NRG-X-Change: a Novel Mechanism for Trading of Renewable Energy in Smart Grids

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Abstract: In this position paper we propose a novel trading paradigm for buying and selling locally produced energy in the smart grid. Unlike recently proposed techniques that rely on predictions and a day-ahead market, here prosumers are billed by the distribute system operator according to their actual usage and rewarded based on their actual energy input, similar to the current state of affairs. Our mechanism achieves demand response by providing incentives to prosumers to balance their production and consumption out of their own self-interest. All rewards and payments are carried out using NRGcoin — a new decentralized digital currency similar to Bitcoin, that we introduce in this paper. Prosumers exchange NRGcoins with fiat currency on an exchange market for profit, or for paying their energy bills. We study the advantages of our proposed currency over traditional monetary payment and explore its benefits for all parties in the smart grid.

1 INTRODUCTION

Trading of locally produced renewable energy is addressed in literature from a market perspective where prosumers and consumers (or collectively: agents) participate in a double auction and trade energy on a day-ahead basis (Olson et al., 1999; Kok et al., 2005; Vytelingum et al., 2008; Vytelingum et al., 2010; Kok et al., 2012; Mockus, 2012). Buy and sell orders for energy are submitted to a public orderbook and orders are matched either in a continuous fashion (Vytelingum et al., 2008; Vytelingum et al., 2010), or at discrete market closing times using the equilibrium price (Kok et al., 2012; Mockus, 2012). The advantages of this market-based control concept are that it achieves close to optimal allocation, neatly balances supply and demand and aligns the preferences of self-interested agents. However, bidding for energy ahead of time relies heavily on predictions of future supply or demand, the inaccuracy of which translates to higher costs for both buyers and sellers. In addition, agents need to rely on advanced trading strategies in order to maximise profit (or minimise costs). For example, prosumers unfamiliar with the market may unintentionally set a too high sell price, resulting in an unmatched order for their energy. Since there is no buyer at the time when they produce and inject the energy into the grid, prosumers make zero profit, unless they invest in batteries that can store the untraded energy. Those agents can then inject the energy at the time they find a buyer. Lastly, separate energy balancing mechanisms need to be employed (Kok et al., 2012) to cope with real-time demand response.

Market-based energy trade reduces the dependency of agents on the Distribute System Operator (DSO), as energy supply and demand is matched directly between individual agents, resulting in a more decentralized and competitive environment. However, locally produced energy nowadays covers only a small percentage of all consumption and therefore the DSO still needs to supply a large portion of the energy to cover the total demand. Thus, considering the role of the DSO in a trading mechanism allows for easier implementation of that mechanism on top of the current infrastructure and state of affairs and thus a faster transition to a smart grid setting.

In this paper we propose NRG-X-Change — a novel mechanism for trading of locally produced renewable energy that does not rely on an energy market or matching of orders ahead of time. In our model locally produced energy is continuously fed into the grid and payment is received based on actual usage, rather than predicted, as consumption is measured by the DSO and billed in near real-time. Thus, 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 energy trading paradigm, is the introduction of a new decentralized digital currency for energy exchange, called NRGcoin. All payments by consumers and to producers are carried out in NRGcoins, instead of fiat money. The currency can then be exchanged on an independent open market for its monetary equivalent, e.g. Euro, Dollar, Pound, etc. In Section 2 we outline the advantages of our mechanism and elaborate on the benefits of the proposed currency. In Section 3 we summarize our approach and propose directions for future work.

