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Pricing Strategy Comparison in Blockchain based Distributed Energy Systems

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Abstract

Nowadays, researchers are trying to improve and find new ways and methods to mitigate climate change and increase energy efficiency. Areas of study include smart grid, smart grid, distributed energy systems, accumulative and renewable energy sources. Renewable energy integration, system operation, transparent spending system and data integrity are the common challenges facing distribution network providers. The overall, holistic view of the technologies listed above about delivering and consuming any kind of energy has many aspects that need to be studied and optimized. Good compatibility with distribution systems is characterized by modern blockchain technology and multi-agent system. Blockchain has very good data protection, immutability and transparency properties in transactions. Its decentralized nature and automatic calculation system can bring great potential in terms of financing and calculation in the energy sector. In this thesis article a novel process to coordinate, allocate and settle energy transactions in a district multi-carrier energy system. The process operates in a decentralized way, fully on-chain. The design leaves producers the freedom to choose their preferred pricing strategy for profit maximization. The price-availability-based allocation system guarantees consumers the lowest possible cost.

Keywords: blockchain, district energy system, energy trading, multi-energy system, peer-to-peer, pricing, renewable energy

JEL: C61, C63

Introduction

Distributed Energy Resources (DERs) include small-scale generators (e.g., rooftop solar panels), small-scale energy storage systems, plug-in electric vehicles (EVs), and household appliances with energy storage capabilities and flexible power requirements that permit them to function as virtual batteries [1]. There are primarily renewable energy sources (RES) in the DERs. With the growing penetration of distributed renewables in the market, the traditional electrical grid structure is exposed to the potential risk of broad area failure. A small grid failure may lead to cascading outages and entice large-scale blackout [2]. The need for flexible power and ancillary service provision has increased [3]. One solution is to segment the wide-area synchronized power system into small or medium sized cells at the distribution network level and control the subsystems (or “cells”) asynchronously [4]. The size of these subsystems may vary from

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a single household to a city or region. A district-level multi-energy system is an ideal representative of such subsystem that sits in the distribution network. The electrical network of such a system remains at a low-voltage (LV) level, with the connection to the grid via controllable transformer(s), giving a single connection to the medium-voltage network. The complexity of operation is reduced for such a system in comparison to a system that involves management of a higher voltage network. Within the same setting, a district heating network and other bi-directional DERs, like electric vehicles, batteries and hydrogen storages, could also be added up on top to form a district multi-energy system. The flourishment of distributed renewable energy generation has challenged the operation of modern electric power systems. A TES is defined as a set of economic and controllable mechanisms that permit supply and demand of power to be balanced over time across an entire electrical infrastructure, where these mechanisms are designed to enhance value for the transacting parties consistent with overall system reliability. Since there are mainly prosumers in the aforesaid district-level multi-energy system, the TES model is suitable for the electric network in such a system. To stimulate effective interactions with network users, price signals can play an important role [6]. The design for the policy may be based on various principles, including efficiency, equity, simplicity, consistency, transparency, stability, and additivity [5]. Among the incentive schema, there are two general guiding methods: price-based method and interruptible demand response [7]. As shown in the Figure 1, Eid et al. [5] summarized the appropriate incentives concepts or control methods for different use cases. In our project, we are going to use the direct load control method driven by nodal price signals, to minimize the operational impact technically as well as maximizing the utility function for each prosumer in the district multi-energy system. Many dynamic pricing strategies, meaning a time-varying energy rate, are available and have been investigated by researchers. Figure 2 shows some of the possible ones. Two pricing Zero-Intelligence Pricing and Inversed-Production Pricing are derived from the Real-Time-Pricing (RTP) and Critical Peak Pricing (CPP) models respectively.

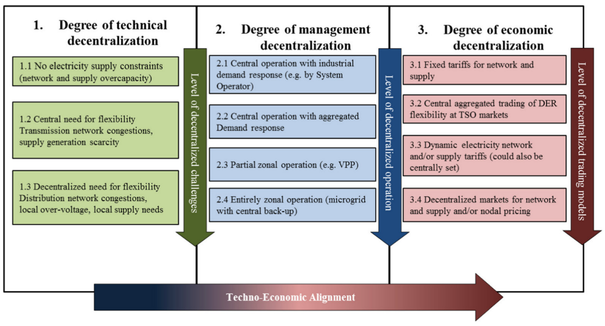

Figure 1. Techno-Economic Alignment of Decentralization in Electricity Markets

The intersection between blockchain and distributed energy system is the inherently distributed nature, as well as the need for keeping a record of the energy and financial transactions. As the features of both systems tend to go into the same direction, many studies and applications are carried out in this field.

