# STOCHASTIC BOTTOM-UP FRAMEWORK FOR LOAD AND FLEXIBILITY FOR AGENT BASED CONTROLS OF ENERGY COMMUNITIES

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## *ABSTRACT*

*This paper introduces a simulation framework to test agent based energy management systems during the development state. The management target is to match electrical demand and supply within a given energy community. To reach this goal, a pricing mechanism provides an economic incentive for agents to shift the controllable load to favourable times. The agent itself consists of a communication module, a Blockchain based billing module, a flexibility forecast tool, a decision making module, and a control unit. To test the performance of multiple agents, a simulation framework is presented which uses the bottom-up load and flexibility generator synPRO. The functionality of the whole framework is explained with special emphasis on the modules using the load and flexibility generator.*

## INTRODUCTION

As the energy system continuously changes from a top down structure with central power plants and monopolistic energy companies to a distributed energy network with many small production and consumption units owned by various small parties, decentralized energy management systems (EMS) are on a rise. Agent based EMS enable various prosumers to manage the balance between production and consumption on a local basis. In this context, agents are characterized following the definition by [1] as multiple interacting computing elements which can act autonomously to reach their individual goals and cooperate to optimize a greater system. Developing and testing agent based control algorithms for decentralized energy systems requires simulation models that incorporate the most important energy carriers while taking into account user behaviour and the resulting stochasticity of demand. In the context of optimal control decisions flexibility of individual consumers and producers within a decentralized system are of high interest. This paper presents a simulation framework using the stochastic bottom-up load and flexibility generator synPRO, which is extended to develop and test agent based energy management systems on a neighbourhood scale. The innovation of the agent simulation framework lies in its detailed energy technology models and the possibility to simulate not only load but also flexibility corridors. Furthermore a modular approach guarantees an easy real world implementation by simply replacing the technology simulation with real controllable devices. In the first section of this paper the EMS concept is explained. With the management goals in mind, the agent's structure and functionality is outlined in the second section. In the third section, the load simulation tool is presented in detail. Finally, an exemplary simulation result for the load shifting potential of an electric vehicle agent is shown.

## ENERGY MANAGEMENT CONCEPT

The EMS is developed within the research project EnStadt:Pfaff with the aim of matching on site consumption and production within a given energy community. In this context, an energy community consists of at least one photovoltaic (PV) system and various loads, which can be controllable or non-controllable.

### Pricing Incentive

As an economic incentive for agents to reschedule the device usage of controllable loads, two prices are used. A variable price is used for PV energy that is consumed within the community, and a fixed price is used for externally purchased energy. The variable price increases linearly with an increase in the communities' self-consumption share, but always stays lower than the external price. Based on individual energy shares a separate bill is calculated for each person within the EMS community.

### Forecasting and Communication

For the pricing incentive to work, the agent's need to have an idea about how the price will develop over a given time period in the future. The length of the relevant forecasting time period depends on the individual agent. Each agent forecasts its consumption and makes it public to all others. In addition to the communicated load prediction, a flexibility corridor is forecast to be used by the agent's internal control strategy. With all forecasts available and the knowledge on the pricing mechanism, agents with controllable devices can reschedule their expected controls and update their communicated predictions. It is important to note that the estimated price is just a guideline, and not binding.

The billing algorithm considers the measured energies of all smart meters within the community in a 15 minute resolution.

## Individual Control Signals

A user can have one or multiple agents, and decides sovereignly which control strategy each agent should follow. This way, the agent traces only the target given by its owner and will not be controlled remotely by a central optimizer. Nevertheless, since the energy price is determined by just one mechanism and not negotiated between the agents, the cooperative target to balance production and consumption is the only profit oriented target to reach for. With the management concept in mind, the implementation of the agent, the Communication Network and the Simulation Framework is explained in the following section.

# AGENT SETUP AND FUNCTIONALITY

An individual agent's setup with its connected simulation environment is shown in Figure 1. The simulation framework and network setup with multiple participating agents is visualized in Figure 2.

