This is an extended and earlier version of our paper.
The final publication is available at Springer via http://dx.doi.org/10.1007/978-3-319-43904-4_6.

Shared Energy Storage and Neighbourhood Energy Exchange: A Smart Neighbourhood Simulation Environment

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***Abstract*—Funding policies and legislation by the European Union – and the German government in particular – for the installation of photovoltaic (PV) arrays in the residential sector, has led to a steady and successful increase in renewable energy generation by small-scale private producers. This proves beneficial to consumers as they need not spend as much money buying electricity from the utility. Additionally, consumers sell excess energy to the grid, receiving reimbursement via feed-in tariffs. At peak production times however, consumer-produced energy may endanger grid stability. One approach to mitigate this issue, is to reduce the amount of energy sold to the grid by installing battery storage, thus greatly increasing the use of locally generated energy on-site.**

Another approach to increase local consumption is through the use of neighbourhood energy exchange, in which one participant's excess production may be applied towards another member's consumption needs. This trade might take place by connecting all homes in a given neighbourhood to a *Microgrid Controller* (MGC), which takes care of the electricity routing and load balancing process. With feed-in tariffs declining, investing into shared energy storage and a Microgrid Controller might prove profitable. Setups such as these will be referred to as "smart neighbourhoods" from here on in.

In this paper, we present a software tool which allows for the simulation of such smart neighbourhoods. Additionally, we present outputs generated by our tool, for inputs that base on the German market and realistic neighbourhood scenarios. Possible implications from these results are made apparent, allowing for the influence of investment decisions.

***Index Terms*—Battery storage, energy self-use, energy trading, feed-in tariff, microgrid, model, photovoltaics, renewable energy, simulation, smart neighbourhood.**

I. INTRODUCTION AND MOTIVATION

ACCORDING to the European Photovoltaic Industry Association (EPIA), as of 2012, over 70% of all PV installations in the European Union were rooftop mounted (aggregate for both commercial and residential installations) [1].

The increasing uptake of residential PV is a welcome development in regards to eased market introduction of renewable energy sources, an acceleration of the decarbonisation of the electricity grid, as well as improvements in security and efficiency of electricity transmission and distribution, and the stabilisation of market prices for electricity in the long run [2]. However, it also brings with it a range of challenges. For example, during low load periods that overlap with high production periods (e.g. sunny days in the summer, where production starts early, but consumption might be relatively low) one of the major problems is grid over-voltage which can result in outages [3]. Responding to these and other challenges, battery storage is being used more and more frequently, to the point where PV owners are presented with attractive loans to invest in such technology [4].

Additionally, maximising self-use (i.e. the consumption of as much locally generated electricity as possible) can be considered desirable on the customer-side.

While advantages of battery storage are numerous [2], installation remains expensive and may not pay off for a single household. Instead, an automated controller unit might be added to a neighbourhood, which can in turn be connected to a central unit of energy storage. This spreads the burden of investment more evenly among investors, while also allowing for energy to be traded directly between participating homes.

What we present in this paper is twofold: 1) A tool for interested people to experiment with and simulate connected neighbourhoods. 2) Results for datasets of our choice that showcase some of the conclusions that might be drawn from results our tool can generate.

A. Related Work

Considering the field of renewable energy sources and smart grids of varying sizes and definitions (from single home microgrids [5] to entire cities [6]) is burgeoning, a wide array of research has been conducted (especially since 2010). We will thus briefly present an overview of works related to our own.

As early as 2000, Hansen et al. created a model for a standalone PV system in Simulink [7]. While a first foray into the area, they only examine singular houses at most. Similarly, Ursachi and Bordeasu implement a simulation for single houses with the addition of renewable energy sources [8], while omitting battery storage, which was already present with Hansen et al. Morvaj et al. go further still, modelling the connection of multiple houses via a central microgrid controller and adding batteries to store locally produced energy [6]. However, they omit any monetary considerations and only look at time scales of a day each. The System Advisor Model (SAM) developed by the National Renewable Energy Laboratory (NREL) provides "a performance and financial model designed to facilitate decision making for people involved in the renewable energy industry"

[9] thus addressing monetary considerations (while it "[…] does not model systems with electricity storage batteries"). Velik implements and investigates energy trade between houses in conjunction with local energy storage [10]. Economical considerations regarding battery capacity or the question of viability due to feed-in tariff compensation are however not addressed.

In addition to these theoretical approaches, real-world implementations of neighbourhoods that consider exchange of energy within and between them have been implemented, or are currently being worked on:

Van der Burgt et al. look at the concept of bringing together multiple microgrids (as small as a single house) into larger, so called *virtual microgrids* through the VIMSEN project [5]. They propose this in order to increase market visibility, i.e. allowing for connected neighbourhoods to sell their generated electricity at an attractive price in a larger, more competitive marketplace. While they address the exchange of energy between virtual microgrids, trade within the virtual microgrids themselves is not investigated. VIMSEN is currently in development and software tools are expected to result from work on the project.

Karnouskos et al. developed a web application for monitoring and managing Smart Grid neighbourhoods which was "used operationally in the second half of 2012 as part of the NOBEL project trial which took part in the city of Alginet in Spain." [11].

Finally, beyond simulations, a vast array of research has been conducted on the topic of analyses regarding optimisation strategies for smart grids. Refer to [12]–[16] for a few examples of such efforts. Our focus, however, lies with simulations. Hence, we did not concern ourselves with scheduling such demand response.

What we seek to address is the overall interaction between many of the factors studied in greater detail above – battery storage, renewable energy sources in the form of photovoltaic arrays, feed-in tariffs, internal energy trade – in the context of financial viability ("When do I break even, if I invest into a Microgrid Controller and a battery?") and increased self-use over extended periods of time (e.g. 10+ years).

B. Contributions

The nature of our work presented herein is thus twofold. Firstly, to form a better understanding of the interactions between the factors mentioned above, and to assess first intuitions ("Does internal energy trade change amortisation? How does battery size impact self-use?") we developed a tool to simulate said complex environment, focussing on simple subsystems and connecting them, giving rise to emergent properties. This tool then allowed for the specific manipulation of a subset of parameters, providing us with a more controlled environment from which to draw conclusions. These conclusions make up the second major contribution of our paper. Specifically, we looked at the outputs of several neighbourhoods for increasingly complex questions, make use of PV production and feed-in tariff data from Germany and consumption data from the Netherlands.

This paper presents the implementation details, as well as results and implications which can be drawn from the simulation outputs. More specifically, we look at the increase of self-use and financial viability or even advantage of examined scenarios.

To the best of our knowledge no such toolkit has been implemented as of yet. What we thus hope to provide is a way of bringing together complex interactions into an easy to use interface, which allows additional research to be performed by outside parties. These might include scientists, home owners, utility or housing development companies, for example.