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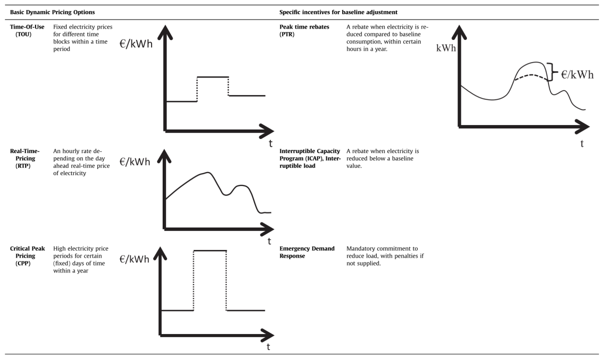

Figure 2. Possible Dynamic Pricing Options for DER Management [85]

This article is going to propose an innovate process to seamlessly coordinate, allocate and settle energy transactions in a district multi-carrier energy system. The process operates in a decentralized way, fully on-chain. The design leaves producers the freedom to choose their preferred pricing strategy for profit maximization. A price-availability-based allocation system guarantees that consumers pay only the lowest possible cost for their energy. An incentive mechanism is introduced. Each device reacts for the common good of the community and follows the principle of relieving the stress of operational limits. This design is implemented on Ethereum blockchain and tested with real consumption and production profiles of electricity and heating systems. Three pricing strategies, namely zero-intelligence real-time-pricing, inversed-production peak pricing, and game-theory based pricing, are compared and evaluated. An analysis of the energy consumption and operation cost of such systems is performed in the end.

Design of Energy System

As shown in figure 3 and figure 4, there are three households, three photovoltaic (PV) panels, one battery, three heat pumps and four hot water tanks in the two networks of our project. Each device included in the system - represented as a node i - can be characterized by its energy load. During one day in the near real-time energy trading system, a node can consume or supply energy. When a device consumes energy, meaning it receives electricity or heat from other devices, its energy load is denoted as li(t) > 0. Such a device is considered as Consumer C. Examples for kind of devices are households and offices. When it produces energy, meaning there is electricity or heat generated by the device, flowing to other devices, the energy load of such a device is li(t) < 0. Such device is classified as Producer P, for instance, PV panels. If a device can store energy, there are three possible behaviors at that time t. If the device charges at time t, it acts as a Consumer, thus li(t) > 0. If it discharges energy, it works as a Producer, thus li(t) < 0. li(t) = 0, if the device is not active. Such a device is called Storage S, by which load can be shifted.

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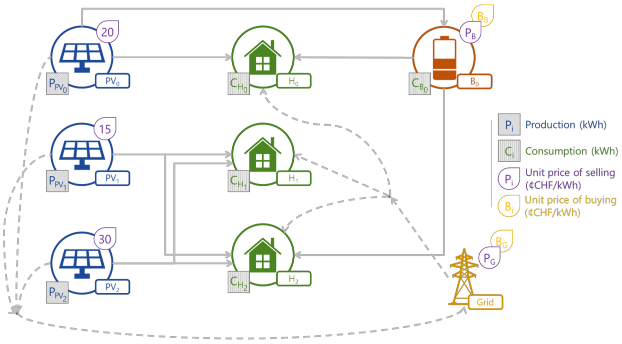

