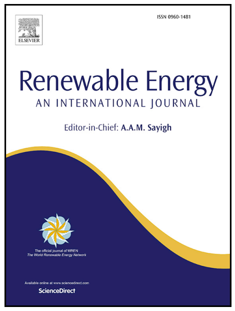
Accepted Manuscript



Comparing stakeholder incentives across state-of-the-artrenewable support mechanisms

Mihail Mihaylov, Roxana Rădulescu, Iván Razo-Zapata, Sergio Jurado, Leticia Arco, Narcís Avellana, Ann Nowé

PII: S0960-1481(18)30866-8

DOI: 10.1016/j.renene.2018.07.069

Reference: RENE 10343

To appear in: *Renewable Energy*

Received Date: 4 May 2017

Revised Date: 19 June 2018

Accepted Date: 14 July 2018

Please cite this article as: Mihaylov M, Rădulescu R, Razo-Zapata Ivá, Jurado S, Arco L, Avellana Narcí, Nowé A, Comparing stakeholder incentives across state-of-the-artrenewable support mechanisms, *Renewable Energy* (2018), doi: 10.1016/j.renene.2018.07.069.

Comparing stakeholder incentives across state-of-the-art renewable support mechanisms

Mihail Mihaylov[a,b,1,*], Roxana Rădulescu[a], Iván Razo-Zapata[a,3], Sergio Jurado[b,2], Leticia Arco[a,4], Narcís Avellana[b], Ann Nowé[a]

[a]*Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium*
[b]*Sensing & Control Systems, C./ Arrago 208-210, 08011 Barcelona, Spain*

Abstract

Traditional support policies for green energy have greatly contributed to the rise in prosumer numbers. However, it is believed that they will soon start to exert negative impact on stakeholders and on the grid. Policy makers advise to phase out two of the most widely applied policies – net metering and feed-in tariff, in favor of support policies that scale better with rising renewable generation. This work quantifies the impact of these traditional policies in future "what-if" scenarios and confirms the need for their replacement. Based on simulations with real data, we compare net metering and feed-in tariff to four state-of-the-art market-based mechanisms, which involve auction, negotiation and bitcoin-like currency. The paper examines the extent to which each of these mechanisms motivates not only green energy production but also its consumption. The properties and characteristics of the above mechanisms are evaluated from the perspective of key stakeholders in the low voltage grid – prosumers, consumers and energy providers. The outcome of this study sheds light on current and future issues that are relevant for policy makers in the evolving landscape of the smart grid.

Keywords: Smart Grid, Renewable Energy, Incentive Mechanism, Support policies, Feed-in Tariff, Net metering

*Corresponding author
Email address: mihail.mihaylov@vub.be (Mihail Mihaylov)
URL: www.mikemihaylov.be (Mihail Mihaylov)
[1]Present address: Enervalis, Centrum-Zuid 1111, 3530 Houthalen-Helchteren, Belgium
[2]Present address: Facultad de Informtica de Barcelona, Jordi Girona Salgado 1-3, 08034 Barcelona, Spain
[3]Present address: Luxembourg Institute of Science and Technology, Avenue des Hauts-Fourneaux 5, 4362 Esch-sur-Alzette, Luxembourg
[4]Present address: Universidad Central "Marta Abreu" de Las Villas, Carretera a Camajuaní 5 1/2, 54830 Santa Clara, Cuba

1. Introduction

If we are to meet our environmental targets, cities must offset their dependence on fossil fuels by relying on renewable energy sources (RES) [1, 2]. To comply with environmental targets, policy makers apply support policies [3], which motivate residential prosumers to feed their produced energy in the grid. Two of the most widely applied support policies to date are net metering (NM) and feed-in tariff (FIT) [4]. NM guarantees that prosumers' injected energy is compensated up to the point it does not exceed their own annual consumption. FIT, in contrast, compensates prosumers' injected electricity at a fixed rate for a given period of time. As of 2015, 52 countries have adopted NM incentives, while 110 jurisdictions at the national or state/provincial level have implemented FIT incentives [4].

These incentives have contributed to the rise of residential RES capacity, defining thus the upward trend in prosumer numbers [4, 5, 6]. However, merely subsidizing production is not sufficient to mitigate the dependence on fossil fuels. Green energy needs to effectively offset the consumption of gray energy (i.e., energy from mixed sources) [7, 8, 9]. Although NM and FIT motivate the injection of clean energy, they provide no incentives for consumers to actually use the injected energy. In addition, these policies reward production without considering the impact of peak supply on the low-voltage grid. The need has already been identified to phase out these traditional subsidy schemes in favor of mechanisms that scale better with growing decentralized generation [10, 11, 12, 13, 14]. However, no quantitative study has been performed to suggest the impact of *not* replacing current support policies in (future) scenarios with large number of prosumers. In this article the term scenario refers to the particular percentage of prosumers in a district. While numerous mechanisms have been proposed as alternatives to the current policies [15, 16, 17, 18, 19, 20], these mechanisms are rarely compared to each other. Furthermore, their improvement over traditional policies has not been quantified considering the trend of growing prosumer numbers.

In this article we compare support policies (also: incentive mechanisms, or subsidy schemes) for production and consumption of renewable energy in the residential sector[5] from the perspectives of key stakeholders in the low voltage grid, namely prosumers, consumers, energy providers and grid operators. We analyze their capacity of scaling with increasing number of prosumers while also highlighting relevant issues and guidelines for policy makers. Thus, the **contribution** of this article is threefold and can be summarized as follows:

[5] Projects of maximum 10kWp capacity.

- First, we evaluate the properties and characteristics of two traditional support policies – net metering and feed-in tariff, and quantify the issues they face with increasing renewable generation capacity. As a result we warn policy makers of the impending risks of these policies, confirming the need for their replacement.

- Second, we review four state-of-the-art mechanisms, namely two auction-based mechanisms (Nobel [17] and PowerMatcher [18]), one negotiation-based (Capodieci [19]) and one based on digital currency for energy (NRG-X-Change [20]). These mechanisms have been independently proposed and can be seen as potential alternatives to the state-of-play, but they have not been compared to each other or to the current traditional support policies.

- Third, we compare the performance of these state-of-the-art mechanisms against each other in simulations with real data, using NM and FIT as baselines. We evaluate their impact on the above stakeholders and study how they scale with increasing number of prosumers. The outcome of our study sheds light on current and future issues that are relevant for policy makers and energy actors in the evolving landscape of the smart grid.

This study differs from related work on support policies in several ways. Firstly, studies typically focus on evaluation of NM and FIT against other existing support policies (or variants thereof) that are already implemented in countries across the globe [13, 21, 22, 23]. In contrast, here we examine mechanisms proposed in the literature in order to consider alternatives that have not yet been introduced in any country. Secondly, existing work typically studies an individual's profitability of investment in renewables along several criteria, such as levelized cost of electricity, net present value, payback period, internal rate of return, return on investment, and so on [24, 25, 26, 27, 28]. Such analysis aims to determine *whether or not it is profitable for individual investors to install renewables* under various support schemes and *to what extent each policy supports a given RES technology*. Here we take a different approach and formulate our study in the following manner: *given that investments in renewables are profitable and continue, we determine what the effects of these continued investments would be on each stakeholder and on the grid*. Lastly, the research in this domain largely studies to what extent policies incentivize renewable generation alone [13]. In this work we also measure how each mechanism incentivizes the *consumption* of green energy in addition to its injection, by considering its price for consumers.

The remainder of this article is structured as follows. Section 2 describes published work related to support policies and state-of-the-art incentive mechanisms. In Section 3 we identify various issues with NM and FIT and speculate on the resulting mid to long-term consequences for the above stakeholders. We then highlight in Section 4 four incentive mechanisms presented in the literature. We compare these mechanisms in simulations in Section 5 and evaluate their performance against each other and against net metering and feed-in tariff. We then draw our conclusions in Section 6.

2. Related work

Feed-in tariff and net metering, as well as numerous other traditional support policies have been widely studied in terms of their investment risk and return, social welfare and electricity rates for the end user [29, 30, 31, 24, 32, 33, 34]. Each scheme brings forth advantages over others, and in turn suffers from drawbacks that other schemes address. While, NM and FIT have already been compared to state-of-the art mechanisms in literature, their performance has not been studied in scenarios with high generation capacity. Recently it has been proposed to replace these two schemes with mechanisms that better align the incentives of all stakeholders [11, 12, 35, 13].

A widely studied class of mechanisms for doing just that are auctions and energy markets. Several approaches have been proposed in literature for trading locally produced energy directly between prosumers and consumers, using energy markets [17, 18]. Others propose a combination between auction and negotiation to incentivize the balance of production and consumption [19]. We draw particular interest to the mechanisms proposed in [17, 18, 19] due to their relative simplicity of implementation and reported benefits. In addition, these approaches are detailed sufficiently well to allow reproducibility and have been extensively tested by their respective authors. These mechanisms will be surveyed in Section 4 and further studied in Section 5.