C. Roadmap

Figure 1 presents a visual overview of our model's workflow. The rest of this paper is loosely structured according to this diagram. Items in blue circles represent data (inputs as well as outputs). *Input Data* is described in Section II, while *User Scenarios* (i.e. neighbourhoods), and *Simulation Results* are addressed in Section IV. Items in green circles relate to implemented components of our model. These and *Runnable Model* – which is considered data, since it is generated by our model – are covered in Section III. Section V sums up our findings and finally, Section VI outlines potentially interesting future developments.

II. MATERIALS, METHODS AND ASSUMPTIONS

This section deals with 1) how and where we acquired the data underpinning our model and its results, 2) how the data was prepared to make it compatible with our use cases, 3) what tools we used to implement our model and 4) what assumptions were made, as well as which restrictions apply in respect to the previous three points.

A. Simulation Software – Simulink

Simulink – developed by *MathWorks* – "is a block diagram environment for multidomain simulation and Model-Based Design." [17]. The program provides users with a graphical user interface which allows them to build models as block diagrams which can subsequently be executed. Additionally, simulation outputs may be analysed from within the program as well. Simulink allows users to build models in a hierarchical manner, i.e. giving them the possibility to view the system at different levels of abstraction. The option to merge multiple blocks into coherent subsystems allows for the creation of so

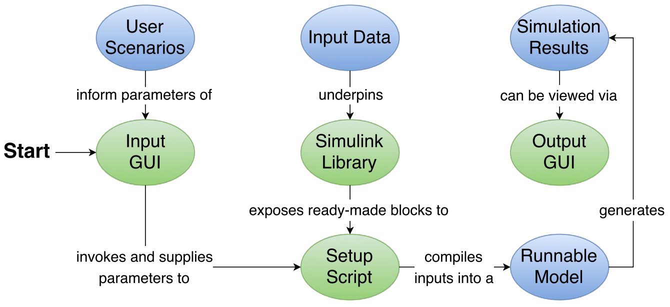

Fig. 1. Overview of the model's workflow. Green items represent implemented components, while blue items denote data that goes into or comes out of the model.

called “libraries”. These hide complexity from other users who might wish to use already implemented blocks, without further concerning themselves with the internal workings of chosen subsystems. This allows for more complex and novel models to be created relatively quickly and easily.

We used default simulation settings for Simulink. In particular, the pre-set *variable step solver* was deemed appropriate, since we designed a continuous model. In contrast, the possibility of a *fixed step solver* was ruled out, as it would have lead to impossible situations, e.g. negative battery charges, due to states being calculated in hour-long intervals.

Program versions used were *2015a* for MATLAB and *8.5* for Simulink.

B. Production Data – PVWatts

Solar panel production data was obtained from PVWatts, a project of the National Renewable Energy Laboratory (NREL). PVWatts ”[e]stimates the energy production [...] of grid-connected photovoltaic (PV) energy systems [and] allows homeowners, small building owners, installers and manufacturers to easily develop estimates of the performance of potential PV installations.” [18]. *Düsseldorf* was chosen as location for which we obtained the measurements.

Data was exported using standard settings (Module Type: Standard, Array Type: Fixed (open rack), System Losses (%): 14, Tilt (deg): 20, Azimuth (deg): 180, DC to AC Size Ratio: 1.1, Inverter Efficiency (%): 96, Ground Coverage Ratio: 0.4), with the exception of *DC System Size (kw)*. This parameter was set to *1* in order to allow for dynamic scaling of solar array size for each house in our simulation. The formula to determine the scaling factor x for a 1 kWp[1] array is $x = 0.16 \cdot y$, where y is the area of the solar panel array. This was determined by simplifying the calculation PVWatts performs internally: Size (kW) = Array Area (m^2) $\cdot\, 1\frac{\text{kW}}{\text{m}^2} \cdot$ Module Efficiency (%). Refer to [19] and [18] for more detailed information. Scaling from 1 kWp was determined to behave linearly, i.e. data supplied by PVWatts for a 10 kWp installation was the same as multiplying the results for a 1 kWp installation by a factor of ten. Given the equation above, PVWatts data indicates 6.25 m^2 of solar panel surface result in a 1 kWp output.

From the exported data set, we extracted the *AC production* column for further use. The values in this column already include losses incurred through conversion from DC to AC (96% efficiency) and other factors, such as light-induced degradation, shading and soiling).

It is worth noting, that we always consider PV installation sizes (m^2) to indicate the *effective* array surface area. That is to say, we do not take into account additional area that might be required for framing and separation between the cells or other structural components like the inverter. Similarly, we do not take into account any additional panel degradation that might arise over the duration of a given simulation, nor do we account for any maintenance or repairs that might arise during the lifetime of the panels.

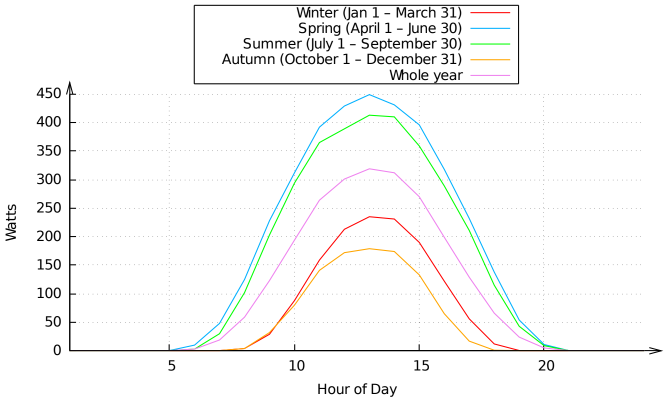

Fig. 2. Production in Watts over the duration of seasonally average days for a PV installation that produces an average of 11 kWh per day using the data supplied by PVWatts.

Refer to Figure 2 for a graphical representation of PV production values over time.

C. Consumption Data – Netherlands

Household load data was acquired from *Nederlandse EnergieDataUitwisseling* (NEDU, “Dutch EnergyDataExchange”), which is an “association [founded in 2007] to develop and maintain market model” for the Dutch energy market [20]. We were unable to determine exactly how big the sample size for this data is; NEDU only states that the data was acquired from their customers during measuring campaigns, as well as derived from allocation data [21]. However, considering the organisation’s size, function and involvement [20] and the fact that Germany and the Netherlands have very similar electricity consumption per capita [22] we consider the data to be representative and valid for our purposes.

From the multicolumn dataset supplied, column ”E1A” was chosen, i.e. loads of $< 3 \cdot 25$ amperes using a single electricity metre. The respective values are given at a resolution of 15 minute intervals and represent the percentage of annual energy consumption during this time frame. However, since PVWatts production data only has a resolution of one data point per hour (see above), four consecutive values of electricity consumption data were added up, thus reducing the resolution of the consumption intervals. At this stage, multiplying each value with a given annual consumption yields results in Watts for any given hour in a year. See Figure 3 for a visual representation of the resulting dataset at 3,500 kWh per annum.