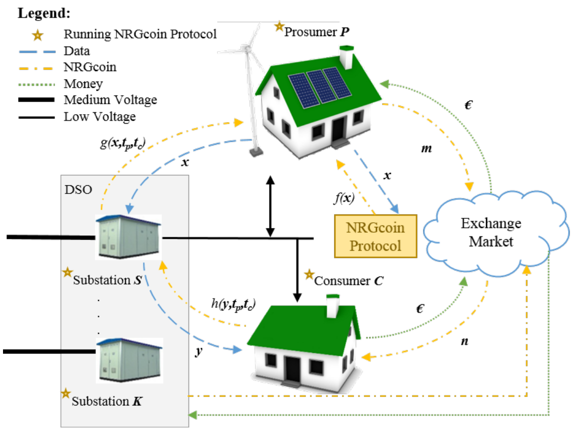

Figure 1: Example scenario

2 THE NRG-X-CHANGE MECHANISM

In Figure 1 we present an example scenario that will help visualize the complete cycle of energy and currency exchange in our mechanism for each 15-minute period (called time slot). Note that since substations are only informed of the injected energy and not the produced energy, henceforth by produced energy we mean energy injected in the grid. Similarly, energy consumption is the energy delivered to the household from the power line, excluding the consumption of the own produced energy.

A given prosumer P generates certain amount of renewable energy and feeds x of it to the grid, simultaneously broadcasting this information to all nodes in the NRGcoin network. These nodes then update the public record of P with $f(x)$ NRGcoins, as defined by the decentralized NRGcoin protocol. Thus, function $f(x)$ is responsible for generating the NRGcoins which then enter circulation. In addition, the local substation S to which P is connected to has measured the total energy production t_p and total consumption t_c in that slot. That substation then publicly transfers $g(x,t_p,t_c)$ NRGcoins from the balance of the DSO to that prosumer, where $g(\cdot)$ is the production price function defined by the DSO. Thus, for injected energy x prosumer P obtains NRGcoins from both the NRGcoin protocol (to ensure new money is generated in the system) and the local substation (to align consumption with production). Note that the amount of received currency only depends on functions f and g (where $f \ll g$) and is not linked to the monetary value of NRGcoins on the market.

At any chosen time slot, P joins an exchange market with an order to sell m of her NRGcoins in exchange for Euro. Similarly, a given consumer C decides to buy n NRGcoins with Euro and places a buy order in the market. If according to the market regulations these two bids are matched, the seller P releases $n \leq m$ NRGcoins to the buyer and receives her asked Euro from the market, while the buyer C releases the offered Euro amount to the seller and receives his n NRGcoins. He then pays $h(y,t_p,t_c)$ NRGcoins for his energy consumption of y to local substation S. Note that P and C need not belong to the same substation. In analogy to the price function for production $g(\cdot)$, the price function for consumption $h(\cdot)$ is defined by the DSO. Below we elaborate on the two components of our mechanism — the trading of energy using NRGcoins (left part of Figure 1) and exchanging the latter for fiat currency (right half of the figure). We also describe how the above price functions balance energy supply and demand, how agents can use learning mechanisms to increase their profits and what the benefits of the new currency are.

2.1 Buying and Selling Energy

Each prosumer may use her produced energy to cover her own demand first. The excess energy is then fed into the grid. Information of local energy production and consumption is sent from smart meters of prosumers to the street-level low voltage energy substations of the DSO at 15-minute intervals. This information is then used to determine the rates at which prosumers are rewarded for their produced energy and consumers are billed for their withdrawn energy. These rates (or functions) are designed to incentivize agents to balance supply and demand, as well as lower production and consumption peaks. For example, during times of low demand or high production, the cost of energy consumption is low, and analogously, low supply or high demand drive the prices up. Thus, every 15 minutes each street-level substation determines the rates for energy consumption and for production using the following functions. The price function $g(\cdot)$ for paying producers is shaped as a bell curve and defined as:

$$g(x, t_p, t_c) = \frac{x \cdot q_{t_p = t_c}}{e^{\frac{(t_p - t_c)^2}{a}}} \tag{1}$$

where $q_{t_p=t_c}$ is the maximum rate at which producers are rewarded for their input energy x when total supply t_p matches total demand t_c and it is defined by the DSO; and a is a scaling factor for the case where $t_p \neq t_c$. When total energy production completely covers total consumption, the function is at its peak and simplifies to $g = x \cdot q_{t_p=t_c}$. On the other hand, when $t_p \gg t_c$ or $t_p \ll t_c$, producers are paid at a rate of $g \to 0$ NRGcoins. The price function $h(\cdot)$ according to which consumers pay for their withdrawn energy y is defined as:

$$h(y, t_p, t_c) = \frac{y \cdot r_{t_c \gg t_p} \cdot t_c}{t_c + t_p} \tag{2}$$

where $r_{t_c \gg t_p}$ is the maximum cost of energy delivered by the DSO when the energy supply by prosumers is low. When production matches consumption, on the other hand, the substation charges consumers with $\frac{r_{t_c \gg t_p}}{t_c}$ per kWh. Lastly, when $t_c \ll t_p$ then $h \to 0$ and thus the cost of consumed energy during overproduction is close to 0, motivating consumers to shift their energy usage to periods of overproduction.