A relatively new take on incentive mechanisms is the idea of using energy as currency [36]. A number of articles envision the introduction of digital currency as financial incentive for energy exchange in smart grids. For example, Ergos is currency based on energy unit expenditure [37]. Ergos are distributed to consumers on a subscription basis and are surrendered in return for the energy content of a service, incentivizing the reduction of CO_2 emissions. Deko is another currency for energy [38]. It regards energy as an asset with better characteristics than gold or government debt and represents a promise to deliver electricity from producers. A related concept has been proposed, called SolarCoin [39], which works alongside traditional support policies to provide small supplementary monetary incentives to prosumers for their solar energy. As such, it behaves more as an auxiliary support scheme, such as tax reductions, than a primary incentive mechanism. Moreover, similar to FIT, it incentivizes only the production of green energy and it offers no incentives for its consumption.

All these digital currencies have been developed to solve particular problems – lower carbon emissions, price stability, better return on photovoltaics, etc. Similarly, we have previously introduced a currency for green energy, called NRGcoin [40, 41]. It aims to incentivize RES integration and maximize the consumption of renewable energy in the low-voltage grid by balancing the profits and costs of stakeholders. This currency is an integral part of our incentive mechanism that we call NRG-X-Change [20].

3. State of play

We first describe how stakeholders are connected in the physical low-voltage grid. The focus here is on residential homes, for which data were obtained for our study. We then outline two traditional support policies that have received wider attention, namely net metering and feed-in tariff. While these support instruments were beneficial for an incipient boost and integration of renewables, they display several drawbacks that we describe later in this section.

3.1. The physical grid

Households are connected to the electricity grid of the Distribution System Operator (DSO) and are organized in districts. A district is a group of homes connected via the low-voltage grid to the same substation of the DSO. Prosumers in our study are equipped with rooftop photovoltaic (PV) installations of various sizes and use the produced energy to cover their own demand first, before injecting the excess energy to the grid. Note that since substations are only informed of the injected energy and not the produced energy, henceforth by energy injection or supply we mean locally produced renewable energy injected in the grid. Similarly, energy consumption or demand is the energy delivered to the house from the power line, excluding the consumption of the own produced energy, which is not measured by the meter. In other words, all data refer to measurements "before" the meter from DSO's point of view. Injection and consumption are measured at 15-minute intervals, called time slots, which also define the granularity of the data. Electricity consumption is billed by the energy provider (EP), based on the smart meter measurements.

3.2. Current support policies

We outline here two of the most commonly applied support policies, namely net metering (NM) and Feed-in tariff (FIT). While net metering is a policy effective in numerous countries, FIT is by far the most widely adopted support instrument [4]. We also mention that NM is one of the support policies adopted by Belgium, the country in which our data is collected. We focus on these two support policies in particular, because neither of them rely on market signals, allowing us to better contrast their performance to market-based mechanisms (cf. Section 4).

3.2.1. *Net metering*

On an annual basis, the EP inspects the energy consumption readings of households. Using these readings, the invoice is determined by taking into account a fixed rate per kWh of energy consumption, based on a peak/off-peak tariff. A study of the VREG[6] (i.e., the Flemish energy regulator) estimated the average household electricity price for 2013 – the time period of our data – at 0.215 €/kWh, taking into account that some households have separate day and night meters, while others have a simple energy meter. When producers inject energy into the grid their energy consumption, as registered by their meters, decreases. In other words, the meter counts forward during consumption from the grid, and it counts backwards at the same rate when energy is injected to the grid. Remunerating prosumers at retail price allows them to use the grid as a virtual storage. However, the meter reading at the end of the year cannot be lower than at the start. In order to prevent households from becoming net producers, the EP reimburses each prosumer only for injected energy that does not exceed her[7] annual consumption. As of 2015 the VREG introduced the "prosumer tariff"[8] – an additional capacity charge to residential prosumers with a bi-directional meter. Since our historical data concerns a period before 2015, in our experiments the prosumer tariff does not apply.

3.2.2. *Feed-in Tariff*

Feed-in tariff (FIT) is a standard support policy through which different types of RES are guaranteed a fixed sale price for certain contractual periods [10, 42]. Unlike net metering, FIT rewards all injected energy regardless of the prosumer's own annual consumption, but it does so at prices lower than the retail price of electricity. For this reason, the inflow and outflow of electricity need to be measured separately (e.g. by a separate meter), which cannot be achieved with the traditional single bi-directional "spinning" meter. The actual feed-in tariff must be decided by policy makers, such that it is high enough to be attractive for RES investments, but not too high so as to cause overcompensation of prosumers. This support scheme allows

[6] `http://www2.vlaanderen.be/economie/energiesparen/milieuvriendelijke/monitoring_evaluatie/2013/20130628Rapport2013_2-Deel2Actualisatie-OT_Bf.pdf`

[7] to be read "his or her" from now on

[8] http://www.vreg.be/nl/hoeveel-betaalt-u-qua-prosumententarief (in Dutch)

policy makers to adjust the tariff at any time in order to control the speed of RES integration. Nevertheless, great caution ought to be exercised in these adjustments, as too large, too frequent or retroactive tariff changes undermine investor confidence, which is detrimental to the adoption of renewables [14, 24, 43, 44]. Likewise, these schemes could also lead to undesired societal outcomes by providing benefits to only one part of the electricity users, i.e. prosumers [45, p.1278]

3.3. Drawbacks of NM and FIT

Since NM and FIT have no connection to market price signals, they reward prosumers at a rate disproportionate to the actual demand for energy, which may lead to *overconsumption*. As a result of this drawback, prosumers are either *underpaid* or *overpaid*, where these costs are eventually passed on to end consumers. Moreover, these mechanisms do not incentivize the consumption of green energy injected in the local grid, but only its production. Furthermore, NM and FIT do not consider *grid stability* and lack scalability for future scenarios, as we will demonstrate in the remainder of this article. Below we elaborate on some of the most important drawbacks of the above two non-market-based support policies.

3.3.1. Overconsumption

Net metering caps the amount of green energy for which a given prosumer is paid, based on her own consumption. This policy encourages prosumers to withdraw from the grid *at least* as much energy as they inject on an annual basis, because the excess green energy that prosumers inject in the summer will discount their winter consumption of gray energy.

Evidence for overconsumption of prosumers under NM can be seen in Figure 1. Prosumers have significantly higher demand during the cold months, i.e. September to March, compared to that of consumers, and only slightly lower demand in summer. In fact, the excess supply from April to August matches closely with the higher demand of prosumers, i.e. the difference between prosumer's and consumer's consumption, between September and March. This observation supports the argument that **prosumers have incentives to use the grid as virtual storage**. Although numerous reasons can be attributed to the higher consumption of prosumers (e.g. prosumers may be wealthier and have larger homes), the support policy remains an important drive.

Prosumers' behavior is rational under this policy, but not in line with the need for reducing the overall consumption, especially that of gray energy. A more environmentally efficient policy should not encourage prosumers to use the grid as a virtual buffer, storing "free energy" for months with low production, due to the stress it exerts on the grid infrastructure. FIT, on the other hand, rewards prosumers at a rate lower than

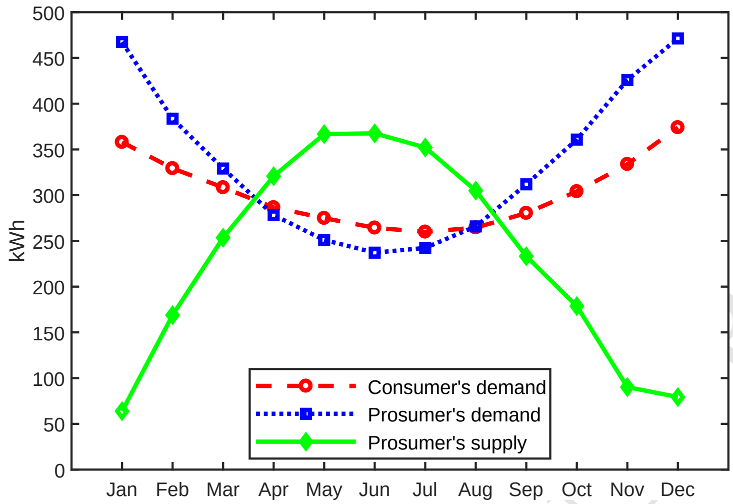


Figure 1: Median electricity supply (injection) and demand (consumption) per home in 2013. Data from 3100 Belgian homes under net metering policy.

the retail value of electricity. This policy encourages consumption of own produced energy and only then feeding the excess production in the grid.

