the network and the loads within the home. In addition, the controller must manage the storage devices (EVs battery), allowing the user to actively participate in the electricity market, in relation to energy prices deriving from renewable sources even self-produced. The operability between the Smart meter and the intelligent electrical devices, such as Smart appliances, and the bidirectional connection between the distribution network and the intelligent building/house, allows to optimize consumption of each user and guarantee the efficiency of all the SG. [5-7]

Prosumer Side Management proposed is a management system for the optimization, through the management of intelligent electric loads, day by day, in a house, reducing the peak of daily load, through load shifting, but using a Smart Agent system that can over time learn the prosumer's habits to adapt to his needs. In addition to the SG connection, the photovoltaic production installed and the batteries of an EV used by Prosumer are included.

The PSM model is based on the appliances inserted in the Smart Home, evaluated through utilization coefficients and contemporaneity, over a day, divided into 96 time slots of 15 minutes each, with the objective function of reducing the peak load, which must in some way rewarded, in the same way as renewable production, through the mechanism of RESCoin, that is, virtual currency, defined by Blockchain, linked to RES.

To satisfy the electric demand of every prosumer belonging to a Micro Grid, it is necessary to size the electricity generation capacity of the network directly on the peak of electric load rather than on the average value. The (1) is the objective function to be optimized, when the ratio between the peak of electric load (Lpeak) and the corresponding average value (peak-to-average ratio, Lavg), if PEL >> 1 the maintenance costs are high,

$$\text{PEL} \quad = \frac{L_{peak}}{L_{avg}} = \frac{\max_{t \in T} L(t)}{\frac{1}{T}\int_T L(T)dt} \tag{1}$$

where L (T) is the electric load curve at time T.

To determine the power actually used by each single device of the plant, we will refer to the utilization coefficients the conventional load of the plant is obtained; to determine the power actually used by each single device of the plant, we will refer to the utilization coefficients the conventional load of the plant is obtained. Moreover, some users and devices do not work at the same time, therefore the values of the sum of the conventional loads of the system must be multiplied by the appropriate coefficients of contemporaneity, to obtain the average load absorbed by the apartment, in order to have a predictive analysis:

$$P_{ma} = \sum n \cdot k_c \cdot P_{ca} = \sum n \cdot k_c \cdot (k_u \cdot P_N) \tag{2}$$

where kc is the coefficient of contemporaneity of the user/ household appliance, dimensionless; ku is the coefficient of use of the user / household appliance, dimensionless; Pca is the conventional load absorbed, in W; n is the number of users/household appliances and P_N the nominal power.

The case study is an apartment, about 100 m^2, the nominal powers and the utilization coefficients and contemporaneity of the tables I, will be used in (2), to obtain the contracted power of the plant will be about 6 kW.

The system takes into account the energy produced by photovoltaic panels (PF) with power equal to 3kWp, and the respective gain in the electricity market.

DEVICE	n	P_N [W]	k_u	Pca [W]	k_c	Pma [W]
10 A plug sockets	8	300 *	0,20	60	0,30	144
16 A plug sockets	8	300 *	0,15	45	0,30	108
Light points 100 W	5	100	0,75	75	0,30	112,5
Light points 60 W	5	60	0,75	45	0,30	67,5
Light points 40 W	5	40	0,75	30	0,30	45
Light points 13 W	5	13	0,75	9,75	0,30	14,625
Refrigerator A +++	1	500	0,70	350	0,30	105
Washing machine A +++	1	2200	0,70	1540	0,30	462
Small kitchen	1	3000	0,70	2100	0,30	630
Dishwasher	1	2200	0,70	1540	0,30	462
LCD TV (1)	1	150	0,70	105	0,30	31,5
LCD TV (2)	1	120	0,70	84	0,30	25,2
Computer	2	150	0,70	105	0,30	63
Electric oven	1	1800	0,70	1260	0,30	378
Vacuum cleaner (10 A socket)	1	500	0,20	100	0,30	30
Hairdryer (10 A socket)	1	350	0,20	70	0,30	21
Toaster	1	500	0,70	350	0,30	105
Conditioner A +++	2	1300	0,70	910	0,30	546
Electric radiator for the bathroom	1	1000	0,70	700	0,30	210
Induction plate	1	10800	0,70	7560	0,30	2268
Dimmable spotlights and	10	5	0,70	14	0,30	42
LED A ++ lamps	10	10	0,70	7	0,30	21
TOTAL *: 230 V · √3 · cos ϕ = 230 V · √3 · 0.75 =298.78 W = 300 W						5891W ~ **6 kW**

Tab.I: contracted power

To facilitate the activation and management of the various devices during the day, the 24 hours daily were divided into 96 time slots t (time slot) from 15 minutes each, set is T.

