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MODELING ENERGY REGULATED BY BLOCKCHAIN SYSTEM PRODUCTION

A. Guardiola Mouhaffel[1] and F.J. Díaz Pérez[2]

[1]Las Palmas de Gran Canaria University, Spain

[2]Institute of Environment, Faculty of Health Sciences, University San Jorge, Zaragoza, Spain

ABSTRACT: The management of the energy produced by photovoltaic panel stations can be converted into a management where the consumer himself can have a tendency in the final price of the price of the energy he pays. The system of generation and sale of energy by means of photovoltaic systems can be managed through global BLOCKCHAIN type procedures.

KEYWORDS: management of energy, photovoltaic panel station, consumer, BLOCKCHAIN.

1 INTRODUCTION

Locally produced renewable energy trade is addressed in the literature from a market perspective where producers and consumers participate in a double auction and trade energy daily. Energy purchase and sale orders are sent to a public order book and orders are combined continuously or at discrete closing times using the equilibrium price. The advantages of this concept of control based on the market are that it achieves an allocation close to the optimum, balances orderly supply and demand and aligns the preferences of the interested agents. However, bidding for energy ahead of time depends to a large extent on predictions of future supply or demand, whose inaccuracy translates into higher costs for both buyers and sellers [1]. In addition, agents need to rely on advanced business strategies to maximize profits (or minimize costs). For example, producers who are not familiar with the market may inadvertently set a selling price that is too high, resulting in an unequalled order of their energy. Since there is no buyer at the time they produce and inject the energy into the grid, the producers get zero profits, unless they invest in batteries that can store the non-commercialized energy.

These agents can inject the energy at the moment they find a buyer. Finally, separate energy balance mechanisms must be used to cope with the response to demand in real time. Market-based energy trade reduces agents' dependence on "Distribute System Operator" (DSO), since energy supply and demand are combined directly between individual agents [3,4] , resulting in a more decentralized and competitive environment. However, locally produced energy currently covers only a small percentage of all consumption and, therefore, the DSO still need to supply a large part of the energy to cover the total demand [2, 5]. Therefore, considering the role of the DSO in a negotiation mechanism allows an easier implementation of that mechanism in addition to the infrastructure and the current state of things and, therefore, a faster transition to an intelligent network configuration. In this document, we propose NRG-X-Change, a novel mechanism for the trade of locally produced renewable energy that does not depend on an energy market or on the adequacy of orders ahead of time. In our model, the locally produced energy is continuously fed into the network and the payment is received based on actual use, instead of the expected, since the DSO measures the consumption and bills it almost in real time. Therefore, our mechanism maintains the important role that the DSO currently plays in the energy market. The second component of our mechanism, and a novel contribution to the paradigm of energy trade, is the introduction of a new decentralized digital currency for the exchange of energy, called NRGcoin[1,6]. All payments from consumers and producers are made in NRGcoins, instead of fiduciary money. The currency can be exchanged in an independent open market for its monetary equivalent, p. Euro, dollar, pound, etc.

1.1 MANAGEMENT SYSTEM

We will have a system that will generate a model where the production of energy through photovoltaic solar panels, where there is a cycle of sale between private production and purchase through a currency accessible to the international market and supported by the BlockChain system[2,6]. The system consists of substations that are only informed by the injected energy and the transmission every 30 minutes of the energy production managed, henceforth the energy produced means energy injected into the network. Similarly, energy consumption is the energy delivered to the home from the power line, excluding the consumption of the own energy produced. A given consumer generates a certain amount of renewable energy and sends it to the network, simultaneously transmitting this information to all the nodes of the NRGcoin network [2,4].

These nodes then update the public record of P with f (x) NRGcoins, as defined in the decentralized NRGcoin protocol. Therefore, the function f (x) is responsible for generating the NRGcoins that then enter the circulation. In addition, the local substation S to which P is connected has measured the total energy production tp and the total consumption tc in that slot.