3.3.2. Underpayment

While FIT rewards all injected energy, NM caps these rewards according to prosumer's own annual consumption. Consider a district with a majority of consumers and only few prosumers who have large production capacity (present scenario). Despite the large demand created by all consumers, those few prosumers will not be paid for all their injected energy if their own annual consumption remains lower than their own injection. In other words, NM does not reward excess annual supply per home even if it can actually be consumed locally in the district. **Net metering, therefore, does not sufficiently encourage the offset of gray energy in favor of green**.

3.3.3. Overpayment

NM and FIT reward injected energy without taking into account the actual energy demand. Consider a district where most homes are prosumers with sufficient production power (future scenario). The total consumption from the grid during daylight hours will be negligible compared to the amount of injected energy. All prosumers will be rewarded for the injected energy, even though there are not enough consumers to withdraw it. As the number of producers continues to increase [4, 6], **both NM and FIT will become costly to the energy provider** as we will demonstrate in Section 5. These costs will naturally be passed on to end consumers, threatening to rise the overall cost of electricity.

3.3.4. Grid stability

The above described drawbacks have implications on grid stability. Since net metering rewards injected energy at retail price, prosumers are indifferent between feeding their energy or self-consuming it. Using the grid as virtual storage exerts stress on the grid infrastructure (cables, transformers, etc.), requiring more frequent maintenance and reinforcements to prevent blackouts. Although the feed-in tariff policy does incentivize self-consumption by offering lower than retail price for fed-in green energy, it rewards all injected energy even when it is in surplus, which again strains the grid. **Both traditional policies, therefore, incentivize green energy without considering its impact on the grid infrastructure**.

3.4. The need for an alternative

Despite their drawbacks, NM and FIT have contributed to the rise in residential RES capacity. These policies have been the first step towards RES integration, performing relatively well when the number of producers is low compared to that of consumers. While this assumption has been true until recently, the number of prosumers is now sharply on the rise [46, 4]. With growing decentralization of renewable production and number of prosumers, issues like those above will exacerbate and impact all stakeholders in the low voltage grid. Experts advice to replace these traditional support policies with market-based incentive mechanisms in order to improve the incentives for renewable energy generation and its consumption [10, 11, 12, 13].

4. State-of-the-art incentive mechanisms

The recent expansion of research on smart grids has produced numerous incentive mechanisms for rewarding renewable energy production and consumption [15, 16, 17, 19, 20, 47]. We focus here on three approaches in particular — Nobel [17], PowerMatcher [47] and Capodieci [19], as they have been presented in sufficient detail to allow for reproducibility and have been extensively tested by their respective authors. However, they have not been compared to each other, in order to study what benefits each one offers over the rest. We also include our previously proposed incentive mechanism called NRG-X-Change [20], which has not yet been compared to other mechanisms as well. Below we describe the four incentive mechanisms in more details and in Section 5 we study how they compare to each other and to the current state of play.

In the **Nobel** approach [17], producers make predictions on the amount of green energy they are going to generate at each slot ahead of time and offer the excess energy (after own consumption) on an open bi-lateral energy market. Consumers submit scalar bids to buy green energy on that market, based on their predicted future demand for each slot. Buy and sell orders for green energy are submitted to the orderbook and are matched in real time according to a Continuous Double Auction mechanism [48, 49]. Naturally, all demand that is not traded on the market is covered by gray energy and billed by the EP. The cost of renewable energy is determined based on demand and supply on the energy market.

The **PowerMatcher** approach [47] resembles Nobel in the sense that it relies on a market mechanism to buy and sell renewable energy. While in Nobel agents submit a scalar bid for buying or selling a specific quantity of energy at each slot, in PowerMatcher agents submit a curve, i.e. a continuous function mapping price with demand (or supply). These bid curves are not submitted to a central orderbook, but to the local substation instead. After collecting the bid curve of each household for the given slot, the substation computes the equilibrium price at which supply matches demand and communicates this price to each household, along with the corresponding quantity of green energy to be traded, based on the submitted bid curves. Any demand outside this equilibrium is covered by gray energy.

The trading technique proposed by **Capodieci** *et. al* [19] also requires agents to make predictions of their future supply and demand. However, energy is not traded on an exchange market, but it is contracted using negotiation between individual producers and consumers. Agents negotiate in pairs by gradually updating their offers until a consensus on the price is reached, or until the maximum number of negotiation steps have passed.

The **NRG-X-Change** approach [20] has elements of both traditional and market-based mechanisms. Similarly to NM and FIT, NRG-X-Change does not rely on an energy market — locally produced renewable energy is simply fed into the grid, and is withdrawn by consumers. Incentives, however, are distributed in near real-time and based on the total supply and demand in the local district at each time slot, rather than based on the individual's annual supply and demand. During overproduction prosumers are paid proportionally to the injected energy that covers the total demand in the district, such that the overproduced energy is not remunerated. In doing so, prosumers are always rewarded for the maximum amount of renewable energy that is withdrawn by consumers at the time it is injected. Therefore, similarly to other market-based mechanisms and unlike NM and FIT, under NRG-X-Change it matters *when* the energy is injected.

All payments for green energy are carried out in NRGcoin instead of fiat money [40, 41]. This decentralized digital currency is based on Blockchain technology and shares characteristics with Bitcoin [50].

Independently from injection and offtake of energy, NRGcoins are traded on open *currency* exchange markets for their monetary equivalent, e.g. Euro, Dollar, Pound, etc. Buy and sell orders for NRGcoins are matched using an orderbook, similarly to the energy exchange market in the Nobel approach. However, unlike the energy market, the currency market is not tied to energy time slots – the currency is traded continuously, as in traditional FOREX markets. The value of NRGcoin is determined based on free market rules and on the principles of supply and demand.

Consumers, who can purchase coins from the market, pay 1 NRGcoin to the EP for each kWh of green energy they use. Note that the coins are not destroyed upon payment, but remain in circulation. Each prosumer who injects energy into the grid is then paid by the EP with NRGcoins as described above – based on the balance of supply and demand in the district. For each 1 kWh of injected energy that matches demand, the prosumer receives 0.5 NRGcoin from the EP. In addition, the prosumer also *creates* (or mints) 0.5 new NRGcoins, which are securely issued by the decentralized NRGcoin protocol [40, 41]. This decentralized protocol running on each smart meter is responsible for generating currency equal to the coins received from the EP. Thus, for each 1 kWh of green energy, the prosumer receives 0.5 NRGcoin from the EP and creates 0.5 NRGcoin from the decentralized protocol. The newly generated coins serve to bring new currency in circulation without a centralized issuer, relying instead on cryptographic mechanisms as in Bitcoin. As with all other studied mechanisms, any demand that is not covered by green energy (here paid for with NRGcoins), is covered by gray energy and paid in the local fiat currency to the energy provider.

The six studied approaches differ in the amount of green energy they support and the rate at which they support it. These parameters have important implications on the stability of the grid. As explained in Section 3.3.4, NM and FIT do not consider the impact of injected green energy on the stability of the (local) grid. The state-of-the-art approaches, in contrast, employ market mechanisms where only "matched energy" is paid. By matched energy we refer to green energy that was sold to or withdrawn by a consumer from the grid. Such mechanisms offer no incentives to inject energy that is in excess, though they also do not penalize it. Nevertheless, these state-of-the-art approaches show characteristics that are more favorable than those of NM and FIT in terms of grid stability. The studied approaches also differ in the incentives they offer for consuming the injected green energy. We summarize the properties of all six studied mechanisms in Table 1 and subjectively indicate their readiness for implementation.

Table 1: Summary of studied support mechanisms

support mechanism	amount of green energy supported	rate of support	green energy consumption incentives	concept readiness for implementation
Net metering	all injected energy below own annual consumption	retail electricity price	none	already operational
Feed-in tariff	all injected energy	adjustable pre-set rate	only self-consumption, if rate < retail price	already operational
NRG-X-Change	injected energy consumed in district	1 NRGcoin/kWh	yes, if NRGcoin price < retail price	in development, relies on emerging technology
Nobel	auctioned energy (scalar bids)	market rate	yes, if market rate < retail price	ready, relies on established technology
PowerMatcher	auctioned energy (bid curves)	market rate	yes, if market rate < retail price	ready, relies on established technology
Capodieci	energy sold through negotiation	negotiated price	yes, if negotiated price < retail price	ready, relies on established technology

5. Results and comparison

In this section we evaluate the performance of the incentive mechanisms described above for each stakeholder in the low-voltage grid, using NM and FIT as baselines. We demonstrate how state-of-the-art mechanisms scale with growing number of prosumers according to several indicators, such as revenues from injection and costs for consumption of green energy. We implemented each state-of-the-art mechanism as documented in their respective publication. For those values that are not explicitly specified we selected a favorable parameter configuration by trial and error. For this reason, all measurements shall be regarded as only relative for the purpose of comparison between the studied mechanisms. Nevertheless, our simulations run with real consumption and production data, and thus we can draw conclusions for the performance of each approach in different (future) smart grid scenarios. Again, we use the term "smart grid scenario" to distinguish between different densities of prosumers in a district, e.g. 10%, 30%, etc.