2.2 Earning and Exchanging NRGcoins

Similarly to Bitcoin (Nakamoto, 2008), NRGcoin is not issued or controlled by any central authority and its monetary value is determined solely by trading the currency on an open exchange market – higher demand for NRGcoins increases their monetary value, while a large number of sells drives their value down. However, unlike Bitcoins, which are generated by sheer computing power and hence energy expenditure (in a process called "mining"), NRGcoins are generated by injecting locally produced renewable energy to the grid. The rate $f(x)$ at which NRGcoins are generated depends only on the amount x of renewable energy fed into the grid. This amount is broadcast[1] by the smart meter of the producer to all other smart meters running the NRGcoin protocol, allowing all participants in the NRGcoin network to keep track of the earnings of each smart meter and their transactions. Note that although transaction information is associated with smart meters, the latter are not publicly linked to actual prosumers and therefore all earnings and transactions are anonymous as far as agents are concerned. The process of generating NRGcoins draws parallels to the process of mining in the Bitcoin protocol and similarly, the bookkeeping of earnings and transactions resembles the Bitcoin blockchain (Nakamoto, 2008). NRGcoins are earned according to function $f(\cdot)$ defined as:

$$f(x) = b \cdot x \tag{3}$$

where b is a constant specifying the rate at which NRGcoins are rewarded to prosumers for their injected energy x and is defined by the NRGcoin protocol, running on all smart meters.

As mentioned in Section 2.1, in addition to the NRGcoins generated by injecting energy to the grid, the local substation rewards prosumers based on current energy supply and demand at that substation. Note that the DSO does not *issue* the currency, but simply collects and distributes payments, based on the consumption and production price functions.

To procure or sell NRGcoins agents participate in an online currency exchange market. An agent who needs NRGcoins (e.g. in order to pay for his energy consumption) can place a buy bid on the market, and analogously, an agent with excess amount of NRGcoins can submit a sell bid. Each buy bid contains the requested amount of currency and the price at which the agent is willing to buy. In addition, the bid contains order configurations (Ilic et al., 2012), such as whether the agent prefers partial or full match of her bid, and whether the bid needs to be discarded if not matched immediately, or can stay in the orderbook and possibly be matched at a later time. For ease of exposition, in the remainder of this section we assume that all bids can be matched partially and remain in the orderbook if not matched immediately. When a buy bid is submitted to the market, all sell orders with a price lower than the buy price are matched (lowest sell orders first) until the buy quantity is fulfilled. Any remaining unmatched buy quantity is added to the orderbook. All sell bids are processed in analogous fashion, starting with the highest buys first. Thus, orders are matched only if the buy price is higher than or equal to the sell price. The buyer pays the price he has specified in his bid and the seller — her specified sell price. The owner of the market earns profit from the difference between matched buy and sell bids, as well as a possible commission fee to keep the market running.

The smart meters of agents can employ learning techniques that automatically determine the optimal quantity of NRGcoins to trade in the market and an acceptable bidding price. The learning mechanism selects a bid quantity that aims to minimize the amount of excess currency, i.e. the difference between the

[1] It is assumed here that security mechanisms are in place to prevent tampering with the smart meter.

current amount of NRGcoins the prosumer owns and the amount it is expected to need in the future. In addition, the bid price is determined by observing the inside-market, i.e. the difference between the lowest outstanding sell and the highest outstanding buy in the orderbook, and taking into account the risk preference of the prosumer. For example, placing a very high selling price bears a high return, but also a high risk, meaning that the probability of finding an appropriate match with a consumer agent is low. Thus the learning mechanism aims to maximize the revenue of the agent, considering its preferences.