Figure 3. Layout of the Electricity Network in our District Multi-Energy System

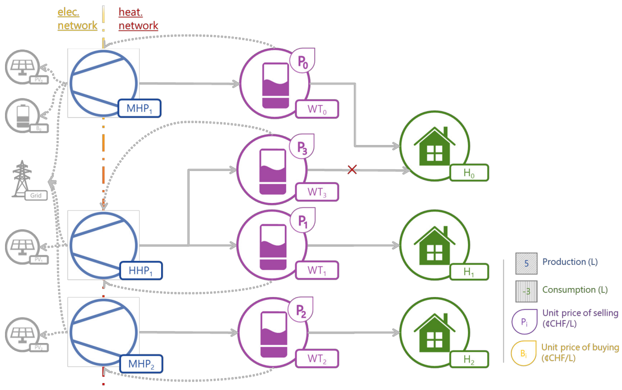

Figure 4. Layout of the Heat Network in our District Multi-Energy System

In residential and commercial building, there are two types of heat supply, i.e. Domestic Hot Water (DHW) at medium temperature and Space Heating (SH) at low to medium temperature [8]. Fischer et al. [9] introduced a stochastic bottom-up model for space heating and domestic hot water load profiles, in which both physical (e.g. ambient temperature equation 4 and season fluctuation equation 5) and behavioral equation 6 aspects are considered. This model is used to describe the heat consumption of households in our system. Equation 1 shows the model for calculating SH energy consumption. Equation set 3 shows the model for DHW. The total demand for domestic heating is finally calculated.

$$T_{room,set}(T) = T_{setpoint}(T) + \Delta T_{user}(T) * n_{pers,active}(t)[K] \quad (1)$$

$$Q_{sh} = Q_{l,vent} + Q_{l,trans} - Q_{g,sol} - Q_{g,int} - C_m \frac{\Delta T_m}{\Delta t}[W] \quad (2)$$

Where,

$T_{room,set}(T) =$ *temperature set point of the building model*

$T_{setpoint}(T) =$ *room temperature set point for space heating*

$\Delta T_{user}(T) =$ *temperature increase per person*

$n_{pers,active}(t) =$ *number of people at home and not sleeping*

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$\mathrm{Q_{sh}} = energy\ balance\ of\ the\ building$

$\mathrm{Q_{l,vent}} = ventilation\ losses$

$\mathrm{Q_{l,trans}} = transmission\ losses$

$\mathrm{Q_{g,sol}} = solar\ gains$

$\mathrm{C_m} = building\ mass$

$\Delta \mathrm{T_m} = temperature\ change$

$\Delta \mathrm{t} = time\ step$

$$Q_{dhw}(t) = f_{season}(t) * [Q_{losses}(t) + m(t) * c_w * (T_{w,h}(t) - T_{w,c,0})][w] \quad (3)$$

$$T_{w,c}(n_{day}) = \overline{T_{amb}} - 3K * (\frac{2\pi}{365} * (n_{day} - n_{day,offset}))[k] \quad (4)$$

$$f_{season}(n_{day}) = 1 + \frac{T_{w,c,nominal} - T_{w,c}(n_{day})}{\Delta T_{w,0}} \quad (5)$$

$$Q_{g,int} = P_{el}(t) + n_{pers}(t) * 65.0\ [W] \quad (6)$$

Where,

$Q_{dhw}(t) = energy\ needed\ to\ heat\ up\ the\ water\ at\ time\ t$

$Q_{losses}(t) = circulation\ losses, optional\ term$

$Q_{g,int} = internal\ gains\ through\ human\ presence$

$and\ electric\ appliances$

$c_w = specific\ heating\ capacity\ of\ water$

$m(t) = tapped\ mass\ flow$

$f_{season}(t)\ factor\ for\ the\ seasonal\ effect\ of\ the\ cold$

$water\ temperature\ on\ the\ DHW\ demand$

$P_{el}(t) = electricity\ consumption\ of\ appliance\ use$

$n_{pers}(t) = number\ of\ present\ person$

$n_{day} = number\ of\ the\ date\ in\ the\ calendar\ year$

$n_{day,offset}\ offset\ days\ based\ on\ the\ coldest\ day\ of$

$the\ year\ and\ on\ the\ temperature\ change\ delay$

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$f_{season}(n_{day})$ *factor correcting for the fluctuating*

cold water temperature

$T_{w,c,nominal}$ = *nominal cold water temperature*

$T_{w,c}(n_{day})$ = *cold water temperature of the day nday*

$T_{w,h}(t)$ = *temperature of the hot water at the tapping point*

$T_{w,c,0}$ = *nominal cold water temperature*

$\overline{T_{amb}}$ = *mean yearly ambient temperature*

$\Delta T_{w,0}$ = *nominal temperature difference between cold and*

hot water

Among all the possible renewable electricity technologies, PV is the most viable and cost effective for distributed households. Also, as there are PV panels installed on the NEST demonstrator, we can leverage the real-time data input. PV panels are the only energy producer in this system. PV systems can be acquired by single households or jointly by multiple members of the system.