5.1. Experimental Setup and Data

All experiments are performed in Repast (Recursive Porous Agent Simulation Toolkit) Simphony, which is a robust simulator that supports agent-based modeling techniques [51, 52]. Repast is composed of six modules: the Engine (responsible for controlling the activities in a simulation), the Logging Module (responsible for recording simulation results), the Interactive Run Module (responsible for managing simulation runs under the direct control of a user), the Batch Run Module (responsible for completing a set of simulation runs without requiring the direct intervention of a user), the Adaptive Behaviours Module (responsible for providing adaptive components for implementing agent behaviors), and the Domains Module (responsible for providing area-specific functions) [52]. Besides the engine, for our experiments, we only use the logging, batch (to automate the execution of scenarios), and adaptive behaviours (to implement the behaviour of support mechanisms as well as consumers and prosumers) modules.

We investigate various smart grid scenarios, where each scenario is repeated 100 times in the same setting, but with a different seed for the pseudo-random generator.[9] A set of 100 runs in the same setting constitutes a sample. Each scenario is evaluated in a district of 60 houses, i.e. a scenario of 10% prosumers refers to the setting in which only 6 houses can generate renewable energy, while the remaining 54 houses are pure consumers. According to the data, the average number of homes behind a single medium-to-low voltage transformer (i.e. substation) is indeed 60. The data consist of 2804 consumers and 289 prosumers in a single town in the countryside of central Belgium. The current percentage of prosumers in this town is around 10%. All energy production in the data is by photovoltaic panels and no energy storage units are present.

A given percentage of prosumers in a district constitutes a scenario. At each run of the simulations 60 houses are selected uniformly at random from the entire set of houses in the data, such that the ratio of prosumers to houses in the desired scenario is achieved. For the selected houses, during one simulated year, we then register and evaluate a number of indicators for each incentive mechanism. Each simulation run uses the real injection and consumption values of the selected houses. The data has a granularity of 15 minutes per slot t, accounting for 96 injection and 96 consumption values in each day. In all graphs henceforth each data point is the median of a sample of 100 runs, while error bars, wherever present, indicate one standard deviation above and below the median.

5.2. Assumptions

Note that all experiments are performed using real data, resulting from the currently implemented net metering policy in Belgium. Deploying one of the state-of-the-art mechanisms as a *de facto* policy may alter the behavior of agents, leading to different consumption/production patterns than those in our data and therefore different results. Unfortunately, we cannot anticipate the true behavior of agents under these new

[9] Simulations were performed on an Azure Vitrual machine with 8-core 2.4 GHz Intel Xeon CPUs and 53GB of RAM memory and took 340 hours (14 days) in total.

mechanisms relying on data from the current state of play. For this reason, our numerical values serve only as a relative comparison between the chosen mechanisms.

Lastly, throughout our analysis we assume production from residential PV panels, due to the data we have available. Production from other renewable energy sources may lead to other supply-demand (im)balance altogether. We also study the what-if scenarios independently from each other over the period of one year. We do not consider the effect of changes in prosumer numbers over this time period, nor any differences between the tariffs for old or for new installations. Similarly, we do not factor in potential changes in the efficiency of RES technology in future scenarios.

5.2.1. Bidding Strategy

To submit market orders agents use the Adaptive-Aggressiveness (AAggressive) bidding strategy [53], which is composed of four basic blocks: equilibrium estimator, aggressiveness model, adaptive layer and bidding layer. Based on historical record of prices, the *equilibrium estimator* computes the target price for the trader, whereas the *aggressiveness model* determines the trader's risky behavior to submit high bids (or low asks). The *adaptive layer* implements both short-term learning that updates the agent's aggressiveness, as well as long-term learning that modifies the agent's overall bidding behavior. Finally, the *bidding layer* implements a set of rules to determine whether the trader will submit bids (asks) or not.

Parameter tuning for AAggressive was done based on the sensitivity analysis provided in [53]. While the sensitive parameters were fixed according to the authors' suggestions, the rest of the parameters are randomly initialized within the suggested limits at each run in order to generate a heterogeneous population of traders. In this way, some traders may learn faster than others and be more (or less) aggressive, which enables the diversity of market orders. Likewise, other bidding strategies could also be explored. For instance, in [54], the authors have proposed a bidding strategy to be used for an aggregator that aims to simultaneously provide electricity and thermal balance.

5.2.2. Prediction

Besides bidding on the price of energy, agents need to predict *how much* energy they need to bid for. The real data contain the actual production/consumption values for the entire time interval we simulate. However, we need to simulate the effect of prediction error, i.e., buying more/less energy (or NRGcoin) than needed and then re-selling the excess or purchasing the deficit. For this reason, agents "predict" their future consumption/production by taking a uniformly random value in the 5% interval around the true value from the real data, in order to emulate prediction inaccuracy. We use this simplification, rather than implementing and tuning a fully-fledged prediction algorithm, since the effects of prediction (in)accuracy are not the aim of this study, but cannot be entirely discarded. In fact, since all above state-of-the-art mechanisms rely on prediction, the particular choice of prediction technique or emulated inaccuracy is not relevant, as we are interested in the relative performance of the surveyed approaches.

5.3. Numerical results

Through a number of charts we study the implications of each incentive mechanism for prosumers, consumers and energy providers. We also examine the relationship between prosumer numbers and energy injection and consumption.

Nomenclature

N	number of houses in a district (60)
i	house index ($\in N$)
Y	number of days in a year (365)
d	index of days over the year ($\in Y$)
T	number of 15 minutes time slots in a day (96)
t	time slot index in a day ($\in T$)
p	percentage of prosumers in the district
χ^p	percentage of prosumers in the district under which a variable χ is calculated
C	total consumption in the district over one year
D	portion of the total consumption during sunlight hours
r_d	sunrise time slot in Belgium on day d of the year
s_d	sunset time slot in Belgium on day d of the year
G	total locally supplied renewable green energy over one year
R	maximum consumption of locally injected energy per slot summed over one year

5.3.1. Implications of Prosumer Numbers

Based on production and consumption data from Belgium, we carry out simulations to investigate possible future scenarios concerning the percentage of prosumers in a district. Figure 2 displays measurements in these scenarios, where the random selection of 60 houses in each run accounts for the variance in the data. Note that in this graph we are not comparing support policies, but we are simply looking at energy injection

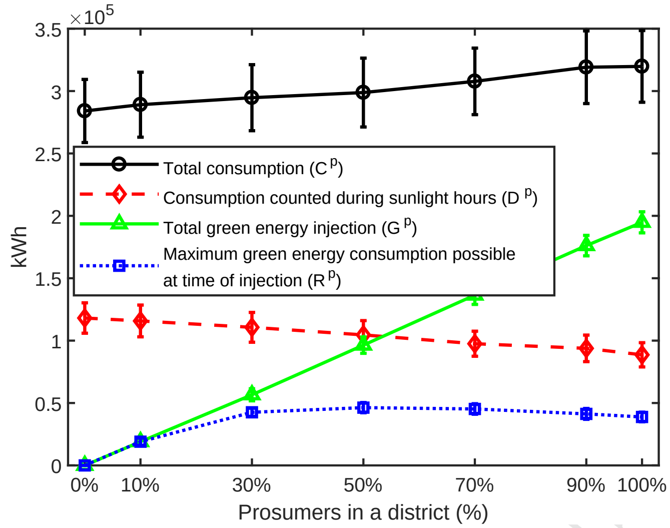


Figure 2: Injection and consumption measurements for different densities of prosumers in a district of 60 houses. C^P, D^p, G^p and R^p are defined in Equations 1, 3, 4 and 6 respectively. Measurements are for the entire district for one year.

and consumption. We display the total consumption C^p of all $N = 60$ houses during one year, $Y = 365$ days with $T = 96$ time slots in a day, where the superscript p defines the percentage of prosumers in the district for each considered scenario:

$$C^p = \sum_{d=1}^{Y} \sum_{t=1}^{T} C^p_{t,d} \tag{1}$$

$$C^p_{t,d} = \sum_{i=1}^{N} C^p_{i,t,d} \tag{2}$$

where $C^p_{i,t,d}$ is the home's real-time demand for energy, i.e. total consumption of home i during slot t of day d. By "real-time demand" we refer to the energy demand within one time slot (15 minutes) and not the instantaneous demand at sub-second intervals. We also display the portion of the total consumption during sunlight hours D^p, according to the sunrise r_d and sunset time slot s_d for each day d in Belgium:

$$D^p = \sum_{d=1}^{Y} \sum_{t=r_d}^{s_d} C^p_{t,d} \tag{3}$$

We measure consumption during sunlight separately, because in this period prosumers consume their own generated energy and inject the excess to the grid. Recall that by demand (or consumption) we mean the energy withdrawn from the grid, which does not include consumption of own produced energy. Similarly, supply (or injection) indicates the energy injected to the grid after self-consumption. We observe that the daytime consumption D^p decreases when number of prosumers p increases, because the latter consume their own energy during sunlight hours, resulting in a lower demand in the district. The total consumption C^p, however, is positively correlated with the number of prosumers, i.e. the more prosumers there are in a district, the higher the total consumption. This result signifies that **on average prosumers consume more energy than consumers**, which is consistent with Figure 1.