Bidding strategies for trading agents have been a hot research topic for the last decade. For example, the Power Trading Agent Competition (TAC)[2] (Ketter et al., 2011) is a yearly competition simulating future retail electric power markets. The agents in the market act as retail brokers in a local dwelling, purchasing power from a retail market as well as from local sources, such as homes and businesses with solar panels, and selling power to local customers and into the wholesale market. Retail brokers use learning mechanisms for their bidding strategies in order to make profit, while balancing supply and demand (Reddy and Veloso, 2011). As the environment involves a highly dynamic setting with competitive agents, adaptive algorithms that learn by observation (Kuate et al., 2013) have proven to be very successful at this competition. The difference between our approach and Power TAC is that the latter involves self-interested *brokers* that aim at making profit through offering electricity tariffs to customers and trading energy in the wholesale market. The brokers attempt to contract consumers, prosumers and electric vehicle customers by offering specific tariffs and by negotiating individual contracts. The brokers balance the fluctuating energy demands of their contracted power consumers against the actual output of their contracted energy producers. In our NRG-X-Change model, there is no need for brokers or long-term contracts, as NRGcoins are traded between consumers and prosumers directly.

2.3 Benefits of the NRGcoin currency

NRGcoins offer a number of advantages over traditional money and other digital currencies. According to our mechanism, locally produced renewable energy is continuously "converted" to NRGcoins. Their advantage over fiat currency is that they serve as the right to receive an equivalent quantity of energy in the future independent of NRGcoin market value. Therefore, what this new "green currency" brings for agents is security towards increasing energy prices, by for example purchasing NRGcoins at low prices and then spending them on energy when prices are high. Thus, the currency can be spent to buy renewable energy at a later point in time, or traded for fiat money on a market, whichever is more profitable for the agent. In this way NRGcoins act as a form of efficient and infinite battery for agents, in the form of green certificates for companies, or simply as a business of buying and selling the currency for profit. In general, it gives individual agents accessible means to not only support renewable energy generation, but also 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 using NRGcoins as a "debt instrument" with high liquidity, allowing it to quickly convert this currency to cash. Paying prosumers with NRGcoins instead of fiat currencies enables the DSO to focus a larger portion of its cash assets on investments, rather than rely on bank credits and pay their associated interest rates.

The new currency also resembles tradable green certificates (TGCs) (Schaeffer et al., 2000; Morthorst, 2003) as a measure of produced renewable energy and as a way to purchase its environmental attributes by consumers. As such it can serve as a form of competition between prosumers or an indication of prestige, where companies can be valued for their green energy production. Whereas TGCs only benefit producers by imposing purchase obligation to some consumers, NRGcoins are, among others, a form of investment and thus of potential advantage to both types of agents, as described above. Moreover, unlike TGCs, NRGcoins can be traded across countries and serve as an international currency for green energy.

Similarly to other decentralized digital currencies, NRGcoin is not regulated by any bank or central authority and it is not tied to the stock market or fiat currencies. However, it is generated by producing renewable energy, as opposed to any other digital currency that is mined by computing power and hence energy expenditure. Although NRGcoin is not regulated, it is dependent on its community. Therefore its trade value can have large fluctuations as a result of market speculations.

It should be noted that the NRGcoin currency is an added value to the NRG-X-Change mechanism and not designed to be an indivisible part of it. The trading of energy is also possible using fiat currency instead of NRGcoins by modifying price functions g and h to consider the value of the fiat currency, and dropping function f. Nevertheless, detailed investigations need to be carried out to determine to what extend NRGcoins can be replaced by standard currency in an initial phase, e.g. to simplify deployment.