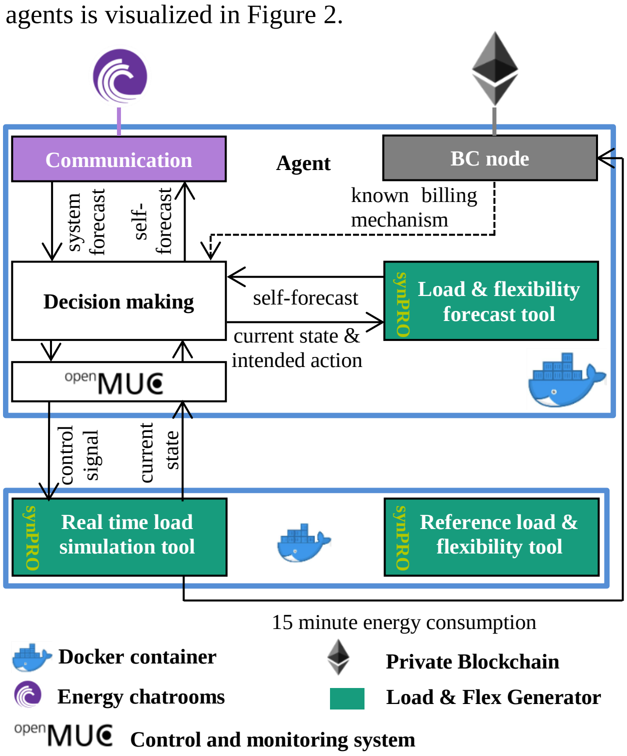


**Figure 1 Individual agent and corresponding simulation environment**

## External Ports

Each agent participates in a shared communication and a shared billing network. A third connection links the agent with a controllable device.

To communicate the individual energy forecasts of the different (virtual) devices within the EMS, a decentralized system based on BitTorrent technology and bitcoin cryptography is used (shown in purple colour). This communication module guarantees a private and resilient information broadcast.

The second network uses Blockchain technology, namely the ethereum-based proof-of-authority protocol clique [2]. This private Blockchain module (shown in grey colour) is used to store energy sums measured by smart meters with a 15 minute time resolution. A smart contract can be called to calculate the individual bill, for all participants within the EMS.

As an interface to a controllable load the OpenMUC [3] control and monitoring framework is used. Using OpenMUC, the agent can be tested within the simulation network and later easily enrolled in a real world implementation. No major modifications are necessary apart from choosing the right communication protocols for the controllable device. A large set of libraries with the most common protocols is already included in OpenMUC. The exchanged information is the state of the designated device, and in return, a control signal.

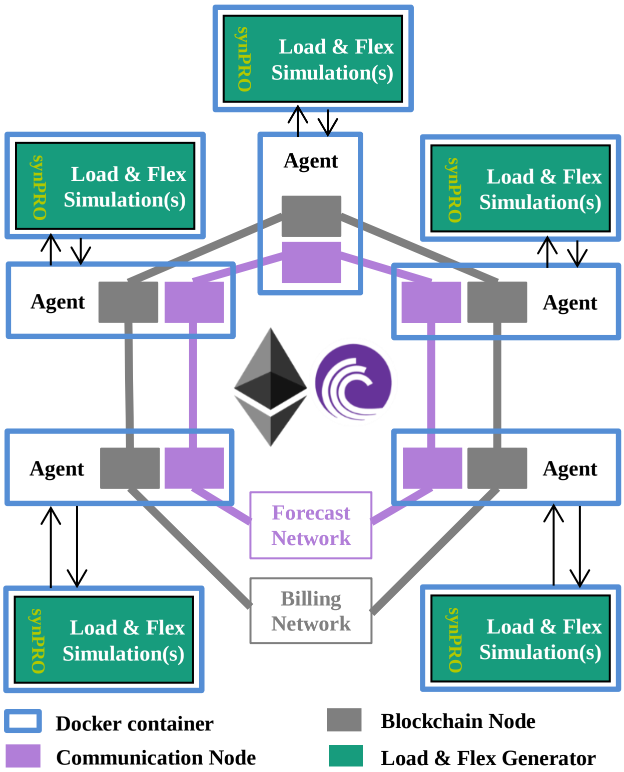


**Figure 2 Overall communication and simulation framework**

## Internal Modules

Apart from the previously described modules that interact with the outer environment, a module for load and flexibility forecast, and a decision making module are used within the agent.