We also display the total locally supplied renewable energy G^p, based on prosumer numbers p:

$$G^p = \sum_{d=1}^{Y} \sum_{t=1}^{T} G^p_{t,d} \tag{4}$$

$$G^p_{t,d} = \sum_{i=1}^{N} G^p_{i,t,d} \tag{5}$$

Naturally, in scenarios with more prosumers, the supply of green energy is higher. In addition, we plot the maximum locally injected renewable energy that can be consumed in the grid at the time it is produced, R^p. In other words, we take the minimum between supply and demand *at each slot t* and sum these values for one year:

$$R^p = \sum_{d=1}^{Y} \sum_{t=1}^{T} min(C^p_{t,d}, G^p_{t,d}) \tag{6}$$

Note that in Figure 2 the lines of total injection (G^p) and consumption during sunlight hours (D^p) are in principle the upper limits for the values of R^p. However, due to the mismatch between injection and consumption at each slot, R^p reaches neither of those limits when $p > 10\%$.

We can observe that with prosumer percentage of $p \leq 10\%$ all produced energy can be consumed in real-time ($G^p \approx R^p$) and therefore demand flexibility would offer little benefit. However, the supply covers only small portion of the demand during sunlight hours ($G^p \ll D^p$). When the percentage of prosumers $p > 50\%$, the amount of injected energy can theoretically cover all demand during sunlight ($G^p \geq D^p$). With prosumer densities $p > 10\%$, however, not all supplied energy can be consumed within the district at the time of injection ($G^p > R^p$), as there is a significant overproduction mid-day. Note that G^p and R^p are measurements over the course of 1 year. Naturally, the overproduction during summer months is much greater than that during winter. Recall that net metering pays prosumers for their *annual* and not real-time supply. As soon as the ratio p exceeds 10%, the real-time demand for energy R^p will remain lower than the supply G^p resulting in overpayment to prosumers. Therefore, in districts with $p > 10\%$ flexibility becomes a necessity. Although the excess energy at noon can be sold to other districts, a city comprised of districts with similar prosumer percentage will still have excess supply at noon if the majority of this energy comes from PVs. These results are yet another evidence that **flexibility is a necessary component in the immediate future if generation capacity continues to rise**.

Lastly, note that the maximum green energy consumption possible at time of injection, R^p, peaks at around $p = 50\%$ prosumers. In districts with larger prosumer numbers the real-time demand for energy, $C^p_{t,d}$, is lower due to self-consumption, and hence R^p declines for $p > 50\%$.

5.3.2. Implications for Prosumers

Issues derived from the increasing number of prosumers include the consequences of overproduction of renewable energy. The issue identified in Section 3.3.3, suggests that NM and FIT will result in significant overpayment of prosumers, considering the amount of energy R^p that can actually be used at the time of injection. We investigate this effect in Figure 3, where we compare the annual revenue of individual prosumers under the studied incentive mechanisms. Although our historical data are from 2013, it is worth noting that, as of 2015 the NM tariff in Flanders has been corrected with the introduction of a "prosumer tariff" (cf. Section 3.2.1). This tariff affects only prosumers and depends on the maximum capacity of the PV installation inverter and it also varies per grid operator. As an example, consider a prosumer tariff of 88.44 €/kW/year. A prosumer with a standard inverter capacity of 3kW would have to pay a prosumer tariff of 265.32 € per year. Thus, in Figure 3 the revenue of this prosumer under NM *with* prosumer tariff would drop to about 360 €, which is highly comparable to his revenue under FIT.

One can observe in Figure 3 that under NM and FIT prosumers will continue to be rewarded at a steady rate, regardless whether their energy can be consumed. These incentives will continuously drive consumers to install renewable generators and become producers, increasing the threat of peak supply and thus endangering the overall stability of the grid.

The alternative approaches, on the other hand, reward prosumers only for energy that matches demand. NRG-X-Change, Nobel, PowerMatcher and Capodieci are mechanisms in which energy is sold based on consumer demand for green energy in the district. Since the overall demand during daylight is low in districts with many prosumers, the revenue of each prosumer in those districts is low too, unless effective flexibility approaches are applied. Since prosumers have no incentives to inject more energy than it is needed, it is therefore expected that these mechanisms exert overall lower stress on the grid infrastructure, even in the absence of flexibility instruments.

Although the four state-of-the-art approaches show similar trend, their performance in terms of revenue

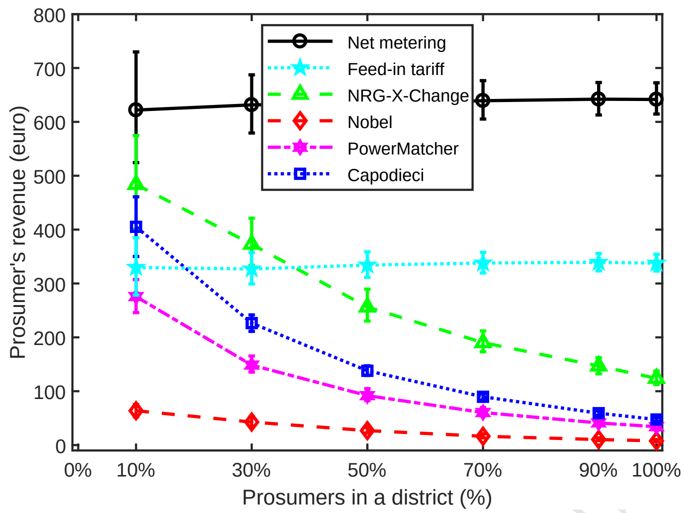


Figure 3: Prosumer's annual revenue for green energy under the studied mechanisms. For NRG-X-Change we display the euro value of prosumer's NRGcoins, which is taken at the current exchange rate at the time of each transaction.

differs. Nobel offers the least revenue for prosumers, with PowerMatcher and Capodieci offering higher incentives for injecting energy. One reason for this result could be attributed to the amount of information contained in agents' bids. In Nobel, agents submit a bid to sell or buy a scalar quantity of energy for a scalar price. The energy is sold only if there is a buy order with price equal to or higher than the sell price. In PowerMatcher the bid is a curve, representing individual price valuations for different quantities of energy. This type of order contains more information on the preferences of agents and increases the chance that (some of) their energy is sold. The Capodieci approach allows agents to relax their initial price during negotiation rounds and therefore more energy is traded. This effect can be observed in Figure 4. The latter shows the amount of green energy that was paid in each mechanism relative to R^p – the total amount of green energy that can be consumed in real-time, i.e. at the time it is injected. These results may suggest that market mechanisms, which allow for more flexibility in the expression of energy price valuation (e.g. through more informative bids or negotiation), can boost the amount of traded green energy and hence offset energy from mixed sources. Ignoring the actual demand, on the other hand, can lead to overpayment of prosumers. FIT pays prosumers for all their renewable energy, even if it is in excess, and hence the ratio exceeds 1. As suggested in Section 3.3.2, NM may result in underpayment of prosumers at low densities ($p = 10\%$), which is evident in Figure 4. At higher prosumer densities, however, similarly to FIT, net metering overpays

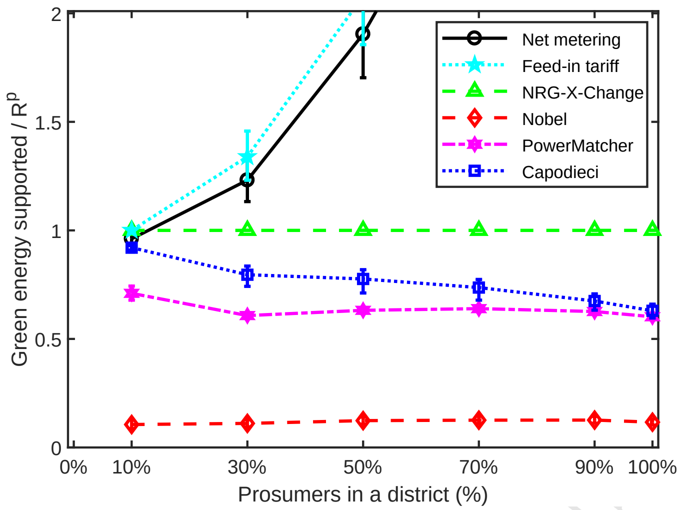


Figure 4: Ratio of injected green energy that was supported (i.e. paid by EP or by consumers) vs. the maximum amount of green energy that could be consumed at the time it is injected (R^p). Ratios below 1 indicate underpayment while above 1 are overpayment.

prosumers (cf. Section 3.3.3). NRG-X-Change always rewards prosumers at a flat rate for the maximum amount of energy that can be consumed, while overproduction is not paid, and therefore the above ratio is 1 in each scenario.