D. Feed-in Tariff

The *Erneuerbare Energien Gesetz* (EEG, “Renewable Energy Sources Act”) [23] is a German law, regulating the compensation of small-scale energy producers who wish to feed energy production surplus into the power grid. This law has been changed multiple times since its inception in 2000. Changes include the categorisation of PV installations by nominal kWp, compensation or deductions for self-use, as well as rates of degression for the feed-in tariff.

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[1] kWp = Kilowatt-peak, i.e. the power rating of a photovoltaic array in kilowatts (kW) at standard test conditions. Standard test conditions are defined as: Solar irradiance of 1,000 W/m^2, cell temperature of 25 °C and air mass of 1.5. [18]

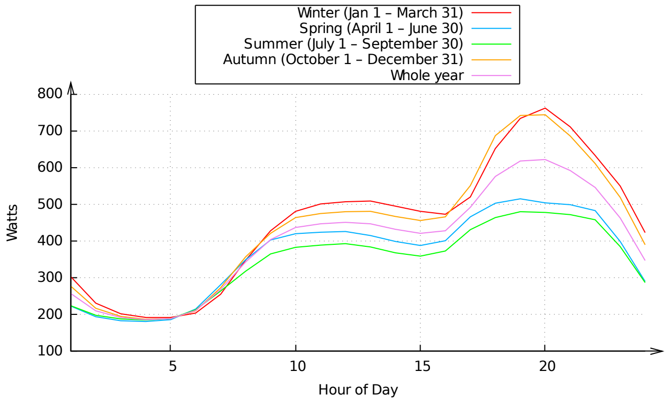

Fig. 3. Consumption in Watts over the duration of seasonally average days for an annual demand of 3,500 kWh, using the data supplied by NEDU.

Feed-in tariff data was acquired from the Bundesnetzagentur, Germany's federal regulatory office for electricity, gas, telecommunications, post and railway markets [24].

To keep the model more comprehensible and consistent, we treat every PV installation as if it were $\leq$ 10 kWp in size. This means arrays larger than 62.5 m^2 are not handled correctly. This was deemed an acceptable trade-off, since installations larger than that rarely occur in a given neighbourhood. It should also be noted that we only consider roof-mounted installations. Legislation and feed-in tariffs for open space PV installation deviate from those applicable to roof-mounted arrays and are not considered in our specialised tool.

Couture et al. present very detailed background information regarding the structure and intricacies of feed in tariffs in [25].

We make no assumptions about the future development of feed-in tariffs. Our data ends with December 2015. The feed-in tariff is paid for a period of 20 years, during which it does not change.

It should be noted that while we have modelled feed-in tariffs, different scenarios can be explored by changing the underlying CSV file. This would also allow for the feed-in tariff mechanism to be disabled entirely. This allows for the tool to be extended beyond its initially intended scope.

E. Simulated Neighbourhood Environment and Additional Assumptions

With data from the Netherlands and Germany, it becomes apparent that we describe neighbourhoods in a middle European market. More specifically, combining data from NEDU, the Bundesnetzagentur and PVWatts firmly puts our simulation in a longitude range of 49°and 55° within Germany.

Additionally, each data set brings with it inherent assumptions, which we have touched on before. However, we would like to point out some additional details that have not become evident yet, but influence our results:

All houses feature the same orientation (due south), roof tilt (20°), and their respective solar panels do not track the sun. Conditions like these might be found in newly-built or later-equipped uniform housing developments. In practice, a mixture of orientations might provide considerably beneficial [26]. See [27] (solar panel sizing), [28] (solar tracking) and [29] (battery sizing) for additional information on how to best inform and adapt scenarios. We assume solar panel arrays to have been installed prior to any Microgrid controller and/or battery.

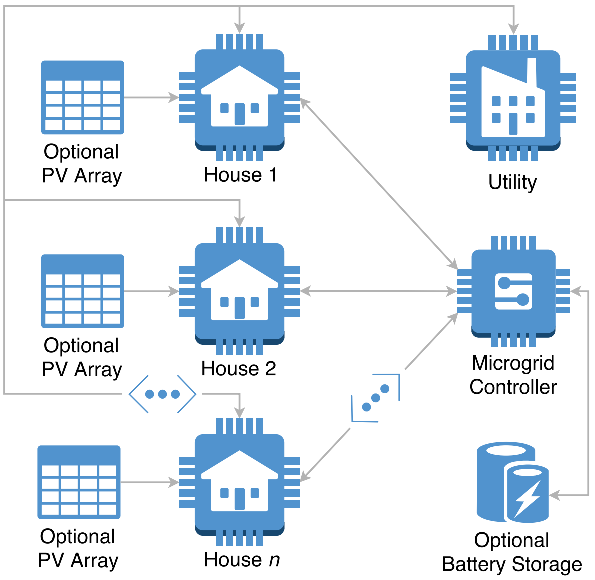

Fig. 4. Schematic representation of the smart neighbourhood model. Arrowheads indicate the flow of electricity. Please note that in one imaginable alternative to this setup, the Microgrid Controller might sit between *Utility* and the houses, thus potentially saving additional wiring and setup cost.

Beyond what is mentioned above, there remain some additional points that we would like to touch on briefly:

- We assume communication between houses and the microgrid controller to be safe, secure and stable, be they wireless or wired [30]–[32]. Manipulation of data sent and received by either parties is not assumed. Privacy concerns are not addressed [33].
- Only solar power generation is being simulated and considered as an energy source, though alternatives like wind turbines exist [34].
- We do not observe leap years. Despite the fact that periods of 20 or more years might be simulated, the effect would be negligible, while unnecessarily increasing complexity of the model.
- The model was not tested or designed beyond neighbourhoods of 20 homes. We do, however, deem simulating larger neighbourhoods feasible. It should be noted that large simulations are computationally expensive and might take considerable amounts of time.
- While we give costs in Euro (€), it should be apparent that any arbitrary unit of money or currency behaves alike, as long as it is decimal.
- As is common with simulations, we do not allow for the optimisation of any one characteristic in our model (i.e. battery or solar panel size). A row of consecutive experiments would allow for trend to become apparent, however.
- The data described in *B*, *C*, and *D* above can easily be exchanged by the user, since it is simply stored using

CSV files. This gives rise to much greater flexibility for future experiments.

III. MODEL IMPLEMENTATION

Previously, we outlined the general considerations underlying our approach. We will now turn to the actual implementation of the model and its components in MATLAB and Simulink. In a similar fashion to the structure of the paper as a whole, this section is also organised with Figure 1 in mind, meaning we will take an approach that follows the workflow a user of our toolkit might experience.

The implementation follows the Model-View-Controller architectural pattern and was programmed using object orientation in MATLAB. The *In-* and *Output GUI* represent the View, while the model consists of the *Library* and the *Script* acts as the controller. These modular and encapsulating approaches were chosen to facilitate modification of the toolkit at its core, if need be, i.e. in case changing input data is not sufficient.