The system has a battery B0 shared among all members of the community. The battery can be connected to PV systems as a solution for system flexibility, where it shaves the production peak and smoothens the consumption peak. At each time-slot t, the battery B0 can decide whether to actively acquire a certain amount of energy or not, to set a certain price for selling stored energy. However, in case of unbalanced demand and supply in the electricity network, the battery must react and is obliged to balance the system. In this case, the amount of energy stored in B_0 follows $0 \leq V_{B_0}(t) \leq V_{B_0}^{max}$ On the contrary to its energetic obligations, the battery can independently set the price for its balancing service.

As a backup for the district energy system, the grid can provide energy in case of surplus or deficiency by virtue of controlling the system and balancing with other users in the same network. The grid can set the energy price and feed-in tariff, based on grid's condition at each time slot. Due to grid security and congestion issues, there is a capacity limit for the grid, denoted as $l_g^{min} \leq l_g(t) \leq l_g^{max}$.

Water tanks provide flexibility for heating supply. As mentioned above, DHW and SH are at different temperature level. To efficiently conserve hot water at two temperature levels, water tanks need to be temperature specific. There is at least one water tank dedicated to each domestic heating supply as shown on figure 2. Each water tank is linked to a heat pump as the only source of thermal energy supply. The reason will be detailed in the paragraph concerning the heat pump. Each household's water consumption is directly requested from the linked water tank with the volume of the hot water at a particular temperature T at time t. Similar to storage capacity of the battery, water tanks operate in the volumetric range of $0 \leq V_{WT_i}(t) \leq V_{WT_i}^{max}$.

A heat pump is an effective means for a real-time setup compared to other thermal generators. It works as an interface between electricity network and the heating network, which uses purchased electricity to heat up the

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ground water to a desired temperature. In order to simplify the model, the heat pump is the only device to supply the heating network. Noted that it is also possible to supply hot water with water at lower-temperature hot water and do the reverse cycle with heat exchanger. However, for the simplicity of the network, we consider the sole option of heating from ambient water resource and stored in the water tank. The performance of a heat pump is characterized by the Coefficient of Performance (COP), where $COP = \frac{Q_H}{W}$, where $Q_H = V \times P_w \times C_w - (T_{w,h} - T_{w,c,0})$ and V is volume of water, Cw is specific heating capacity of water, Pw – density of water, Tw,h – hot water temperature, Tw,c,0 – cold water temperature.

With regard to forging solidarity with the community, increasing the penetration of renewable energies, and minimizing cost of energy, here we present a policy that incorporate metrics for availability, connectivity and priority of devices in the system. The principle of trading in this system is to empower the community and to incentivize the usage of renewable energies while minimizing the cost for each participant. Here I assume that households have the willingness to purchase as much renewable energies as possible compared to conventional energy or mixed energy supplied by the grid, as long as the energy transfer is possible over the grid (connectivity check) and the price is reasonable. All the energy generated or stored in the district multi-energy system is considered as community energy. When households query the available energy supply, the community energy owns a higher priority over the energy from the grid. Within the community, households tend to select the supplier with the lower price, in order to reduce their cost. PV systems have the incentive the sell as much generated energy to the community as possible. PV systems need to set a unit sale's price for the produced energy at a given time interval. Since they are the price setter and the transaction settlement partially relies on the price, they need to use an appropriate pricing strategy to manage the destination of their generated energy. When there is a surplus in generation, there is no other way for PV systems than to sell to batteries at a close-to-zero price or feed back into grid. The general rule for the battery is to purchase energy at low prices and sell it at high prices. Therefore, the battery should have a good overview and prediction on the total energy generation and consumption in the entire system. The battery has the right to decide whether it actively declares the need for charging. If bids, the declared amount of energy is secured to be supplied, at a price defined by the suppliers. However, if the battery chooses not to bid, there is still possibility that it receives some energy. This takes place when there is surplus of energy generation in the system.