[2]http://www.powertac.org/

2.4 Balancing Supply and Demand

Price functions g and h are designed to align the objectives of agents. Since the rates at which substations pay prosumers depend on local supply and demand, different prosumers may earn different number of NRGcoins for the same amount of injected energy at different locations of the smart grid. Again, these rates are independent from the current market value of the NRGcoins. The difference in the rates is related to the balance of local energy production and consumption that the DSO strives to achieve, as well as for flattening supply and demand peaks. For example, the value of generated energy in a neighborhood full of producers will be much lower than the NRGcoins that a single producer will earn in a neighborhood full of consumers. Thus, the value difference imposed by the DSO may stimulate consumers to install renewable energy generators and become producers, while at the same time discourage excess production or consumption that overload the transmission lines. Similarly, consumers are motivated to shift their consumption away from demand peaks and towards production peaks, as that will lower their energy bill.

The more energy supply matches demand, the more NRGcoins producers receive from the substation and the fewer coins are paid by consumers to the substation, as the additional energy it needs to supply to that neighborhood is low. In this way agents strive to balance supply and demand, i.e. achieve demand response, out of their own self-interest. Prosumers are motivated to feed just enough renewable energy to the grid, while consumers minimize their costs by shifting their consumption pattern towards time slots of higher production. Note that the parameters $q_{t_p=t_c}$ and $r_{t_c \gg t_p}$ of price functions 1 and 2 need to be carefully configured to ensure that the profit of the DSO is always positive and covers the costs of energy transmission.

Learning techniques can help agents maximize their revenue using the payments from the substation as a feedback signal. For example, the learning mechanism can switch off (some of) the renewable energy generators of the prosumer during times of overproduction in order to maximize the profit according to Equation 1, while taking into account the agent's own consumption. Similarly, the energy bill of consumers can be reduced by learning to shift the consumption pattern to periods of high production, while preserving the comfort level of the agent. For example, the learning mechanism can learn to shift the operation of the washing machine to time periods when energy is the cheapest, taking into account the requirements of the agent that the operation should be completed by a particular moment in time. The learning mechanism would have to advice the agent on how much to consume at each time slot in order to minimize the price it is expected to pay while taking into account the electricity needs of the occupants. Inherently, this is a scheduling problem with multiple objectives. Various machine learning algorithms have been proposed to address multi-objective scheduling, such as reinforcement learning (Aissani et al., 2009), evolutionary algorithms (López-Ibáñez et al., 2005) and local search (Dubois-Lacoste et al., 2011).

Since locally produced energy nowadays covers only a small percentage of consumption within neighborhoods, the DSO still needs to produce electricity to cover the total demand. Bunn and Farmer (Bunn and Farmer, 1985) pointed out that a 1% decrease in forecasting error implied £10 million savings in operating costs. Therefore, reliable forecasting techniques are needed to improve the energy supply planning of the DSO and decrease its costs. Several prediction techniques can be applied here, such as autoregressive methods (Contreras et al., 2003), artificial neural networks (Khamis et al., 2011), support vector machines (Tan et al., 2010), etc. In addition to global energy prediction, the DSO can aggregate predictions of individual local substations. The advantages of predicting demand at substation level are twofold: on the one hand individual local predictions can improve the accuracy of the global prediction model by employing weighted aggregation; while on the other hand these predictions allow the DSO to exert better control over the load of individual transmission lines and thus improve the quality and robustness of the electric power infrastructure.

3 SUMMARY AND OUTLOOK

In summary, instead of relying on a day-ahead energy market to sell or purchase their energy, prosumers simply inject to or draw from the grid, as is the current state of affairs, but at prices that depend on measured supply and demand of energy. Payment is in the form of NRGcoins, the value of which is determined based on trades in an open currency exchange market. Using concepts from the rising in popularity Bitcoin phenomenon, our novel mechanism creates a microeconomic ecosystem that allows prosumers to trade locally produced renewable energy at competitive prices. At the same time agents are incentivized to balance energy supply and demand out of their own self-interest and thus flatten production and consumption peaks. Lastly, our proposed approach is scalable — newly joining agents do not increase the complexity of the energy trade thanks to the local substations, or of the currency exchange, as the NRGcoin protocol is decentralized.

As this concept is still work-in-progress, extensive simulations need to be carried out, backed up by microeconomic theories, to determine the parameters of the price functions of the DSO and the rate at which NRGcoins are generated in the network. Last but not least, special attention needs to be paid to the privacy and security aspects of the NRGcoin protocol and in the design of the smart meter middleware.

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