As a general rule within the model, negative kWh and monetary values represent demand and expenditure respectively, whereas positive values are considered surplus production and compensation accordingly.

A. Input GUI

The Input Graphical User Interface (Input GUI) presents the user with a convenient way to configure simulations for given scenarios. Through it, an expansive array of simulation-wide settings may be manipulated. Additionally, neighbourhoods – described by their constituent houses – are defined from this interface as well.

The GUI was created using MATLAB's *Graphical User Interface Design Environment* (GUIDE), while its specific functionality – hand-off to the *Setup Script* (cf. section III-C), adding entries to the "Houses" table, etc. – were implemented using standard MATLAB code.

What follows is an explanation of each variable the user can adjust using the interface, as well as information about their respective default values. We hope that this will allow for a more intuitive understanding of what the toolkit accomplishes as a whole.

1) Houses: Houses are defined by three parameters: *Solar panel size*, given in square meters (m^2), *Yearly power demand*, given in kilowatt hours (kWh) and *Date of PV installation*[2], given in the date format MM-YYYY (e.g. *04-2013* for April of 2013). These values default to 30 m^2, 3,500 kWh and 05-2014 respectively, which were deemed to be reasonable values. 3,500 kWh roughly equals the average consumption of a 2-person-household [35]. 30 m^2 translates to a PV output of 4.8 kWp (cf. PVWatts calculation in II). With the supplied data, on average this installation produces 11 kWh per day, i.e. more than the mean consumption of 9.5 kWh per day. Thus, more energy is produced than is being consumed per year.

2) Battery cost per kWh: This defines how much one kWh of battery capacity will cost. The amount in this field will be multiplied by the battery's capacity to determine the overall cost of available energy storage. The value in this field is split evenly among participants in the neighbourhood. It is definitely debatable whether certain parties ought to account for more or less of these expenses, depending on what they add to or remove from the local grid. However, tackling this question was considered to be beyond the scope of this paper.

We arrived at the default value of €500 per kWh by dividing the advertised cost of a *Tesla Powerwall* [36] by its capacity ($\frac{\$3{,}000}{7\text{kWh}} \approx \$430$) and rounding up to the next hundred for good measure. This was done, since Tesla's Powerwall is priced very aggressively. Other products might be twice as expensive per kWh of capacity [2].

3) Battery capacity: Defines the maximum amount of energy storable in the battery. As with PV array surface area before, this figure states the effective (not nominal) capacity of the battery. The value in this field is multiplied with *Battery cost per kWh* described above to arrive at the total cost of desired energy storage.

The default value of 7 kWh was chosen for two reasons. Firstly, Tesla's Powerwall is primarily advertised at this capacity [36]. More importantly however, this value aligns with calculations made by Velik in [29]. Choosing a battery that provides enough capacity to provide half of an average day's demand is shown to cover 70 to almost 80% of said demand, depending on season. Doubling the battery capacity only increases self-use by another 10%, while doubling the acquisition cost.

4) One-time cost: One-time cost subsumes any additional expenses which go beyond the investment for energy storage . This might, for example, include costs for the installation of the Microgrid Controller itself, as well as wiring between the houses, if necessary. Technically, this could also be used to add initial cost for PV installations throughout the neighbourhood. This is not a typical use case however and is strongly discouraged, since there would be no way to apportion costs between houses with regards to their respective arrays. Costs in this field are split evenly among participants in the neighbourhood.

€1,000.- was chosen as a default value, because it seemed like a sensible baseline. Changing this merely shifts the starting point of the corresponding line in the graph up or down along the y-axis.

5) Initial cost per kWh from utility: This parameter defines the amount charged by the utility company for every kWh that is drawn from the external (i.e. non-neighbourhood) grid.

€0.2881 was chosen as a default value since it was the average cost per kWh in Germany at the time of implementation (2015) [37].

6) Annual change of cost per kWh from utility: Determines the annual rate of change regarding the cost per kWh from the utility. This value is calculated using the compound interest formula $x_2 * (1 + x_3/100)^{x_1}$, where x_2 the initial cost per kWh (see above), x_3 percentage change described here and x_1 is the year for which the cost is to be calculated.

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[2] Please note that "Date of PV installation" is not technically accurate. The formulation was chosen for reasons of constrained space in the Input GUI. Compensation only starts being paid out from the first day the installation produces electricity and feeds it into the grid [23], rather than its date of installation.

The default value of 3.4% was chosen because it was the average rate of change between the years of 1998 and 2014 in Germany [37]. It is to be noted though, that for time frames exceeding 15 years, this assumption might no longer hold. In fact, the cost of electricity might or might not stabilise within a given number of years [38].

7) Date of battery installation: The date on which the battery becomes operational within the neighbourhood. Chronologically, this date must occur *after* every PV installation date in the neighbourhood, since our simulation begins on the date entered in this field. The difference between these respective dates is used to calculate the remaining hours of feed-in tariff payout, which therefore must not result in a negative value.

January 2016 was chosen as a default value since it is the first date for which no feed-in tariff data is being provided by us any more.

8) Solar panel efficiency: Tweaking this value directly influences the amount of energy that is being produces by PV installations. Refer to Section II-B for the calculations involved.

The default value of 16% for this field reflects the value provided by PVWatts.

9) Cost per kWh bought from battery and *Compensation per kWh sold to battery:* These values determine the amount of money that is being exchanged when handing off electricity to, or receiving energy from the microgrid controller.

The values chosen (i.e. 18 cents per kWh) were determined by rough estimation of a value between 28 and 12 cents, with the result showing a slight bias towards buyer's advantage. Refer to "Internal Trade" further down for a more detailed discussion of the mechanisms behind this and additional resources in this area. *Future Work* (Section VI) points out some advanced considerations.

10) Duration of simulation: This field determines the number of years for which the simulation will be run. Internally, this number is multiplied by 8,760 (hours in a year), as we simulate at the resolution of hours.

The default value of 15 years was chosen because our experiments have shown that this allows for a reasonable assessment of whether and, if so, when amortisation will occur. A value of 20 or 25 years might also be considered, but will naturally result in the simulation process taking longer to complete.

B. Simulink Library

In this section, the block diagrams we have created using Simulink are described in greater detail, with their functionality being the primary focus.

The library provides two blocks: a *House* and a *Microgrid Controller*. The former can (and typically does) exist multiple times in a given setup, while the latter only exists once within the context of a given simulation. As outlined below, through the use of the *Setup Script*, a runnable model is created using these components.

All of these blocks have been implemented from scratch, making use only of components available through the basic Simulink block library. In the following, select aspects from each block are highlighted. We encourage the reader to explore the model on their own in detail to gain a more in-depth understanding of how components interact with one another. Additionally, we recommend reading the accompanying `README` file, which provides detailed usage instructions.