In each time slot, can be performed an activities for each household appliance and device of the dwelling, in particular in each time interval, a load phase f relating to the activity of each household appliance can be performed; these phases are contained in the whole F. The set of activities associated to each appliance and device is the set A. For each phase and activity there is associated a Ptaf load profile related to the consumption of electric power, or the variable of load, in kW, assigned to a device with a, phase fe time slot t activity. If an appliance is to be used at different times of the day, it will be treated as two different luminaires, but with the same load profile (eg dishwasher n.1 and n.2). For each activity a start time tst is defined and an end-of-tend time within which the activity must be performed, whose duration of the operating cycle is defined by nta. The variables that indicate the electricity purchase and sale tariff in the time slot t are defined as Ct and gt respectively (cost and income). In order for the activity of each household appliance to be planned, a binary variable xtaf is introduced which is 1 when the activity a with load phase f begins in the time slot t, 0 otherwise.

The variables used are summarized into tab II.

Variables	Description
a	Activity associated with each appliance
f	Load phase related to each activity
t	Time slot (time slot) in which the 24 h are divided
A	Set of home appliance activities
F	Set of loading phases
T	Time slot of time slots
P^t_{af}	Power consumption of the activity a, during the phase f, in the time slot t
G^t_{af}	Power produced by the photovoltaic panel, during activity a, in the loading phase f and in the time slot t
t_{st}	Start time of an activity
t_{end}	End time of an activity
nt_a	Duration of the operation cycle of the activity a
C^t	Electricity purchase price, to the distributor company
g^t	Electricity sales price, produced by the photovoltaic panel
x^t_{af}	Decision binary variable with value 1 if the activity a starts in time slot t, 0 otherwise
E_{af}	Daily energy requirement of an appliance
q	Upload average of all applications
p_{af}	Preception of interruptible activities
Π^t_{af}	Power produced by the appliance during operation a in the time slot t
$\Pi^t_{af,PF}$	Power produced by the photovoltaic panel during the activity in the time slot t
Π^{MAX}	Maximum power withdrawable from the grid, equal to the contractual one
Π^{PF}	Maximum power that can produce a photovoltaic panel
l_p	length of the loading profile
d	Duration of the operation phase of an activity a

Tab. II: variables used for optimization

The first objective of the program is to minimize the total cost of electricity for the operation of household appliances. The objective function also takes into account the gain generated by the sale of energy produced by photovoltaic panels. The rate used for simplicity is the two-hour rate, which guarantees lower energy costs during the evening hours and at the weekend, thus simulating a market that varies over time.

For non-interruptible activities, in which each activity must comply with every single phase and load profile, the objective function to minimize the cost of energy C, expressed in €, is the difference between the cost of energy sold by the network and the energy purchased by the network, and is given by the equation (3):

$$F.O.1: \quad C = \min_{\mathbf{x}} \sum_{t\in T}\sum_{a\in A}\sum_{f\in F}\left(C^t P^t_{af} x^t_{af} - g^t G^t_{af} x^t_{af}\right) \quad (3)$$

where C^t and g^t are respectively the two-hour electricity purchase tariff and the sale price of the energy produced by the photovoltaic panel, in € / kWh, xtaf is the binary decision variable, x is the vector of the variables and P^taf and G^taf are the powers respectively consumed by household appliances and produced by photovoltaic panels, expressed in kW, but since they are multiplied by a factor of time equal to 15/60 = 0.25, they will be changed in kWh. The second objective function serves to minimize the maximum load function L, expressed in kWh, of the apartment, during the day, the total power of the appliances, which operate simultaneously, does not have that peak power. This objective function has an equation:

$$F.O.2: \quad L = \min_{\mathbf{x}} \sum_{t\in T}\sum_{a\in A}\sum_{f\in F}\left(P^t_{af} x^t_{af} - q\right)^2 \quad (4)$$

where q is the average load of all household appliances, expressed in kWh, given by the equation:

$$q = \frac{\frac{1}{4}\left(\sum_{a\in A}\sum_{f\in F} P_{af}\right)}{24} \quad (5)$$

with P_{af} indicates the power load assigned to the activity a in the loading phase f, for each household appliance and ¼ is given by the ratio 15 minutes / 60 minutes.

For non-interruptible activities, the loading phases f have a very precise duration, while for interruptible activities it is necessary to make some adjustments to the constraints as the phases f can now be interrupted and subsequently reactivated.