SynPRO [4] is used as a load and flexibility forecast tool. It will be described in the following section in detail, since it is also used for the simulation environment.

The decision making module is the coordinating heart of the agent. It manages the communication with other agents, sends control signals to be translated and forwarded to the controllable devices and exchanges information with the forecast tool. The decision of how to schedule the connected device is based on:

1) The energy system forecast provided by the communicational node.
2) The current state of the assigned device gathered by OpenMUC.
3) The flexibility range of the connected device as calculated by the synPRO forecasting module.
4) The knowledge of the pricing mechanism used in the billing smart contract.

The updated device control schedule is sent back to the forecasting tool which returns an updated forecast. This iteration between forecast and decision making module can take several rounds until an updated load forecast is sent to the communication node and broadcast to the other agents. Note that the real time control signals can deviate from the publicly communicated behaviour. Nevertheless, it is beneficial for the individual agent and the whole energy system to match forecast and actions.

## SIMULATION FRAMEWORK

To measure the performance of different multi agent energy management systems (MAEMS) and compare these results with a centralized EMS approach, the bottom-up load and flexibility generator synPRO is used. The interconnection with an individual agent is shown in Figure 1.

### Load and Flexibility Tool

The tool can be divided in two consecutive models, one for basic household appliances and thermal loads and one for detailed technologies, such as heat pumps or battery systems.

The first model uses a stochastic bottom-up approach to generate energy demand profiles for electricity, domestic hot water (DHW) and space heating (HTG) demand. It uses a behavioral model based on probability distributions for time-usage and mobility. As described in [5], activity probabilities for daily frequency, start times and running duration are derived from over 40,000 data sets based on a time-use survey. For the electric load profile generation, individual activity is linked to a specific electric device usage. The devices are represented by a set of different measured load traces. From this information, a load profile for electricity is generated. The generation of DHW load profiles follows the same approach, linking behavior with hot water demand by using tapping profiles based on [6]. The heat loads are generated using simplified building models, implemented according to DIN13790 [7], where the presence of persons in the building, as well as the electric and DHW load profiles, are used as input to the heat load calculation. The electric and thermal load profile models are presented and validated in [8] and [9].

For the agent's simulation environment the model described above is used prior to the real-time simulation run. The generated electric load profiles will be used as the non controllable loads for apartment agents. The flexibility potential of devices like washing machines, dryers and dishwashers together with fridges and freezers is not used in this simulation framework, since the shiftable energy is small compared to the potential of major technologies mentioned later. Furthermore, the first three mentioned devices are dependent on user behavior and therefore far more speculative than behavioral independent ones. Nevertheless, flexibility models for these devices are developed and provide additional information on the flexibility potential, which could be activated by a sensible user.

The second model of the load and flexibility tool uses the demand profiles from the first model to simulate the following technologies: Heat pumps (HP), combined heat and power plants (CHP), direct electric heating devices (DEH), photovoltaic systems (PV), stationary batteries and electric vehicles (EV). Here physical models are used to simulate the different technologies. For the heating technologies, thermal storages are included to extend their flexibility potential. The HP model is introduced, validated and demonstrated in [10]. The EV model is introduced and validated in [11].

The diversity of the different systems leads to highly individualized load and flexibility profiles. The agents' performance can be analyzed in a highly flexible environment. The building type, size, insulation standard, heating technology, number and socioeconomic settings of tenants, EV penetration and EV models, PV generator size and orientation, household appliance pool and efficiency are the most important factors that can be varied and lead to a highly individualized agent system behavior.