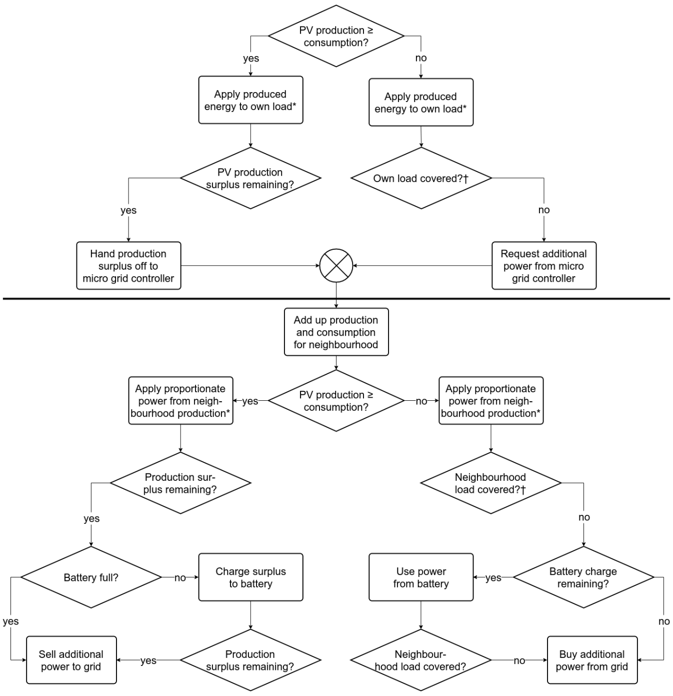

Fig. 5. Logic flowchart for internal trade, storage to and retrieval from battery as well as sale to and purchase from the utility grid. The horizontal bar delineates the switch between which components are involved in making the decisions. Above the bar, each house applies as much of its production to its demand as possible. Below the bar, the microgrid controller takes over and handles further decisions (see above). * Consumption and/or production can be 0 at these stages. † Will always evaluate to false, since for these paths PV production $<$ consumption holds.

1) House – Variance: Since we rely on averaged consumption data, a small variance was added to each house, so consumption diverges slightly and trade can occur, if and when houses are identical otherwise (same PV array area and power demand).

2) House – Electricity Cost Calculation: Taking a wide array of parameters, this MATLAB function calculates cost/compensation while taking into account the current battery charge. Since connections within the model carry vector information, cost is calculated for all available strategies simultaneously, as well as for one vector which behaves like no Microgrid Controller were present at all.

3) Microgrid Controller – Charge and Trade Logic: One of the major advantages of a smart neighbourhood is the ability to share energy between participating houses. This exchange does not necessitate the presence of a battery within the neighbourhood. A given house may transfer "excess" energy at the time of its production to houses which may not have their own demand covered yet. Such exchange reduces the total amount of energy sold to the grid and increases local self-use. In order to make this a fair process for all parties involved, an internal compensation scheme is necessary. The exact values per kWh are not easily determined, since members of the neighbourhood who produce more, would profit from higher compensation when selling, whereas members with little or no production would prefer costs to be minimal. However, it stands to reason that appropriate values would be no higher or lower than external grid prices, for both sale and purchase of electricity respectively.[3]

In our model each house has a consumption and a production output, whose respective values are added up and fed into the Microgrid Controller in order to calculate how much energy will be traded, stored, sold or bought. For each battery strategy described below, the controller returns a signal to each house with information about the current energy usage. This signal is made up of three floating point numbers per strategy, which represent percentages of energy that was either sold (p1), traded internally (p2) or bought from the grid (p3). For example a signal of (0/0.58/0.42) would inform a house the energy demand of which has not yet been sated, that 42% of the required energy had to be bought externally and 58% were purchased at a cheaper rate from the neighbourhood. On the other hand, the same signal would inform a house with excess production, that all its energy could be sold to the neighbourhood, since no energy needed to be sold to the grid. The sum of all floats always ought to be 1, which can be used as sanity check by the houses to assure correct communication.

In both strategies present, the "sold" signal will only change once the battery is full. The "buy" signal only triggers on an empty battery (or 30% empty in case of the smart strategy). This might make our solution look overly complicated, but it ensures easy integration of more complex battery strategies in the future.

4) Microgrid Controller – Battery Strategies: In the version presented in this paper, only two battery management strategies have been implemented. Those strategies being *Greedy* and *Smart*. Greedy is characterised by making full use of the battery's capacity at all times, i.e. completely charging and depleting it whenever possible. With the *Smart* strategy, during normal operation, the battery is only ever emptied to the point where 30% of its charge remains. This is done for two reasons: 1) to prolong the battery's life, as completely depleting it repeatedly has averse effects on its chemistry in the long run, thus reducing the number of life cycles [39] and 2) increasing survivability for connected houses [39].

Throughout the results presented later, it will become apparent that this naïve approach of implementing these strategies makes using the *Smart* strategy entirely unattractive. Practically, it degrades a battery to only employ 70% of its nameplate value. Effectively, this results in slower amortisation at the same initial investment. However in reality, the *Smart* strategy might prove to be the better choice over more extensive periods of time, if we consider that it might keep the storage in working order at higher capacity for longer.

C. Setup Script and Runnable Model

The *Setup Script* acts as the connecting layer between the library blocks and the input data from the GUI (see above). Written in the MATLAB language, it creates a runnable model, which can then be executed and/or saved for later use by the user.

In reality, the *Setup Script* consists of four different scripts, or classes. *GridController.m* and *House.m* pull in and set the values of their corresponding blocks from the library. *Simulink.m* merely contains static values which are referred to in other files. Finally, *System.m* connects all the blocks, sets up Workspace Variables and creates the actual runnable model.

D. Output GUI

At the end of our toolkit's workflow we find the Output GUI. It allows users to view and compare their simulation results. Through a drop-down menu, all generated data can be viewed in the form of graphs. There are four major graphs that can be displayed:

Grid Sale Gradient graphs show the amount of energy sold to the utility for each battery strategy (see above). Additionally, a graph is shown that represents the energy that would be sold to the grid if no Microgrid Controller were present at all. The more shallow these lines, the more energy is used locally.

Split Amortisation graphs show gains and/or losses incurred through the sale and/or purchase of electricity to/from the grid and internal trade. As with the grid sale gradient, a line for each battery strategy is shown, plus an additional one, representing the absence of a Microgrid Controller. Please note that any of these lines may rise or fall, or even change their trajectory entirely throughout the course of a simulation. Falling means spending, rising means earning money.

Merged Amortisation graphs present money saved and/or directly gained through feed-in tariff compensation and neighbourhood trade. They basically show the delta between how much would have had to be spent if there were no Microgrid Controller and the different battery strategies *with* a Microgrid Controller. This also explains why for the merged graphs there always exist two lines: one for each battery strategy.

Neighbourhood Battery Charge Over Time graphs show the neighbourhood battery charge state over time. For long periods of time this graph might be difficult to discern. We recommend examining it for simulation durations of just one year to get a better idea of how it works.