The constraints related to the two objective functions are the following:

P^taf ≥ 0 grid power purchased by the user, ∀t ∈ T

G^taf ≥ 0 power sold by the user to grid, ∀t ∈ T

P^taf ≤ Π MAX is max power from the grid, ∀t ∈ T

G^taf ≤ Π PF is max power transferable to the grid, ∀t ∈ T

in the case of the apartment in question, the contracted power Π MAX is equal to 6kW and that of the photovoltaic panels Π PF is equal to 3kWp.

In order to ensure that the loading phases of each appliance meet their energy requirements, the sum of the loads of the a and phase f activity must be equal to the energy requirements of the appliance of activity a and phase f. the ¼ value is due to the fact that the time interval of the load profiles is 15 minutes each, ie 15/60: p.

$$\frac{1}{4}\left(\sum_{t\in T} P^t_{af}\right) = E_{af} \quad (6)$$

The planning of the activities takes place according to:

$x^t_{af} = 1$ if the activity a begins in the time slot t

$x^t_{af} = 0$ no activity

the activity must be carried out in a time interval between t_{st} and t_{end} and therefore must be started in a range between t_{st} and t_{end} + 1:

$$\sum_{t_{st}}^{t_{end}-nt_a+1} x^t_{af} = 1 \qquad \forall a \in A \quad (7)$$

It is necessary to impose that the power in kW of the activity in the time slot t and load phase, is equal to the load profile of that phase:

$$\pi^t_{af} = P^t_{af} x^t_{af} \qquad \forall a\in A, \forall f\in F, \forall t\in T \quad (8)$$

For interruptible activities, it is necessary to make changes to the programming constraints:

- if p_{af} = 0 the activities remain the same as the non-interruptable loads and the load phases last 96 time slots
- if p_{af} = 1 then the binary variables x^t_{af} taking this time into account that the phases f no longer last 96 time slots:

xtaf = 1 if the phase f of the activity a begins in the time slot t

xtaf = 0 no activity

where f and t are defined in the intervals:

$1 \leq f \leq nt_a$ and $t_{st} \leq t \leq t_{end}$.

As interruptible activities must take place within these intervals, the constraint (7) must be changed:

$$\sum_{t=t_{st}}^{t=t_{end}} x_{af}^{t} \geq 1 \qquad (9)$$

$\forall a \in A$, $\quad 1 \leq f \leq nt_a \quad$ and $\quad t_{st} \leq t \leq t_{end}$.

The constraint on power (8) remains the same, but taking into account that phases f do not last longer than 96 time slots and are within the range of f and t defined before: $\forall a \in A$, $1 \leq f \leq nt_a$ e $t_{st} \leq t \leq t_{end}$.

Time preference constraints can be set, when the appliance must be used. A time interval is set within which the activity must be performed, this interval corresponds to the duration d of the activity. The duration available for activity a is given by:

$$d = t_{st} - t_{end} + nt_a + 1 \qquad (10)$$

where t_{st} and t_{end} are the start and end times of the activity, it is the duration of the appliance operating cycle (for example for a dishwasher it can be two hours).

III. RESCoin algorithm

Once the various constraints have been set, the optimization model can be defined, formulating an algorithm for the minimization of the objective functions.

As previously described, the time interval of 24 hours has been divided into 96 time slots of 15 minutes each. Home appliances and devices are assigned to a load phase f within the 96 intervals. If the device has an uninterruptible activity, it will have a well-defined phase, if instead it has an interruptible activity, it will have a duration given by (10).

Table III shows which appliances and devices come into play in the process of optimizing, the cost of electricity, with the values assigned to the decision variable yi: 7 devices for a total of 7 variables; while y8, will be related to PV, which will have its load profile Gtaf related to diagram in fig. 2:

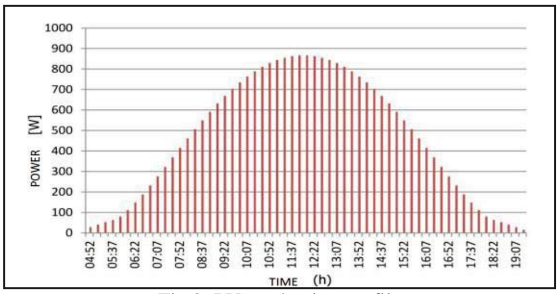

Fig.2: PV production profile

Home appliance	Variable number	Activity	Start time	Time to end	Market energy rate
Dishwasher	1	not interruptible	t.s. 85 (time 21:00)	t.s. 93 (time 23:00)	F23
Washing machine	2	interruptible	t.s. 81 (time 20:00)	t.s. 85 (time 21:00)	F23
Fridge	3	not interruptible	t.s 1 (time 00:00)	t.s. 96 (time 23:45)	F1 and F23
LCD TV stage 1	4	interruptible	t.s 49 (time 12:00)	t.s 53(time 13:00)	F1
LCD TV stage 2	5	interruptible	t.s 77 (time 19:00)	t.s 85 (time 21:00)	F23
Laptop	6	interruptible	t.s 61 (time 15:00)	t.s 77 (time 19:00)	F1
Dimmable LED lighting	7	interruptible	t.s 73 (time 18:00) (in relation to the season)	t.s 96 (time 23:45)	F2