### Making synPRO Agent Ready

The existing bottom-up load and flexibility generator was further developed to be used in a real-time simulation framework. Therefore, specific control signals were defined based on the idea of smart grid ready signals for heat pumps as described in [10]. The defined signals for the specific technologies are listed in Table 1.

**Table 1 Control Signals for the Specific Devices**

| System | Signals | Types, Range |
|---|---|---|
| All | Business as usual, Action | Bool, 0,1 |
| HP, DEH, CHP | On, off, on with increased hysteresis, superheat to max storage temperatures, (superheat + backup heater) | Integer, 1-6 |
| PV | Power curtailment | Float, 0-100 |
| Battery, EV | Percentage of nominal power | Float, -100-100 |

All technologies have a Boolean signal in common, specifying if a control action is given by the agent. If no action is provided the device runs in business as usual operation. If active control is required different sub signals are sent depending on the specific technology. For the heating technologies an integer representing the states "on", "off", "on with increased storage temperature hysteresis" and "superheating of the storage to maximum temperature" are possible. Additionally if there is a backup system installed (e.g. air sourced HP + heating rod) the backup system can be operated by the agent. For a PV agent the possibility to curtail the power output is represented by a float number between 0% and 100% as the maximum percentage of the nominal power currently allowed. For battery systems, either stationary or in an EV, a percentage of the nominal (dis-)charging power can be communicated in the range of -100% to +100%.
The simulation process for a controllable agent is shown in Figure 3. Starting the MAEMS, each simulation tool calculates the first time step and communicates its calculated system state to the connected agent. Afterwards the simulation is paused and waits for a returning control signal. Optionally, a maximum response time can be used after which the simulation proceeds in normal mode. With the control signal received, the simulated system aims to follow the instructions within its operational limits. This means that not all signals will necessarily provoke the expected actions but since the agent knows the operational limits of its connected device and the current state, the derivation should be small. The next step is calculated and the process repeats.

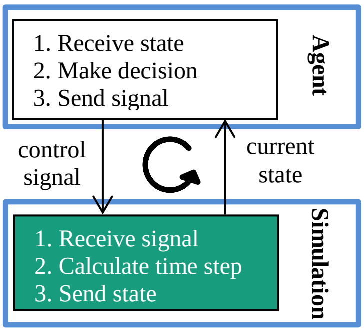


**Figure 3 Simulation steps for a controllable agent**

## Implementation and Scalability

For a modular implementation of the simulation framework, Docker containers [12] were chosen. This way multiple virtual agent environments can be set up on different hardware requiring only a running Docker installation. Docker also offers the ability to scale the system meeting the needs of the energy community to be simulated. Depending on which particular systems shall be simulated the corresponding containers are chosen accordingly and are run multiple times.
For the agent containers there are two options available, one for controllable loads and one for uncontrollable loads. For uncontrollable loads, a light version with no decision making module is used, instead the forecast tool communicates the prospected energy consumption based on the current state of the uncontrollable load directly to the network. Within the group of controllable loads, individual decision making and forecast tools for HP, CHP, DEH, EV and battery systems can be tested.
Furthermore, for uncontrollable loads, the simulation framework is reduced using just the reference load simulation and no real-time simulation tool, since no control signals are sent. The reference module communicates its state to the agent's forecast module and the past 15 minute's energy to the Blockchain module.

## Running the Simulation

Previous to the actual MAEMS run, a baseline simulation for the individual households and houses is done, providing information on the non controllable electrical loads together with the thermal demand and mobility profiles. Following this, a reference simulation is started. This reference simulation is the benchmark to compare with. It shows the system behaviour of an uncontrolled load and also simulates the flexibility outlines in which an agent can operate. The main simulation is then used to operate based on the real-time control signals provided by the agent. This second simulation is done without a flexibility simulation, since the flexibility is already being used by sending control signals. Reference and main simulation are started using the same behavioural settings provided by the baseline simulation, so that the thermal heating and domestic hot water demand for heat pumps, or the trips of electric vehicles are identical. This is based on the assumption that the flexibility usage is not affecting the behaviour of the people living inside the community. A change of usage patterns due to the current energy system state is desirable in the real world, to evaluate an individual agent's behaviour in the simulation it is not considered. Additionally, the sizing parameters for the different devices are identical in both simulations.