All graphs except for the battery charge graph exhibit what could be called a staircase pattern, i.e. areas in which the slope changes relatively drastically. This behaviour is easily explained by looking at seasonal changes in production and consumption. In summer and spring, more electricity is produced, while in autumn and winter, energy consumption rises. This means that profits are mostly made during the warm and sunny months of the year, while the typically overcast seasons result in slower amortisation, or even additional expenditure of money.

E. Validation

To assure a reasonable level of confidence in the accuracy of our model, multiple steps were taken, which we will briefly describe.

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[3] Please refer to Section VI for references on this topic. We considered tackling this question to be outside the scope of this paper.

Firstly, throughout the development process, output values were checked for each component at multiple points in time (via *Scopes* in Simulink) to make sure they were in line with our expectations.

Secondly, whenever an error was found, it was fixed and documented. This was done so that a list of regression tests could be implemented. These were then run for subsequent iterations of the model, increasing the likelihood that previously present mistakes had not been reintroduced in later revisions.

Next, edge and corner cases were tested (e.g. houses with no PV generation or consumption, only just one house etc.). This was done to make sure the model did not show any unexpected behaviour at a basic level already.[4]

Additionally, results of our model were cross-checked with online tools for consumers where they were available (e.g. "amorisation calculators" for solar panels). Also, our results were considered to be in line with what other researchers have concluded (this holds true for papers by Velik in particular).

Finally, a spreadsheet was created that uses formulae to simulate the behaviour we were intending to implement in our model. We then cross-checked the values where we expected critical value changes in the model (like the battery being charged for the first time or it being depleted) as well as in semi-random spots throughout. The results of this verification lined up with our expectations. The spreadsheet can be accessed via [40] (partially in German).

Altogether, we thus deem our toolkit to be working within specifications.

IV. Simulation Results and Discussion

In this section, we will 1) present interesting scenarios, 2) show the data gathered from their respective simulations and 3) discuss in which cases energy trade and / or shared energy storage benefit a smart neighbourhood.

Results are only shown and considered using the *Greedy* battery strategy. This is to make key outcomes more apparent to the reader – adding another strategy would have doubled the number of lines in each graph presented below, while sacrificing only very little in the way of significance. Refer to section III-B4 to gain an understanding as to why the overall implications do not change for the "Smart" strategy. Additionally, when showing graphs for scenarios involving more than one house (e.g. Figure 8), only one house per scenario is shown, as it is representative of each house in that neighbourhood scenario. Additionally, graphs always are of the *merged* kind. Please refer to Section III-D for general information on how to interpret each of the following graphs in more detail.

Results and Discussion were unified into one section since each simulation builds on the results of the previous ones.

A. Results with a single house using a battery

In order to develop a first idea of which "types" of houses (i.e. combinations of solar array size, yearly consumption and PV installation size) will benefit from neighbourhood trade and/or a battery, we simulated 6 houses with different parameters. The parameters chosen are listed in table I. The rest of the variables were set to the following values: €500,– per kWh battery storage, €0.2881 initial cost per kWh from utility, annual change of 3,4% per kWh from utility, with a battery installation date of January 2016 and a solar panel efficiency of 16%. Houses 1 through 4 from Table I correspond to an average 4 person home, while Houses 5 and 6 would roughly equal an apartment building for 6 families with 2 to 3 people living in each household.

As we can see in Figure 6, House 1 does not benefit from battery storage during the first 8 years. However, it turns a profit of €1,040.50 within the last two years of the simulation.

This can easily be explained. Due to its PV installation date of January 2004, the feed-in tariff for this house is €0.574 for each kWh it sells to the utility. Meanwhile, buying electricity from the utility would cost €0.2881 per kWh. This means it would actively lose money any time it consumes its locally produced energy.

The upwards bend after 8 years can be explained by the 20 year period of feed-in tariff compensation running out. After that point in time, it becomes cheaper to consume locally produced electricity. The same logic holds true for House 2, as it starts out with a feed-in tariff of €0.3914.

Our first observation therefore is, that battery storage only saves money, when compensation through the feed-in tariff is less than the cost per kWh from the utility. This observation influences the following simulations in that we only look at PV installations that began operation on or after January 2015.

When comparing House 3 and 4, we can see that a battery with double the capacity only makes a difference of 9.69% in additional money saved/gained. So in this scenario House 3 has managed to amortise 84.57% of its investment, while House 4 did not even manage to gain back 50% of its initial investment, despite an overall faster amortisation.

On the other hand, when we compare Houses 5 and 6, we see that doubling the battery capacity, leads to a difference of 31.12% in terms of money saved. We can also see that the 7 kWh battery has only amortised 51.33% of the investment, while House 6 managed to get back 37.26% of the investment. This is easily explained when we compare the size of the solar panels in relation to the huge consumption we have. Most of the energy we produce on average days gets consumed immediately, instead of filling the battery. So a larger battery does not improve the situation on days where the produced energy gets consumed. It only improves the self-use on days with high solar production. However with a solar panel this large, at peak hours, the house will highly benefit from a larger battery since the demand is comparatively small during peak hours.

In general terms, it becomes clear that battery amortisation is highly dependent on the consumption of the house in relation to its solar panels size and the solar panel installation date.

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[4] We would like to point out, that we did encounter reproducibly unexpected behaviour when attaching a scope – which, for all intents and purposes, should *not* affect the model in any way – to a certain line connecting two blocks. We can only assume that the rest of our testing has precluded similar issues, but can, of course, make no guarantees. We assume this to be due to a software bug in Simulink.

TABLE I
SETTINGS USED TO COMPARE THE HOUSES IN FIG. 6

Identifier	**YC [kWh]**	**Size of PV [m^2]**	**Date of PV Installation**	**Battery Capacity [kWh]**
House 1	5,000	40	01-2004	7
House 2	5,000	40	01-2010	7
House 3	5,000	40	01-2015	7
House 4	5,000	40	01-2015	14
House 5	27,000	60	01-2015	7
House 6	27,000	60	01-2015	14

YC = Yearly Consumption

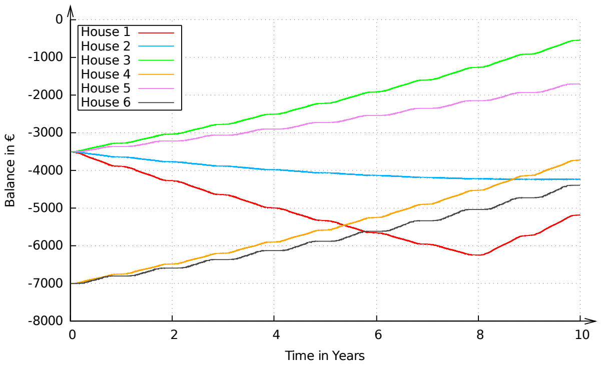

Fig. 6. Amortisation of battery purchases by independent houses

B. *Results with houses of the same type*

In this section we will compare scenarios where houses with the same of solar panel array area and annual consumption will form a connected neighbourhood. We will also compare these results to having only 1 house invest in a battery. Additionally, we will also simulate investing in a Microgrid Controller without a battery, so we can see how profitable energy exchange is on its own. The exact scenarios are described in Table II.