Tab.III: characteristics of appliances used in the model and times of use

The decision variable that is assigned to the Smart Agent is as follows:

$$y_{ai} = [x_{ai}^{1}\ x_{ai}^{2}\ x_{ai}^{3}\ x_{ai}^{4} \ldots x_{ai}^{96}] * [P_{aifi}^{1}\ P_{aifi}^{2}\ P_{aifi}^{3}\ P_{aifi}^{4} \ldots P_{aifi}^{96}\ ]^{T} \qquad (11)$$

with $i = 1, 2, \ldots 7$ appliances and $t = 1, 2, \ldots 96$, where the first vector is that of the binary variables x^{t}_{af} that is worth 1 or 0, while the second matrix is that of the load profiles, obtained from the load diagrams. The y_{ai} vector also as:

$$y_{ai} = \text{binvar } [1,96] * [P_{aifi}^{1}\ P_{aifi}^{2}\ P_{aifi}^{3}\ P_{aifi}^{4} \ldots P_{aifi}^{96}\ ]^{T} \qquad (12)$$

For example, considering activity 1 related to the dishwasher, the variable decision y_1 become:

$$y_1 = [x_1^{1}\ x_1^{2}\ x_1^{3}\ x_1^{4} \ldots x_1^{96}] * [P_{1f1}^{1}\ P_{1f1}^{2}\ P_{1f1}^{3}\ P_{1f1}^{4} \ldots P_{1f1}^{96}]^{T} \qquad (13)$$

The dishwasher activity can not be interrupted, and it is possible, for example, to set a duration of a single washing phase, from 21:00 to 23:00, when the peak is not high, ie from the time slot 85 at 93, the duration of the operation will be:

d = 93-85 = 8 time slot

while the vector of the loading profile of the dishwasher will instead be given by the values obtained from the load diagram of this appliance:

$$P_{1f1}^{1} = [22{,}51\ 36{,}04\ 30{,}79\ 36{,}16\ 20{,}73 \ldots 42{,}92\ 52{,}13] \qquad (14)$$

Then define the decision variables yi, the two objective functions become:

$$C = \text{sum}\left((y_1 + y_2 + y_3 + y_4 + y_5 + y_6 + y_7 - y_8) * 0{,}25\right) * [\text{rate}]^{T} \qquad (15)$$

$$L = \text{sum}\left((y_1 + y_2 + y_3 + y_4 + y_5 + y_6 + y_7 - y_8 - q).\hat{}2\right) * [\text{rate}]^{T} \qquad (16)$$

[rate] is the 1x96 vector containing the bi-hour rate values in €/kWh which, taking into account the price of energy and 24 hours divided into 96 15-minute time slots, will be set with values equal to 0.064650 for range between 19:00 and 8:00, or for time slot from n. 1 to n. 32 and from n. 77 at n. 96, and with values of 0.070320 for the time between 8.00am and 7.00pm, ie for the remaining time slots.

The smart meter, trought Smart Agent, will solve the proposed optimization problem by means of a Smart Agent initialization algorithm. This algorithm proceeds allowing each household appliance to solve the problem, finding the most effective response strategy to send to the Prosumer:

Smart meter algorithm: performed for each activity at ∈A:

1 Initializes the load P_{ai}^{t}

2 **Repeat**

3 Solve problems (15) and (16)

4 **If x** changes from the previous schedule **then**

5 Update **x** to a new solution.

6 Transmit a control message to the Smart Meter Prosumer

7 **end if**

8 **if** a new update is received **then**

9 Update P_{ai}^{t}

10 **end if**

11 **Until** the Smart Meter Prosumer at new planning.

IV. Smart agent and RESCoin-Blockchain for Smart City

A smart city, being a highly dynamic model, must also have a certain degree of autonomy and therefore imply the ability to make independent decisions. For this reason we can think of using intelligent agents that can learn and adapt to new environments. This is even more effective for Multi-Agent systems, where complexity increases with the number of agents acting in the environment. Machine learning is an important technology that must be considered by designers of intelligent agents and multi-agent systems.