That substation then publicly transfers g (x, tp, tc) NRGcoins of the balance of the DSO to that consumer, g, is the function of the production price defined by the DSO. Therefore, for the energy injected x the consumer P obtains NRGcoins both from the NRGcoin protocol (to ensure that new money is generated in the system) and from the local substation (to align consumption with production). Note that the amount of currency received depends only on the functions f and g (where f g) and is not linked to the monetary value of NRGcoins in the market. At any chosen time interval, P joins an exchange market with an order to sell m of its NRGcoins in exchange for euros[3-7]. Similarly, a given consumer C decides to buy NRGcoins with Euro and places a purchase order in the market. If according to the market regulations these two offers are matched, the seller P releases n ≤ m NRGcoins to the buyer and receives his requested euro from the market, while buyer C releases the amount in euros offered to the seller and receives his n . Then pay h (y, tp, tc) NRGcoins for their energy consumption from and to the local substation S. Note that P and C do not need to belong to the same substation. In analogy to the price function for production g, the price function for consumption h is defined by the DSO. We then develop the two components of our mechanism: energy trading using NRGcoins and exchanging the latter for fiduciary currency. Bfi We also describe how previous price functions balance energy supply and demand, how agents can use learning mechanisms to increase your profits and what are the benefits of the new currency[5,6].

1.2 NRGcoins through the BockChains

Each producer can first use their energy produced to meet their own demand. The excess energy is fed into the network. Information on local energy production and consumption is sent from producers' smart meters to the low-voltage power substations of the street-level DSO at 30-minute intervals.

This information is then used to determine the rates at which producers are rewarded for their energy produced and consumers are billed for their extracted energy. These rates (or functions) are designed to encourage agents to balance supply and demand, as well as lower production and consumption peaks. For example, in times of low demand or high production, the cost of energy consumption is low, and analogously, low supply or high demand drives prices. Therefore, every 30 minutes each substation at street level determines the energy consumption and production rates using the following functions. The price g function for paid producers is configured as a bell curve and is defined as

$$\text{g (x, tp, tc)} = \frac{\text{x q}}{e^{-\frac{(tp-tc)^2}{a}}} \qquad (1)$$

where q = tc is the maximum rate at which producers are rewarded for their input energy x when the total supply tp matches the total demand tc and is defined by the DSO; and a is a scale factor for the case where tp 6 = tc. When the total energy production completely covers the total consumption, the function is at its maximum point and is simplified to g = x • qtp = tc. On the other hand, when tp tc or tp tc, producers are paid at a rate of g → 0 NRGcoins. The price function h (•) according to which consumers pay for their extracted energy is defined as:

$$\text{h (y, tp, tc)} = \frac{\text{y r tc}}{(tp-tc)} \qquad (2)$$

Where r is the maximum energy cost delivered by the DSO when the energy supply by consumers is low.

When production coincides with consumption, on the other hand, the substation charges consumers with rtctp tc per kWh. Finally, when tc tp, then h → 0 and, therefore, the cost of energy consumed during overproduction is close to 0, which motivates consumers to change their energy consumption to periods of overproduction

NRGcoin is not issued or controlled by a central authority and its monetary value is determined solely by currency trading in an open stock market - a higher demand for NRGcoins increases its monetary value, while a large amount of sales decreases its value. However, unlike Bitcoins, which are generated by pure computing power and, therefore, by energy expenditure (in a process called "mining"), NRGcoins are generated by injecting renewable energy produced locally into the network. The rate f (x) to which NRGcoins are generated depends only on the amount x of renewable energy fed into the grid. This quantity is transmitted1 by the intelligent meter of the producer to all other smart meters that execute the NRGcoin protocol, allowing all the participants in the NRGcoin network to track the profits of each smart meter and its transactions. Note that although the transaction information is associated with smart meters, the latter are not publicly linked with real users and, therefore, 1 it is assumed that there are security mechanisms to avoid manipulations of the smart meter. All profits and transactions are anonymous with respect to the agents. The generation process of NRGcoins has a parallel with the mining process in the Bitcoin protocol and, similarly, the accounting of profits and transactions resembles the chain of Bitcoin blocks [5,8]. The NRGcoins are obtained according to the function f defined as:

$$f(x) = b \bullet x \qquad (3)$$

where b is a constant that specifies the speed at which NRGcoins is rewarded to consumers by its injected energy x and is defined by NRGcoin protocol, running on all smart meters. As mentioned above, in addition to the NRGcoins generated by injecting energy into the network, the local substation rewards consumers based on the current supply and demand of energy in that substation. Note that the DSO does not issue currency, but simply collects and distributes payments, depending on the consumption and production price functions. To acquire or sell NRGcoins agents participate in an online currency exchange market. An agent that needs NRGcoins (for example, to pay for its energy consumption) can make a purchase offer in the market and, analogously, an agent with an excessive amount of NRGcoins can present a sale offer. Each purchase offer contains the requested quantity of currency and the price at which the agent is willing to buy. In addition, the offer contains order configurations for example, if the agent prefers the partial or total match of your offer, and if the offer should be discarded if it is not immediately matched, or it can remain in the order book. and possibly be paired at a later time. To facilitate exposure, in the rest of this section we assume that all offers can partially match and remain in the order book if they are not combined immediately.

When a purchase offer is sent to the market, all sales orders with a price lower than the purchase price are matched (the lowest sales orders first) until the purchase amount is met. Any remaining amount without purchasing is added to the order book. All sales offers are processed analogously, starting with the highest purchases first. Therefore, orders are combined only if the purchase price is greater than or equal to the sale price. The buyer pays the price that he has specified in his offer and the seller, his specified sale price [9,10]. The market owner profits from the difference between equal purchase and sale offers, as well as a possible commission to keep the market functioning. Intelligent agent counters can employ learning techniques that automatically determine the optimal amount of NRGcoins to trade in the market and an acceptable bid price. The learning mechanism selects an amount of offer that aims to minimize the amount of surplus currency, that is, the difference between the current amount of NRGcoins that the consumer has and the amount that is expected to be needed in the future. In addition, the offer price is determined by observing the domestic market, that is, the difference between the lowest pending sale and the highest pending purchase in the order book, and taking into account the consumer's risk preference. For example, placing a very high sales price generates a high yield, but also a high risk, which means that the probability of finding a suitable combination with a consumer agent is low. Therefore, the learning mechanism aims to maximize the agent's income, taking into account their preferences. Tender strategies for commercial agents have been a hot topic of research in the last decade. For example, the Power Trading Agent Competition (TAC) 2 is an annual competition that simulates future retail electricity markets. Agents in the market act as retail brokers in a local home, buying energy from a retail market as well as from local sources, such as homes and companies with solar panels, and selling energy to local customers and the wholesale market. Retail intermediaries use learning mechanisms for their supply strategies in order to make a profit, while balancing supply and demand. As the environment implies a highly dynamic environment with competitive agents, adaptive algorithms that learn by observation have proven to be very successful in this competition. The difference between our approach and Power TAC is that the latter involves selfish brokers who aim to make a profit by offering electricity tariffs to customers and marketing energy in the wholesale market. Brokers try to hire consumers, consumers and customers of electric vehicles by offering specific rates and negotiating individual contracts [11,13].. The corridors balance the fluctuating energy demands of the contracted energy consumers with the actual production of contracted energy producers. In our NRG-X-Change model, there is no need for intermediaries or long-term contracts, since NRGcoins are sold directly between consumers and consumers.

1.3 COIN PROFITS

NRGcoin NRGcoins offers a number of advantages over traditional money and other digital currencies. According to our mechanism, locally produced renewable energy is continually "converted" to NRGcoins. Their advantage over the fiduciary currency is that they serve as the right to receive an equivalent amount of energy in the future regardless of the market value of NRGcoin. Therefore, what this new "green currency" brings to the agents is the security to increase the prices of energy, for example, by buying NRGcoins at low prices and then spending them on energy when prices are high. Therefore, the currency can be spent to buy renewable energy at a later time, or it can be exchanged for fiat money in a market, whichever is more profitable for the agent. In this way, NRGcoins acts as an efficient and infinite form of battery for agents, in the form of ecological certificates for companies, or simply as a business of buying and selling foreign currency for profit. In general, it provides individual agents with an accessible means not only to support the generation of renewable energy, but also to invest in the energy market as a whole, something that is not trivial in the current state of affairs. The DSO, on the other hand, benefits from the use of NRGcoins as a "debt instrument" with high liquidity, which allows it to quickly convert this currency into cash.