We have consistently chosen to pick €1,000 for one-time costs, since it is impossible to calculate accurate wiring costs without making far-reaching assumptions, for example about the distance between buildings. This does not affect the results in a major way, since it only pushes the initial starting point of the amortisation graph downwards.

In Figure 7 we see that scenarios without shared energy storage (2, 4, 5) have not amortised yet. In Scenario 2 the representative house was able to save €38.25, in Scenario 4 €42.94 and in Scenario 5 €43.93 due to the trading of energy. Considering that we simulated 10 years, the internal trading does not improve the situation significantly. This is easily explained because the only time trading occurs is when the variance shifts the consumption patterns of houses in a way that one house is producing more energy than it consumes and at least one other house has an energy demand it can't cover itself.

Comparing a house which has a Microgrid Controller as well as shared energy storage (Scenarios 3 and 6 respectively) to a house which only has a battery (Scenario 1), we notice that the only difference in money made/saved over the 10 years, is in the amounts earned from the internal trade.

TABLE II
SETTINGS USED TO COMPARE THE DIFFERENT SCENARIOS IN FIG. 7

Identifier	**YC [kWh]**	**Size of PV [m^2]**	**Number of Houses**	**Battery Capacity [kWh]**
Scenario 1	27,000	60	1	7
Scenario 2	27,000	60	5	0
Scenario 3	27,000	60	5	35
Scenario 4	27,000	60	10	0
Scenario 5	27,000	60	15	0
Scenario 6	27,000	60	15	105

YC = Yearly Consumption

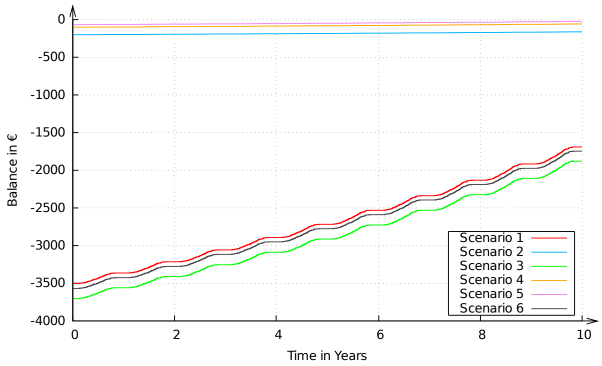

Fig. 7. Amortisation of neighbourhoods investing in a microgrid Controller

Considering the minimal improvements caused by the internal trade, when comparing houses that are identical to each other, it would make more sense to not invest the extra money for the microgrid Controller.

C. *Results for Houses with Different Setups*

In the previous section, we noticed that comparing houses with the same settings leads to nearly no internal trading. To compare if more widely spread setups of consumption and production lead to more trading, we will simulate a small neighbourhood consisting of only 3 houses both with and without a 14 kWh battery and show the different amortisations. To be able to compare these houses better to each other we assume that all those houses were producing energy in January 2015 for the first time.

In Figure 8 we see that House 2 has already amortized within 10 years and has made around €488 of profit on top of that. The other 2 houses have not amortized yet. House 1 has gained €2,853.– and house 2 has gained €2,413.– during the 10 years.

When comparing the houses that only invested in the Microgrid Controller and no battery, we see that neither house indicates major improvements and the best of the 3 – House 2 – has only saved €49.94.

In the real world, we do not have only just one averaged pattern across multiple houses which is only varied by a mathematical variance. Instead, consumer exhibit different patterns. However, results by Velik suggest that even with more varied patterns, internal neighbourhood trade only improves self-use by a maximum of 6.9% [10].

TABLE III

SETTINGS USED TO COMPARE THE DIFFERENT SCENARIOS IN FIG. 8/9

Identifier	YC [kWh]	Size of PV [m^2]
House 1	4,200	35
House 2	6,000	45
House 3	3,200	40

YC = Yearly Consumption

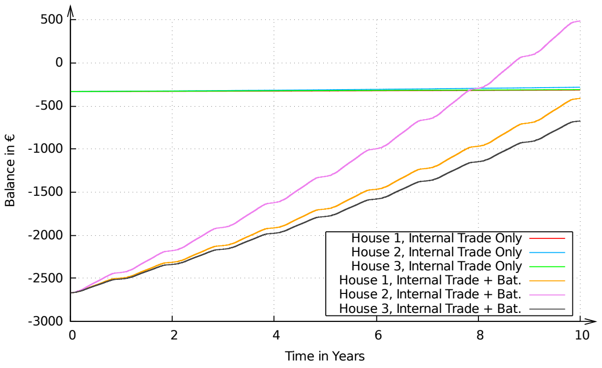

Fig. 8. Amortisation of houses investing in a microgrid Controller

When looking at Figure 9, we see that all houses profit from the battery, because they use more of the energy within the neighbourhood. All 3 houses have reduced the amount of energy sold to the utility by around 30% to 35%.

D. Results with houses without Solar Panels added to the neighbourhood

In this section we will discuss how adding houses to the neighbourhood that do not have a solar panels to the smart neighbourhood might result in all houses and the utility gaining an advantage.

To increase comprehension and clarity, graphs in this section will not include House 1 from IV. Instead, we considered it more interesting, to look at the best and worst houses from Figure 8. On top of that we do not include House 5 in the graph since its behaviour is identical to House 4, only with a steeper amortisation curve, since it is able to buy more energy from the neighbourhood.

In Figure 10 we see that the Houses 2 and 3 have amortised in both cases. When comparing the results of those 2 houses with the results we saw in Figure 8, we notice that they traded a lot more energy. House 2 has made €518.40 with only just trading (i.e. no battery storage). This is more than 10 times the amount it would earn when only houses with solar panels were in the neighbourhood. House 3 has earned €647.44 in 10 years.

The immense improvement in profit through trade, as well as the cost of the 14 kWh battery being split evenly between 5 houses has also led to House 2 to amortise its investment in less than 8 years. Even House 3 – which had performed worse in Figure 8 – has now made money from investing into the Microgrid Controller.

Houses without any solar panels are currently saving the most money. This could be ameliorated by choosing a higher internal trading price or shifting more of the initial costs for the wiring onto these houses. However this is nothing we can optimise with our model.