5.3.3. *Implications for Energy Provider*

The energy provider bills customers for gray energy at the retail value of 0.215 euro/kWh. The EP buys this energy on the wholesale market at 40 euro/MWh.[10] We can therefore calculate the profit of the energy provider under each mechanism by subtracting the expense of the support policy and the purchase of energy from the revenue collected. Note that here we do not factor in any additional taxes and grid costs, as they are identical for all studied approaches.

As a result of the overpayment of prosumers under NM and FIT (cf. Section 3.3.3), the profit of the energy provider is expected to decline with the installation of new residential renewable generators. This trend can be observed in Figure 5. It is likely that this loss in revenue will be transferred to the end consumer instead, by increasing the overall cost of energy in the future.

In contrast, state-of-the-art approaches display a different behavior altogether. Under the Nobel mech-

[10] Average price on https://www.belpex.be/ for 2013.

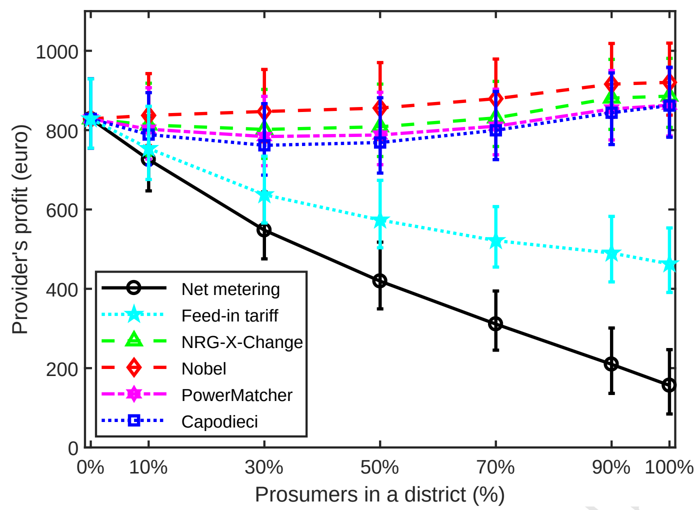


Figure 5: Energy provider's annual profit per house.

anism prosumers are able to sell the least amount of renewable energy among the different approaches (cf. Figure 4). All energy that is not bought on the market is billed by the EP at retail price. Since the EP does not pay any support to producers, it earns the highest revenue among the different mechanisms. However, since very little locally produced renewable energy is traded under this mechanism, the energy provider would need to find other sources of clean energy in order to comply with future environmental targets, imposed by regulatory bodies. In fact, all four state-of-the-art mechanisms generate comparable profits for the EP. The reason for the slight increase of these profits in scenarios with more prosumers is the mismatch between supply and demand, i.e. in those scenarios less green energy can be consumed at the time it is produced (cf. Figure 2) and hence prosumers need to purchase slightly more energy from the grid. Note also that in none of these state-of-the-art mechanisms does the energy provider pay any support to prosumers. This is the reason behind the large difference in profit compared to NM and FIT.

Although state-of-the-art mechanisms deliver roughly the same profits to the EP, the amount of green energy consumed and paid to prosumers differs across the studied policies. Since the energy provider aims to maximize its revenue while complying with (future) renewable targets it is important to study the relationship between EP's profits and the green energy incentives that each mechanism offers. In Figure 6 we display this trade-off. We show the effect of each mechanism along two axes – the amount of supplied green energy for which prosumers receive revenue and the overall profits of the EP. Combining this information allows

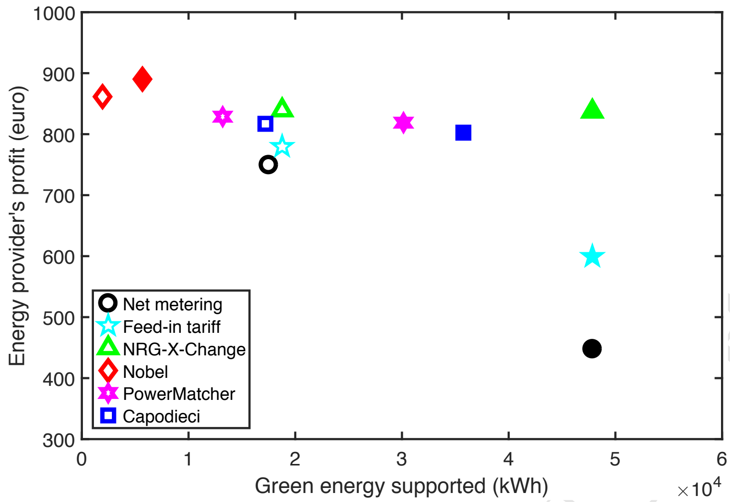


Figure 6: Energy provider's annual profit per house versus the amount of injected green energy that is supported (i.e. paid by the EP or by consumers) in each mechanism. Empty markers show scenario with 10% prosumers and full markers stand for 50% prosumers.

us to better observe the trade-offs between these mechanisms and their current and future performance. For example, while the Nobel approach ensures the highest profits for the EP, it provides the least support for renewable energy. Moreover, this effect is expected to not change much with the installation of more renewables in the future. Conversely, while NM and FIT reward (nearly) all green energy supplied, they incur high costs for the energy provider as a result of overpayment. As mentioned earlier, these costs will continue to grow with the further proliferation of distributed renewable generators, which is what we observe in this figure. In contrast, NRG-X-Change shows high support for green energy at little expense to the EP. Although it strikes a good balance between these trade-offs, NRG-X-Change relies on the novel Blockchain technology, which has not yet been sufficiently tested in the smart grid sector. PowerMatcher and Capodieci, on the other hand, can already be implemented in the current state of play and offer relatively good green energy incentives and high profits to the EP.

5.3.4. Implication for Consumer

Each mechanism results in a different cost of energy for consumers. This cost is computed by taking into account the amount of green and gray energy bought by consumers and the price they have paid per kWh for each. Figure 7 shows these unit costs averaged over one year for different scenarios. Under NM and FIT consumers are billed at the fixed rate of 0.215 €/kWh for both renewable and non-renewable energy and

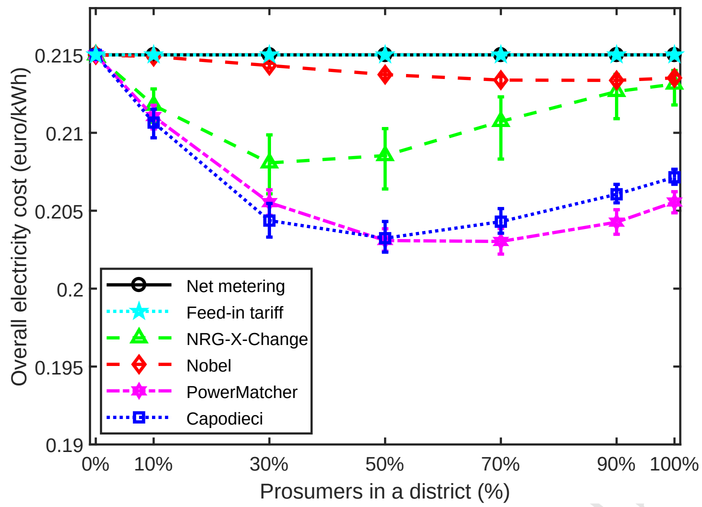


Figure 7: Unit price of energy averaged over one year. The cost involves renewable and gray energy.

therefore there is no variance among the different runs, unlike the other approaches.

485 In Nobel, PowerMatcher and Capodieci the price of renewable energy is determined according to bidding and negotiation. The maximum bid for 1 kWh of green energy is capped at 0.215€, which is the fixed price of gray energy that agents can withdraw from the grid at any time. Hence, the price at which consumers buy green energy is always less or equal to the retail price of gray energy. Since less of the (cheaper) renewable energy is sold in Nobel, its overall cost of energy is higher than that of the other studied state-of-the-art

490 mechanisms. In PowerMatcher and Capodieci the unit cost of energy is at its lowest point at $p = 50\%$ prosumers as this is the scenario in which the most renewable energy can be consumed in real time (cf. Figure 2). In NRG-X-Change renewable energy is not traded on the market, but is paid with NRGcoins at a fixed rate of 1 NRGcoin for the consumption of 1 kWh of locally produced green energy. For more details on NRG-X-Change and the function of the NRGcoin currency we refer the interested reader to [20, 41]. The

495 NRGcoins are traded against euro on a currency market. We therefore calculate the unit price of green energy under NRG-X-Change as the euro value of 1 NRGcoin at the time the green energy is used. We observed that for prosumer percentage of $p = 30\%$ the currency supply on the market exceeds the demand.[11] This effect causes the NRGcoin exchange range to drop, leading to cheaper green energy for consumers.