Paying consumers with NRGcoins instead of fiduciary currencies allows the DSO to concentrate a greater portion of its cash assets on investments, instead of relying on bank loans and paying its associated interest rates. The new currency also resembles green negotiable certificates (TGC)) as a measure of the renewable energy produced and as a way to buy its environmental attributes to consumers. As such, it can serve as a form of competition among consumers or an indication of prestige, where companies can be valued for their green energy production. While TGCs only benefit producers by imposing purchase obligations on some consumers, NRGcoins are, among others, a form of investment and, therefore, a potential advantage for both types of agents, as described above. In addition, unlike TGCs, NRGcoins can be traded between countries and serve as an international currency for green energy. Like other decentralized digital currencies, NRGcoin is not regulated by any central bank or authority and is not linked to the securities market or fiduciary currencies. However, it is generated by producing renewable energy, unlike any other digital currency that is extracted from the calculation power and, therefore, the energy expenditure. Although NRGcoin is not regulated, it depends on your community. Therefore, its commercial value may have large fluctuations as a result of market speculation. It should be noted that the NRGcoin currency is an added value to the NRG-X-Change mechanism and is not designed to be an indivisible part of it. The commercialization of energy is also possible using fiduciary currency instead of NRGcoins modifying the functions of prices g and h to consider the value of the fiduciary currency and the function of fall f. However, it is necessary to carry out detailed investigations to determine to what extent NRGcoins can be replaced by standard currency in an initial phase, p. to simplify the implementation.

Balancing the supply and demand functions g and h are designed to align the agents' objectives. Since the rates at which substations pay consumers depend on local supply and demand, different consumers can earn different amounts of NRGcoins for the same amount of energy injected at different locations in the smart grid. Again, these rates are independent of the current market value of NRGcoins. The difference in rates is related to the balance between production and local energy consumption that DSO strives to achieve, as well as the objective of reducing supply and demand peaks. For example, the value of the energy generated in a neighbour-hood full of producers will be much lower than the NRGcoins that a single producer will get in a neighbour-hood full of consumers. Therefore, the difference in value imposed by the DSO can stimulate consumers to install renewable energy generators and become producers, while at the same time discouraging excess production or consumption that overloads the transmission lines. In the same way, consumers are motivated to change their consumption from the peaks of demand and towards production peaks, since that will reduce their energy bill. The more energy supply matches the demand, the more NRGcoins producers will receive from the substation and the lower amounts of coins will be paid by consumers to the substation, since the additional energy that needs to be supplied to that neighborhood is low. In this way, agents strive to balance supply and demand, that is, achieve the response to demand, for their own interest. Consumers are motivated to feed the network with sufficient renewable energy, while consumers minimize their costs by changing their consumption pattern towards longer production time intervals. Note that the qtp = tc and rtctp parameters of price functions 1 and 2 must be carefully configured to ensure that the benefit of the DSO is always positive and covers the costs of power transmission. Learning techniques can help agents maximize their income by using the payments from the substation as a feedback signal. For example, the learning mechanism can disconnect (some of) the renewable energy generators of the consumer during times of overproduction to maximize the benefit according to equation 1, taking into account the consumption agent itself. Similarly, the energy bill of consumers can be reduced by learning to change the consumption pattern to periods of high production, while preserving the comfort level of the agent. For example, the learning mechanism can learn to change the operation of the washing machine to periods of time when energy is the cheapest, taking into account the agent's requirements that the operation must be completed at a particular time in time. The learning mechanism should advise the agent on how much to consume in each time interval to minimize the price that is expected to pay, taking into account the electricity needs of the occupants. Inherently, this is a programming problem with multiple objectives. Several machine learning algorithms have been proposed to address multi-objective programming, such as reinforcement learning, evolutionary algorithms and local search. Given that locally produced energy today only covers a small percentage of consumption within neighbour-hoods, the DSO still It needs to produce electricity to cover the total demand. Bunn and Farmer pointed out that a 1% decrease in the forecast error implied a saving of £ 10 million in operating costs. Therefore, reliable forecasting techniques are needed to improve the DSO's energy supply planning and lower its costs. Here you can apply various prediction techniques, such as autoregressive methods, artificial neural networks, support vector machines. In addition to global energy prediction, the DSO can add predictions of individual local substations. The advantages of predicting demand at the substation level are two: on the one hand, individual local predictions can improve the accuracy of the global prediction model through the use of weighted aggregation; while, on the other hand, these predictions allow the DSO to exercise better control over the load of the individual transmission lines and thus improve the quality and robustness of the electric power infrastructure.