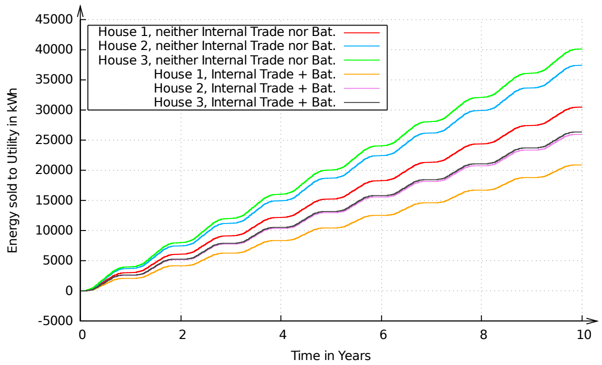

Fig. 9. Gridsales of houses with and without a microgrid Controller and a battery

TABLE IV

SETTINGS USED TO COMPARE THE DIFFERENT SCENARIOS IN FIG. 10/11/12

Identifier	YC [kWh]	Size of PV [m^2]
House 1	4,200	35
House 2	6,000	45
House 3	3,200	40
House 4	5,000	0
House 5	5,500	0

YC = Yearly Consumption

When examining House 1 in Figure 11, we see that it would have sold 30,517 kWh over 10 years without the smart neighbourhood. However *with* the smart neighbourhood and other houses buying a lot of the produced energy, it has only sold 13,839 kWh in total. This means we sold 54.65% less energy to the utility. This is also a great improvement to Figure 9. The other 2 houses have also sold less energy. In total, all 3 houses have sold 48,215 kWh to the utility. Without the 2 houses that have no production, those 3 houses sold 73,234 kWh to the utility.

On top of that, these results behave in a fashion similar to the grid-friendly (i.e. low in sales to the grid) battery strategy *Delayed Loading* [41], which starts charging the battery only when solar production is at its peak. Instead of selling the first produced kWh to the utility, we trade most of our energy. In Figure 12 we see that even on one of the days with highest production throughout the year, we delay selling to the utility by nearly 5 hours. On more average days we delay selling to the utility even more.

In general, adding houses lacking energy production on their own to a smart neighbourhood, results in more trade taking place in the neighbourhood. This means that less energy is sold to the utility and costs of a battery purchase are split more evenly, leading to an improved situation for the grid *and* the customers. On top of this, if all these houses would exhibit more realistic patterns, amortisation might occur even faster, since more strongly divergent patterns result in more trade between these houses, as outlined before.

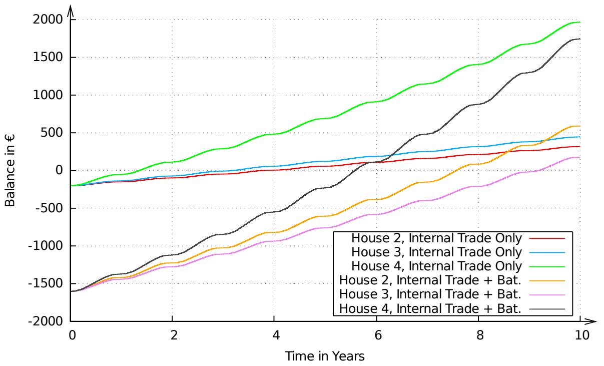

Fig. 10. Amortisation of houses investing in a microgrid Controller

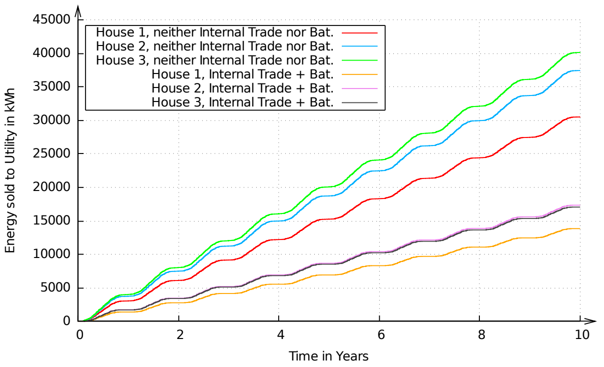

Fig. 11. Energy sold to the utility with settings from Table IV

V. CONCLUSIONS

In this paper, we have presented: 1) a toolkit for the simulation of a smart neighbourhood environments, which allows for energy trade between participants with the possibility of additional battery storage, 2) simulation results of our tool for realistic neighbourhood scenarios based on German and Dutch production and consumption data respectively.

The former allows researchers to conduct further experiments on their own, while the latter has shown that 1) houses with recently installed solar panels benefit the most from investing in energy storage, which is caused mainly by feed-in tariff degression, 2) energy trading within a neighbourhood yields the best results when patterns in production and consumption are dissimilar, 3) adding houses that provide no production to a smart neighbourhood, can improve the situation for all houses, i.e. splitting initial costs while also increasing local energy usage. Thus, ultimately, investing in a Microgrid controller and central battery storage can indeed be profitable for shareholders, if certain conditions are met.

Substituting input data files, researchers and potentially interested consumers alike could modify the model to their needs. This would allow for a flexible analysis of given situations, i.e. the planning of a connected neighbourhood.

We have shown that the results our tool generates line up well with existing literature, suggesting that the described toolkit might well be suited to explore scenarios that have not yet been covered by existing research.

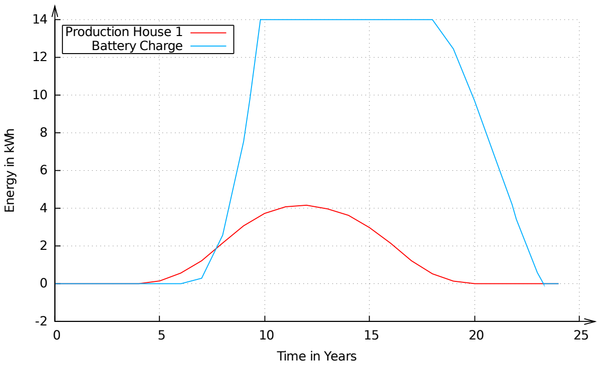

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Fig. 12. Battery Charge and Energy Production on May 20th with settings from Table IV

VI. FUTURE WORK

As a next step, we would like to explore the option of re-implementing our model using non-linear battery models [42]. This would make the simulation and its results represent reality more accurately and might very well yield entirely new insights.

Additionally, we think that it would prove tremendously interesting to implement something akin to the work of Ilic et al. [43]. In the model's current state, once set, the values for monetary compensation when "selling" to the battery and cost when "buying" from the battery remain fixed throughout the run of a simulation. What is proposed by Ilic et al., is employing a stock exchange model to dynamically adjust these values depending on demand and production at any given point in time. Another approach to this angle can be found in game theory, as for example investigated by [44] and [45].

Implementing additional battery strategies (e.g. *Peak Shaving*, *Load Balancing* [41]) and evaluating their behaviour within a neighbourhood might also prove to be worthwhile enhancement, especially from the perspective of utility companies. Adding such strategies would allow for the simulation and evaluation of environments in which energy self-use might not be the decisive factor. Instead, the focus may, for example, lie on more shallow grid-sale gradients. The foundations for implementing additional battery strategies are present. What is currently lacking are translation of those strategies in MATLAB code.

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