## Interpreting the Results

Main and reference simulations generate annual time series data that can be compared with each other. Additionally, a flexibility profile from the reference simulation provides information about the technical potential that could have been exploited by the agent. The results can be compared on a device level or on an aggregated community level. The technical evaluation can be done comparing common energy system parameters such as peak values, residual energy, or the self consumption rate of the community. Additionally, an economical benefit can be quantified, comparing the different bills of the two simulations for an individual person or the whole community balance. An evaluation of a running agent system simulation is not shown in this paper and will be part of future publications. Nevertheless, an exemplary result is shown in the following section as a short prospect on how the simulated output looks like.

## EXAMPLARY RESULT OF THE SIMULATION TOOL – LOAD SHAPE VARIATION USING AN EV AGENT

### Setup

As a simple test case, the behaviour of the MAEMS simulation framework is shown for an agent environment with four non-controllable apartment agents, one agent for a PV plant, and one agent for a controllable charging station for an electric vehicle of a small family. To increase the flexibility of the EV a state of charge (SOC) of 80% is set as a minimum charging target value. The remaining 20% battery capacity is just used to charge with PV surplus energy.

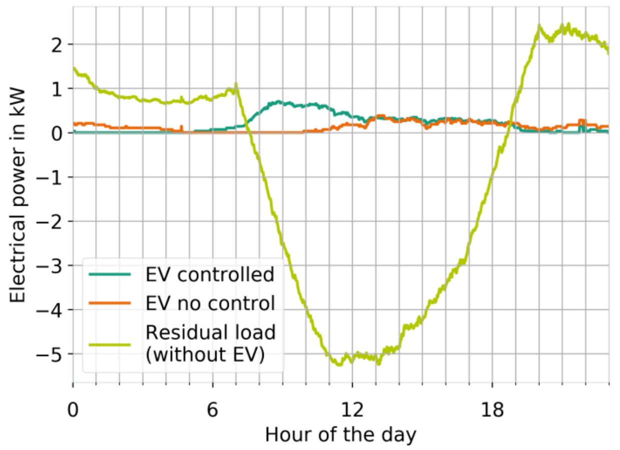


**Figure 4 Mean summer day charging power of an electric vehicle with and without agent control for a 1-minute resolution.**

### Evaluation

It can be seen, that the load of an agent controlled charging station is influenced in a positive way as a reaction to external price signals based on the system forecast provided by all six participating agents in a multi family house. The charging power for an average summer day is shown in Figure 4 for the reference simulation (orange) and the agent controlled simulation (dark green). The residual load of the PV system and all electrical loads, excluding the electric vehicle, are shown in light green colours. In this test case, the usage of the agent results in an annual rise of the self consumption share by 5%. As a side effect, the annually charged energy at home is increased by 45% while other charging locations are used less often. Most of the charging processes got shifted into the hours before noon. This is partly due to the specific usage patterns where the car is frequently used during the day, but also caused by a conservative decision making of the agent. As a result of the analysed agent's behaviour it can be said, that the agent reached the system goal to increase the self consumption share but has still potential to shift charging processes to times with cheaper prices whenever the EV is home during midday.

## CONCLUSION

A simulation framework to generate precise load profiles for the test purpose of multi agent energy management systems is presented in this paper. Detailed technology models for various shiftable loads, together with realistic usage patterns, depending on the different socioeconomic factors of residents, create load and flexibility profiles that can be analysed on a device and community level. An energy management concept with a central pricing mechanism creates the incentive for agents to shift loads to timeslots where a high amount of locally produced energy can be used. The unique bottom up approach of the simulation framework leads to realistic test conditions and first results proof the functionality of the agents.
The approach will be further used to test different control algorithms of agents for large energy communities with a high penetration of controllable loads.

## ACKNOWLEDGEMENT

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