[11]Results on the market dynamics of NRGcoin are not displayed, as they are out of the scope of this article.

5.3.5. Implications for Grid Operators

While NRGcoin is not designed as a demand-response mechanism, it does exhibit similar properties. Since NRGcoin makes green energy cheaper for consumers in all scenarios (cf. Figure 7), they have incentives to shift their consumption to periods when green energy is produced. This shift will result in lower peak demand and in lower peak supply, helping to stabilize the grid and minimize the stress on the grid infrastructure. In addition, NRGcoin has built-in incentives for installing energy storage devices and promoting self-consumption. Prosumers receive less than one NRGcoin per injected kWh and hence they will maximize the value of their renewable generators by storing or self-consuming their produced energy as much as possible before feeding the excess in the grid.

6. Conclusions and Outlook

Incentive mechanisms for residential energy production and consumption are a vital stimulus in the race to meet our environmental targets. Policy makers need to carefully consider their costs and implications not only to prosumers, but also to other key stakeholders in the low-voltage grid – consumers, grid operators and energy providers. Net metering and feed-in tariff were successful in stimulating the initial penetration of decentralized micro-generation units. However, their continued operation threatens to have adverse effects in the long run. These two policies do not consider the issue of grid stability and do not provide adequate incentives for production and consumption of green energy especially in scenarios with high prosumer numbers. With renewable generation reaching critical mass, we highlighted the need to replace these widely applied policies before they exert negative impact on the above stakeholders and on the grid. One way in which these two policies could be improved is to have their remuneration rate dependent not only on the (net) injection of isolated prosumers, but on the overall energy balance of the whole district. In other words, payments should reflect the temporal effect of injected energy and thus reward prosumers only when there is (local) demand.

We focused on four potential state-of-the-art alternatives that are well-detailed and sufficiently tested. We evaluated the incentives that each mechanism offers for feeding in locally produced green energy and the cost of buying that energy by consumers. Using real data, we simulated potential future scenarios concerning the average number of prosumers in a district in order to study the performance and characteristics of these mechanisms in the face of increasing generation capacity. These approaches represent different types of policies for monetizing green energy – using energy markets, negotiation, or digital currencies, each with their own strengths, weaknesses and requirements.

Each approach offers different revenue for the energy provider and prosumers, different unit cost of energy for consumers and different overall support for green energy consumption. PowerMatcher and Capodieci allow to achieve the cheapest unit cost of energy, although not the highest revenue for prosumers. Nobel brings the most revenue for utilities, as it does not sufficiently incentivize the trade of renewable energy. NRG-X-Change, on the other hand, rewards all green energy that can be consumed, brings high revenue for the energy provider and prosumers, but it might not offer the cheapest unit cost of energy for consumers. In addition, it requires a paradigm shift and understanding of the relatively novel blockchain technology. We also observed that markets, in which bids contain more information on agents' price valuation or that allow to relax the initial offer can boost the exchange of renewable energy.

Nevertheless, more research and technological advancements are needed to align stakeholders' incentives to reduce our dependency on fossil fuels. A shift towards renewable resources alone is not enough to completely eliminate the environmental implications of mixed energy production [8]. We need to also reduce our overall demand for energy.

In future work we plan to investigate how the studied mechanisms perform in combination with flexibility instruments, such as energy storage and demand-response. However, developing innovative and intelligent means to support the user in her consumption pattern should not be considered the ultimate goal. In essence, the awareness of people dealing with energy is the critical point that needs attention and it is the inspiration for our current and future work.

Acknowledgements

The research in this article has been made possible thanks to the following research grants: EU FP7 grant 324321 (project SCANERGY); Flanders Innovation and Entrepreneurship grants: SBO 140047 (project Smile-IT), HBC.2016.0239 and HBC.2017.0317; and Fonds National de la Recherche, grant 9132240.

Glossary

auction-based mechanism	incentive mechanism involving trading through auction
Capodieci	incentive mechanism proposed in [19]
CDA	Continuous Double Auction

clean energy	see green energy
consumer	energy consumer
demand-response mechanism	mechanism that incentivizes a shift in energy consumption in time
digital currency	a form of money with no paper bills
DSO	Distribution System Operator
energy injection	when a house feeds green energy into the grid
energy market	market for trading electricity
EP	energy provider
Feed in tariff (FiT)	traditional support policy, in which injection is rewarded at a fixed rate
fiat money	money established by a government as a legal tender (e.g., euro, dollar, etc.)
FOREX	foreign currency exchange market
gray energy	energy from mixed sources
green energy	energy from renewable energy sources
grid stability	the notion of grid balance - when energy supply matches demand
grid stakeholder	a relevant actor in the grid
incentive mechanism	see support policy
low-voltage grid	the electricity grid to which residential homes are connected
market-based mechanism	incentive mechanism involving a market on which trading occurs
negotiation-based mechanism	incentive mechanism involving trading through negotiation
Net metering (NM)	traditional support policy, in which the electricity meter spins backwards during injection
Nobel	incentive mechanism proposed in [17]

NRG-X-Change	incentive mechanism proposed in [20]
NRGcoin	blockchain-based crypto-currency proposed in [40, 41]
peak supply	a setting in which injected energy is at its peak
PowerMathcer	incentive mechanism proposed in [18]
prosumer	energy producer and consumer
PV	photovoltaic installation
Repast Simphony	Java-based simulator for agent-based modeling [51, 52]
RES	renewable energy source
smart grid scenario	particular percentage of prosumers in a district
smart meter	device that measures the energy flow to/from a house
state-of-play	the currently observed state of the grid
state-of-the-art mechanism	incentive mechanism proposed in the literature
subsidy scheme	see support policy
support policy	mechanism incentivizing the integration of RES
traditional support policy	support policy already in place
VREG	the Flemish regulator for electricity and gas

References

[1] European Commission, Europe 2020: A strategy for smart, sustainable and inclusive growth, COM (2010).

[2] European Commission, Energy roadmap 2050: Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions, COM (2011).

[3] L. Butler, K. Neuhoff, Comparison of feed-in tariff, quota and auction mechanisms to support wind power development, Renewable Energy 33 (8) (2008) 1854–1867.

[4] REN21, Renewables 2016 Global Status Report, Tech. rep., Renewable Energy Policy Network for 21st Century (2016).

[5] International Energy Agency – Energy Technology Systems Analysis Programme (IEA–ETSAP), International Renewable Energy Agency (IRENA) , Renewable energy integration in power grids, Tech. Rep. Technology Brief E15, IEA-ETSAP (2015).

[6] International Energy Agency (IEA), Renewable Energy – Market Analysis and Forecasts to 2021, Tech. Rep. Medium-Term Market Report 2016, IEA (2016).

[7] I. Razo-Zapata, M. Mihaylov, A. Nowe, Integration of load shifting and storage to reduce gray energy demand, in: Proceedings of the 5th International Conference on Smart Cities and Green ICT Systems, 2016, pp. 154–165.

[8] D. Phatak, R. Robucci, N. Banerjee, Beyond a Usage Threshold, NO Form of Energy is Sustainable or Green, in: Proceedings of the 3rd International Conference on Smart Grids and Green IT Systems, 2014, pp. 185–190.

[9] P. Bertoldi, S. Rezessy, V. Oikonomou, Rewarding energy savings rather than energy efficiency: Exploring the concept of a feed-in tariff for energy savings, Energy Policy 56 (2013) 526 – 535.

[10] T. D. Couture, K. Cory, C. Kreycik, E. Williams, Policymaker's guide to feed-in tariff policy design, Tech. Rep. NREL/TP-6A2-44849, National Renewable Energy Laboratory (NREL) (2010).

[11] The European Commission, European Commission guidance for the design of renewables support schemes, in: Delivering the internal market in electricity and making the most of public intervention, The European Commission, Brussels, 2013.

[12] C. Greer, D. A. Wollman, D. E. Prochaska, P. A. Boynton, J. A. Mazer, C. T. Nguyen, G. J. FitzPatrick, T. L. Nelson, G. H. Koepke, A. R. Hefner Jr, et al., NIST framework and roadmap for smart grid interoperability standards, release 3.0, Tech. Rep. NIST SP-1108r3, The National Institute of Standards and Technology (2014).

[13] E. Cerd, P. del Ro, Different interpretations of the cost-effectiveness of renewable electricity support: Some analytical results, Energy 90, Part 1 (2015) 286 – 298.

[14] REN21, Renewables 2017 Global Status Report, Tech. rep., Renewable Energy Policy Network for 21st Century (2017).