Instead of relying on a daily energy market to sell or buy their energy, consumers simply inject or extract from the grid, as is the current state of affairs, but at prices that depend on the measured supply and demand for energy. The payment is made in the form of NRGcoins, whose value is determined based on exchanges in an open exchange market. Using concepts of the Bitcoin increase in popularity; our novel mechanism creates a microeconomic ecosystem that allows consumers to market renewable energy produced locally at competitive prices. At the same time, agents feel incentivized to balance the supply and demand of energy for their own interest and, in this way, shorten production and consumption peaks. Finally, our proposed approach is scalable: new partners do not increase the complexity of energy trade thanks to local substations or currency exchange, since the NRGcoin protocol is decentralized. As this concept is still being developed, it is necessary to carry out exhaustive simulations, supported by microeconomic theories, to determine the parameters of the DSO price functions and the speed at which NRGcoins are generated in the network. Last but not least, special attention should be paid to the privacy and security aspects of the NRGcoin protocol and to the design of the smart meter middleware**.**

2 METHODS AND CONCLUSIONS

The model implemented to perform the forecast of monthly energy production for an autoregressive neural network with exogenous inputs (NARX), which is a recurrent dynamic network. Recurrent networks have connections that feed the output states towards the system input, with which the neural network becomes a non-linear feedback system [12,14]. The autoregressive models are based on the fact that the current value of a series y (t) can be explained in terms of past values of the same variable.

This model is characterized by having the formulation expressed in (1), where y (t) is the output that in the case of study would be the average monthly stock price of electric power, d is the number of delays and x (t) It is the exogenous input.

$$y(t)=f(x(t-1),\dots,x(t-d),y(t-1),\dots,y(t-d)) \quad (4)$$

The structure of the selected NARX neural network has 2 layers: the hidden layer that has contact with the network inputs and the output layer related to the output of the model. Both layers are formed by neurons, which are characterized by the function of activation or transfer function responsible for mapping the input data of the neuron in order to give the stimulus of this or output of the network. The activation function of the first layer was the Tansig, and its associated expression is given by (2), in which n is the numerical value of the input of the neuron. The activation function of the output layer is the Purelin or linear (a = n), where the input is equal to the output, this activation function allows the output of the network to take any value.

The structure of this network is represented in Fig. 1, where X1 ... .Xn are the inputs of the network, W are the weights and b the biases that are determined through the training of the network.

In order to complete the NARX model it is necessary to adjust the parameters of the defined structure, that is, the weights (W) and the bias or offset values (b) of the respective layers. This is done by training the network. The selected training method was the Levenberg-Marquardt algorithm, this is a method based on iterative least squares, where the performance of the network is calculated with the mean square error (mse).