An agent is an entity that perceives and acts on its environment through sensors and actuators. The smart agents are independent, must adapt to new circumstances and identify patterns, so it is equipped with a learning algorithm to know the environment in which it must act, this means that the performance of the smart agent, thanks to continuous learning, it continually improves.

The way in which learning is performed by smart agents depends on the algorithms, which can be of different types, depending on the action, the knowledge, the output to be obtained

Smart agents must find optimal behaviors, so to simplify complex dynamics, it is necessary to break down into sub-actions for the environment taken into consideration and interact with the other agents of the system, in order to achieve the global objectives. [25]

In the figure 3 the environment in which the Smart Agent resides and must interact, through the decison algorithm and the measurement activity, is illustrated in order to learn which is the best solution in the global context, concerning the peak of energy, the exchange with the prosumer neighbors of energy, the sale and purchase to the network, through the control over the smart appliances present in a home automation. this determines continuous exchanges of energy and money, which in this case, instead of taking place through the traditional channels of intermediaries, provides for a direct and secure exchange through the Blockchain technology, which translates in this case into a currency linked to the Renewable Energy Sources and this defined RESCoin, like the well-known BitCoin, which in this case is considered the virtual currency, dedicated to the exchange of energy, produced in a green and sustainable way.

In each Blockchain is used an algorithm, with token, also called consensus mechanisms, to generate a unique, specific HASH (encrypted or encrypted) corresponding to the information contained in the block. HASH algorithms, are used to convert arbitrary length data to a fixed length, thus creating a hash. No 2 encrypted messages can be based on the same hash value, nor the hash value will provide information as to the content of the message.

As smart appliance can communicate via IoT, through the BC can send and store informationand transactions, peer to peer, with Blockchain technology, the energy market can reach a point where a single person with single PV panel can participate in the end user market, with especially neighborhood residents being the shareholders of the company [27]. In Blockchain all transactions are in the energy domain are distributed and stored.

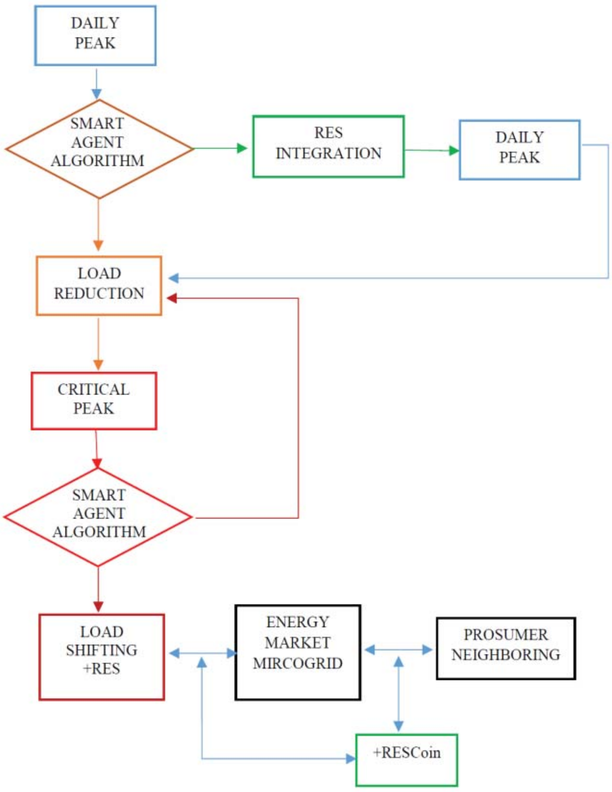

Fig.3: Flowchart of Smart agent.RESCoin environment

V. CONCLUSION

The realization of a Smart City takes place through the use and production of energy in a sustainable way. Through new technologies such as smart appliances, IoT and Blockchain it is possible to create Micro Grids that react in real time to optimize energy flows, in order to avoid peak loads and reward virtuous behaviors such as the energy produced by Renewable Energy Sources, through RESCoin, for the benefit of all the Prosumers of a Smart City.

An advanced communication network that will allow bi-directional communication between the utility and the Prosumer will allow cost optimization without decreasing the quality of life, thanks to Prosumer Side Management algorithms. The variability of the intelligent network will allow a better integration of RES, where their randomness will no longer be a disadvantage, but through real-time decision-making algorithms, thanks to smart agents, manage instantaneously production and energy prices, without intermediaries, thanks to Blockchain, which guarantee secure negotiations, by reducing network losses and through a new virtual currency linked to renewable energies, ie RESCoin.

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