[15] J. A. Lesser, X. Su, Design of an economically efficient feed-in tariff structure for renewable energy development, Energy Policy 36 (3) (2008) 981–990.

[16] P. A. Narbel, Rethinking how to support intermittent renewables, Energy 77 (2014) 414–421.

[17] D. Ilic, P. G. Da Silva, S. Karnouskos, M. Griesemer, An energy market for trading electricity in smart grid neighbourhoods, in: 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST), Ieee, 2012, pp. 1–6.

[18] J. Kok, C. Warmer, I. Kamphuis, PowerMatcher: multiagent control in the electricity infrastructure, in: Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems, 2005, pp. 75–82.

[19] N. Capodieci, G. A. Pagani, G. Cabri, M. Aiello, Smart meter aware domestic energy trading agents, in: Proceedings of the 2011 workshop on E-energy market challenge, ACM Press, 2011, pp. 1–10.

[20] M. Mihaylov, S. Jurado, K. Van Moffaert, N. Avellana, A. Nowé, NRG-X-Change: a Novel Mechanism for Trading of Renewable Energy in Smart Grids, in: Proceedings of the 3rd International Conference on Smart Grids and Green IT Systems, 2014, pp. 101–106.

[21] J. Hirvonen, G. Kayo, S. Cao, A. Hasan, K. Sirn, Renewable energy production support schemes for residential-scale solar photovoltaic systems in nordic conditions, Energy Policy 79 (2015) 72 – 86.

[22] S. Pineda, T. K. Boomsma, S. Wogrin, Renewable generation expansion under different support schemes: A stochastic equilibrium approach, European Journal of Operational Research 266 (3) (2018) 1086–1099.

[23] M. Nicolini, M. Tavoni, Are renewable energy subsidies effective? Evidence from Europe, Renewable and Sustainable Energy Reviews 74 (2017) 412–423.

[24] L. De Boeck, S. Van Asch, P. De Bruecker, A. Audenaert, Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability, Renewable Energy 87 (2016) 42–53.

[25] Fraunhofer – Institute for Solar Energy Systems (ISE), Current and future cost of photovoltaics: Long-term scenarios for market development, system prices and LCOE of utility-scale PV systems, Tech. rep., Agora Energiewende (2015).

[26] E. Vartiainen, G. Masson, C. Breyer, PV LCOE in Europe 2015-2050, in: 31st European Photovoltaic Solar Energy Conference, 2015.

[27] R. Cherrington, V. Goodship, A. Longfield, K. Kirwan, The feed-in tariff in the UK: A case study focus on domestic photovoltaic systems, Renewable Energy 50 (2013) 421 – 426.

[28] S. Comello, S. Reichelstein, Cost competitiveness of residential solar PV: The impact of net metering restrictions, Renewable and Sustainable Energy Reviews 75 (2017) 46–57.

[29] L. C. Wing, Z. Jin, Risk management methods applied to renewable and sustainable energy: a review, Journal of Electrical and Electronic Engineering 3 (1) (2015) 1–12.

[30] Y. Yamamoto, Pricing electricity from residential photovoltaic systems: A comparison of feed-in tariffs, net metering, and net purchase and sale, Solar Energy 86 (9) (2012) 2678–2685.

[31] A. Poullikkas, A comparative assessment of net metering and feed in tariff schemes for residential pv systems, Sustainable Energy Technologies and Assessments 3 (2013) 1–8.

[32] J. Huijben, K. Podoynitsyna, M. van Rijn, G. Verbong, A review of governmental support instruments channeling PV market growth in the Flanders region of Belgium (2006–2013), Renewable and Sustainable Energy Reviews 62 (2016) 1282–1290.

[33] A. Ciarreta, M. P. Espinosa, C. Pizarro-Irizar, Optimal regulation of renewable energy: A comparison of Feed-in Tariffs and Tradable Green Certificates in the Spanish electricity system, Energy Economics 67 (2017) 387–399.

[34] I. Koumparou, G. C. Christoforidis, V. Efthymiou, G. K. Papagiannis, G. E. Georghiou, Configuring residential PV net-metering policies–A focus on the Mediterranean region, Renewable Energy 113 (2017) 795–812.

[35] T. Mai, R. Wiser, D. Sandor, G. Brinkman, G. Heath, P. Denholm, D. J. Hostick, N. Darghouth, A. Schlosser, K. Strzepek, Exploration of High-Penetration Renewable Electricity Futures, in: M. Hand, S. Baldwin, E. DeMeo, J. Reilly, T. Mai, D. Arent, G. Porro, M. Meshek, D. Sandor (Eds.), Renewable Electricity Futures Study, no. NREL/TP-6A20-52409-1, National Renewable Energy Laboratory (NREL), 2012.

[36] S. Sgouridis, Using energy as currency: re-establishing the bridge between the financial and the real world, Network Industries Quarterly 14 (2) (2012) 8–11.

[37] S. Sgouridis, S. Kennedy, Tangible and fungible energy: Hybrid energy market and currency system for total energy management. a masdar city case study, Energy Policy 38 (4) (2010) 1749–1758.

[38] N. Gogerty, J. Zitoli, Deko: An electricity-backed currency proposal, Social Science Research Network, article 1802166.

[39] L. Johnson, A. Isam, N. Gogerty, J. Zitoli, S. Foundation, A renewable energy powered trustless value transfer network, Tech. rep., White paper (2015).

[40] M. Mihaylov, S. Jurado, N. Avellana, K. Van Moffaert, I. M. de Abril, A. Nowe, Nrgcoin: Virtual currency for trading of renewable energy in smart grids, in: European Energy Market (EEM), 2014 11th International Conference on the, IEEE, 2014, pp. 1–6.

[41] M. Mihaylov, I. Razo-Zapata, A. Nowé, NRGcoin – a blockchain-based support policy for renewables, in: A. Marke (Ed.), Transforming Climate Finance and Green Investment with Blockchains, Academic Press, 2018, Ch. 9, to appear.

[42] D. Jacobs, N. Marzolf, J. R. Paredes, W. Rickerson, H. Flynn, C. Becker-Birck, M. Solano-Peralta, Analysis of renewable energy incentives in the latin america and caribbean region: The feed-in tariff case, Energy Policy 60 (2013) 601–610.

[43] M. Rathmann, D. de Jager, I. d. De Lovinfosse, B. Breitschopf, J. Burgers, B. Weöres, Towards triple-a policies: More renewable energy at lower cost, Re-Shaping D16 Report.

[44] J. de la Hoz, H. Martín, M. Montalà, J. Matas, R. Guzman, Assessing the 2014 retroactive regulatory framework applied to the concentrating solar power systems in Spain, Applied Energy 212 (2018) 1377–1399.

[45] A. J. Chapman, B. McLellan, T. Tezuka, Residential solar PV policy: An analysis of impacts, successes and failures in the Australian case, Renewable Energy 86 (2016) 1265 – 1279.

[46] W. Rickerson, T. Couture, G. L. Barbose, D. Jacobs, G. Parkinson, E. Chessin, A. Belden, H. Wilson, H. Barrett, Residential prosumers: Drivers and policy options (re-prosumers), Tech. rep., International Energy Agency (IEA)- Renewable Energy Technology Deployment (06/2014 2014).

[47] K. Kok, The powermatcher: Smart coordination for the smart electricity grid, Ph.D. thesis, Vrije Universiteit Amsterdam, The Netherlands (5 2013).

[48] D. Friedman, The double auction market institution: A survey, The double auction market: Institutions, theories, and evidence 14 (1993) 3–25.

[49] A. Sadrieh, The alternating double auction market: A game theoretic and experimental investigation, Vol. 466, Springer Science & Business Media, 1998.

[50] S. Nakamoto, Bitcoin: A peer-to-peer electronic cash system, Consulted (2008) 1–9.

[51] N. Collier, Repast: An extensible framework for agent simulation, The University of Chicagos Social Science Research 36 (2003) 2003.

[52] M. J. North, N. T. Collier, J. R. Vos, Experiences creating three implementations of the repast agent modeling toolkit, ACM Trans. Model. Comput. Simul. 16 (1) (2006) 1–25.

[53] P. Vytelingum, D. Cliff, N. Jennings, Strategic bidding in continuous double auctions, Artificial Intelligence 172 (14) (2008) 1700 – 1729.

[54] G. Graditi, M. D. Somma, P. Siano, Optimal Bidding Strategy for a DER aggregator in the Day-Ahead Market in the presence of demand flexibility, IEEE Transactions on Industrial Electronics (2018) 1–1.

Article highlights:

1. Six support policies are evaluated in scenarios with various numbers of prosumers.

2. "What-if" scenarios are studied through multi-agent simulations with real data.

3. Net metering and feed-in tariff will cause issues in the immediate future.

4. Market-based support policies are a better fit when prosumer numbers rise.

5. Each policy offers different trade-offs between profits and costs for stakeholders.