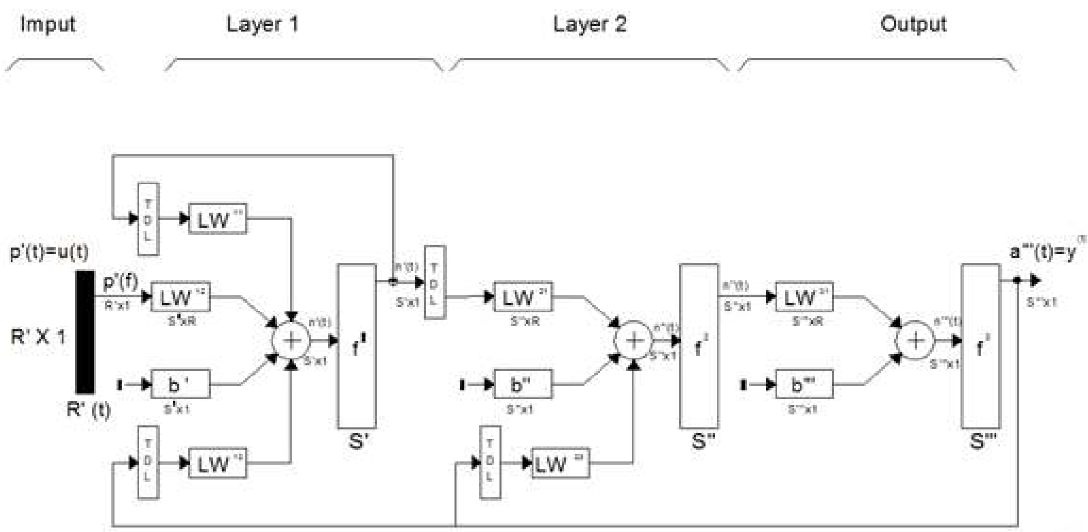

Fig. 1. Structure neural network Architecture

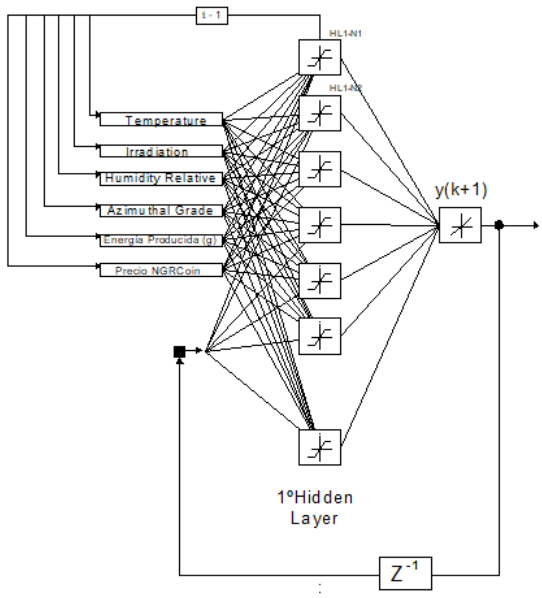

Fig. 2. Inputs and output NARX model

Table 1. Narx Network Data predictions Summary.

Delays	Neurons	Training		Validation		Test		
		mse	R	mse	R	mse	R	Time
2	5	0,0003	0,95	0,045	0,92	0,012	0,92	00:03:11
3	10	0,0003	0,95	0,038	0,92	0,012	0,92	00:05:58
5	10	0,0002	0,97	0,031	0,93	0,021	0,90	00:06:18
5	35	0,0002	0,97	0,020	0,95	0,010	0,92	00:06:35
6	35	0,0001	0,98	0,028	0,96	0,014	0,90	00:07:01
6	40	0,0001	0,98	0,029	0,96	0,010	0,96	00:07:21
6	50	0,0001	0,98	0,011	0,97	0,007	0,96	00:07:45
7	50	0,0001	0,98	0,015	0,98	0,008	0,97	00:08:15

3 Conclusions

The purpose of this study highlights the need to decentralize local energy values to a specific region of the planet and to obtain benefits from them in any part of the world, which would increase the possibilities for cheaper and competitive energy for the consumer.

The study conducted by nonlinear regression of the neural network model confirms the veracity of the study based on the NGR Coin currency, where the feasibility of decentralizing the costs and benefits of production to its sale price can be decentralized through a virtual currency.

In this paper, we have shown that the NARX neural network can successfully use its output feedback loop to improve its predictive performance in complex time series prediction tasks. Time series neural networks provided good predications as well. The output produced promising results.

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