Pricing

From a system-level perspective, a trading mechanism built on a pure financial strategy cannot necessarily perform better technically. This means that an optimization based on price or cost does not lead to an optimization for the system's physical operation. In some cases, technical difficulties (e.g. congestion, instability) may occur and induce an operation default/security concern/damage on the infrastructure, etc. Those increase the maintenance cost and dispatching effort required by the grid operator, who will in return charge the energy users with higher bills. Therefore, a good design of pricing strategy that internalizes all the potential externalities, such as operation constrains, environmental impacts (carbon taxes) and human factors (encourage certain connection within the community) would be beneficial. Pricing strategies are adopted by the devices in the system with information provided by agents. Agents act as the owner of the device, to perform price setting or consumption setting. Here we adapt several pricing scenarios in three categories. First, zero-intelligence pricing, a basic pricing strategy, where agents have little information on both the performance of their own and others' devices. This makes the pricing strategy totally random and independent of any system impulses.

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Secondly, inversed production pricing where agents need to predict the production of their own devices for the next 15 min interval based on historical data and set up the price according to a general demand-supply relation. Each agent performs independently, relying only on the historical information of its own device. Thirdly, a collective non-cooperative pricing where each energy producing agent can adjust the selling price based on the behaviour of other energy producers who hold a similar role, to maximize their utility function. Agents firstly share necessary information among each other and make their own decisions in combination with the historical performance of their own device.

Zero-Intelligence Pricing

The zero-intelligence pricing strategy is one kind of RTP strategy. Pricing signals for PVs are generated randomly with multiple probability distributions for the initial test. This simulates the case where users of the community do not have information on the pricing strategy of the counterparts and do not have the intention to compete with other producers in the system. Their pricing strategies are completely independent and random. Under this category, each device has only limited information on the behaviour of any participant in the system. For the price setter, i.e. PV, no information is available on either its competitors (PV or battery) or its clients (house and heat pump), nor on its' own production profile. This corresponds to the situation that the system might encounter in its early stages. Since there is no information on the market price, a device can only set up a pricing strategy based on its leveraged cost with the desired margin plus a risk premium. Here we assume that the leveraged costs are the same for all the PVs; the preferred margin varies according to the owner, but remains in the range of (10 to 15 %); the risk premium is set based on the market risk assessed by the owner of the device. Producers arrive at different estimates because of the difference in the connection layout of each device. This risk part fluctuates as the other factors, such as weather and consumers' demand, vary along one single day. All of these factors result in choosing different risk Probability Distribution Functions (PDFs). The choice of the exact PDF also depends on the risk adversity of the user.

Inversed-Production Pricing

The inversed-production pricing strategy belongs to the CPP strategy. In this pricing category, PV systems set up their price by applying desired rates to their basic price of production. The basic price includes the market risk premium as well as a fluctuating part which is in reversed correlation its volume of the generated energy. It is based on the assumption that the higher the current production volume one PV system has, the higher the production of PVs in the same community, since they are exposed to similar condition. According to the demand supply theory, assuming that the demand from consumers remains relatively stable (due to a lack of information), the equilibrium price decreases as the quantity of supply increases. It's worth noticing that it is not necessary for all the producers to follow this relation. For those who serve as the unique energy provider to certain consumers, their monopoly status allows them to retain a high price even when the market price drops. In our model, for simplicity, we adopt the same pattern for all the producers regardless their connectivity configuration.

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$$p_{PV_0}(t) = \begin{cases} 10 - \frac{70}{l_{PV_0}(t)} & \text{if } l_{PV_0}(t) < 0, \\ 10, & \text{otherwise} \end{cases}$$

$$p_{PV_1}(t) = \begin{cases} 11 - \frac{80}{l_{PV_1}(t)-2} & \text{if } l_{PV_1}(t) < 0, \\ 11, & \text{otherwise} \end{cases}$$

$$p_{PV_2}(t) = \begin{cases} 6 - \frac{100}{l_{PV_2}(t)-2} & \text{if } l_{PV_2}(t) < 0, \\ 6, & \text{otherwise} \end{cases}$$

Game-Theory Based Pricing

Strategies in this category have an agile approach to modify their offered price based on the planned price, as planned in the Inversed-production pricing. This pricing strategy keeps track of the portion of energy sold out to the community at each timestep, which is defined as the community factor f_C in the equation 7. If a comparison of the community factor of a producer with that of other similar players in the market reveals that it sells less energy, the unit selling price that producer offers will be reduced for the next time interval according to equation 10. The increment in price, $P_{adjustment}$, is adjusted by the internal policy of the producer.

$$\Delta community_{PV_i}(t) = l_{PV_i}^{(4)}(t) - l_{PV_i}^{(1)}(t) \quad (7)$$

$$\Delta grid_{PV_i}(t) = l_{PV_i}^{(5)}(t) - l_{PV_i}^{(4)}(t) \quad (8)$$

$$fc_{,PV_i}(t) = \frac{\Delta community_{PV_i}(t)}{(\Delta community_{PV_i}(t) + \Delta grid_{PV_i}(t))} \quad (9)$$

$$P_{PV_i}^{adjusted}(t + \Delta t) = P_{PV_i}^{original}(t + \Delta t) \pm P_{adjustment}$$

$$if\ fc_{,PV_i}(t) < fc_{,PV_j}(t)\ where\ j \in \{[0,2] \backslash i\} \quad (10)$$

Where,

$\Delta community_{PV_i}(t) = energy\ generation\ of\ PV_i\ that\ is\ actively\ purchased$

$by\ the\ community$

$\Delta grid_{PV_i}(t) = energy\ generation\ of\ PV$ *that is sold to peak shaving devices and the grid*

$l_{PV_i}^{(j)}(t) = load\ of\ PV_i\ at\ the\ end\ of\ step\ j$

$fc_{,PV_i}(t) = share\ of\ energy\ generation\ of\ PV_i\ that$

$contributes\ to\ the\ community$

$P_{adjustment} = adjustment\ in\ price$

$P_{PV_i}^{original}(t + \Delta t) = t + \Delta t -\ original\ unit\ price$

$P_{PV_i}^{adjusted}(t + \Delta t) = t + \Delta t - adjustment\ unit\ price$

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Conclusion

In general, the price influence depends very much on the energy supply distribution. Game-theory based strategy provides a feedback loop for devices to make better decisions with limited information. The agility it provides is essential in the intra-day, high-frequency trading. In all the scenarios, the battery is discharged at the end of the day. It is not a sustainable approach because the situation changes as there is no initial supply from the battery in the beginning of the day, where no renewable resource in the system can generate energy. The community system, as it is now producing too little energy to maintain a strategy in which grid-power is only used for backup. If a real system were to operate using this strategy, the PVs would need to be sized more adequately. Another solution is to include other forms of green energy into the system. Some clean energies like wind and biomass, do not operate depending on the radiation from nature. They can produce energy during at night when PVs are not capable of doing so, or operate for the base-load generation to supply the demand of the community and battery replenishment. Ideally, additional rules would need to be introduced which lead to sustained average levels of both the battery and the heat storage. By choosing a competitive pricing strategy, households pay significantly less than in a determined pricing case. The allocation of renewable energy is more in favor of the community compared to that in the scenario without any feedback loop. The risk of having a monopolistic price setter exists when there is only one available energy provider in the community. According to our current policy, the community green energy supplier holds priority than other suppliers. During the time when there is only one community green energy provider, it appears on the top list of all its connected devices. Therefore, as long as there is demand from the connected devices of this particular provider, its production in that time interval is ensured to be sold out. This leaves this particular energy provider freedom to set up a price where no competitor is in the market, which in contrast, is a risk for consumers. This risk is controlled when there are more energy providers of the same form, meaning competitors, in the market.

According to the ability of blockchain technology, we can track the transactions settled on the chain, control signals can be caught and communicated via API for transactive device control. This leads to a fully automated energy-trading platform. Both heat and electricity can be supplied without brokers or energy companies. This platform enables a complete on-chain trading initiation without the need for cross-platform communication that increases the potential of leakage of privacy. This model provides a fully distributed marketplace, where each device has its own “bazaar”. There is no additional aggregator in the project that collects more information than absolutely necessary. This system prevents the single-point failure because the communication is P2P without any inter-mediator or aggregator. When the system operates within its technical constraints, if one device is disconnected/defective, the entire trading process is not disturbed. Those devices that are not physically connected to the failure point would have zero impact; while those connected devices start to look for the next available device to complete the process until the defective device reconnects to the network. Also, in a distributed contracts structure managed by contract factories, it eases the difficulty of maintaining and upgrading. This trading logic has good scalability. Although the accounts are publicly accessible to all the users, data privacy is well protected in this system, thanks to the previously mentioned original P2P structure. Data privacy and anonymity can be better guaranteed than that in the traditional central database-driven business model because only certain users, i.e., connected devices, can access to the non-public production/consumption and price information when situated in the right time-slot.

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