SEAM: Swarm Algorithms for Energy Allocation in Microgrids

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***Abstract*—Microgrids are local energy distribution cells that include energy consumers and energy generators and may or may not be connected to wide-area transmission grids. By balancing consumption and supply locally, microgrids foster the transition to renewable energy sources that are less predictable than carbon-based ones. In this context, an important issue is to develop scheduling approaches for energy appliances that can be scaled to numerous independent, small energy consumers and generators. We propose SEAM, our approach for Swarm-based Energy Allocation in Microgrids. SEAM allows supply- and demand-side management based on a price signal that reflects over- or undersupply of energy. Together, all individual energy appliances that participate with SEAM form a swarm, which balances generation and consumption of energy. Thus, SEAM provides a distributed platform for transactive energy management with low entry barriers for participants and without a third party learning personal details from consumption data. To acknowledge that SEAM works as intended, we provide a formal framework that allows us to derive important properties regarding grid stability. Furthermore, we describe a model prototype using SEAM. Our prototype shows that SEAM can be realized easily and copes very well with fluctuating energy sources, as predicted by our framework.**

Keywords–Smart Grid; Demand Response, Swarm Approaches

I. Introduction

Right now, the number of renewable sources that feed energy into local energy grids ("Microgrids" [1], [2]) is growing worldwide, at an amazing pace. However, this comes with a number of open issues. First, existing power grids have not been designed to cope with numerous small energy sources that feed energy at variable rates. With classical energy grids, such fluctuating energy generators increase the need for spinning reserve energy. Second, most existing smart grid technologies that are available on the market yet focus on large installations, such as megawatt-sized power plants and industrial consumers in the same range. However, such technologies are by far too complex and too expensive to be deployed to many small, independent energy generators and consumers, e.g., roof-top photovoltaic (PV) installations or cold warehouses. Third, existing storage approaches, be it power-to-gas, compressed-air storage or battery banks, are unlikely to be deployed at a sufficiently large scale to keep pace with the installation of renewables in the near future.

In Germany, the highest peak in power consumption is at noon when the electrical ovens are turned on (e.g., see [3]). This fits with the peak generation of PV power plants. However, other countries face different problems when integrating renewables [4]. Furthermore, it can be regularly observed [5] that the price on the spot market for energy drops below 0 ct or that renewable energy sources are regulated down in favor of less adjustable traditional power sources [6]. In consequence, there is a clear demand [4] for smart grid approaches that focus on the prosumer market (cf. Figure 1). Prosumers generate and/or consume energy at a small scale and may or may not have some flexibility to shift the energy supply and demand in time.

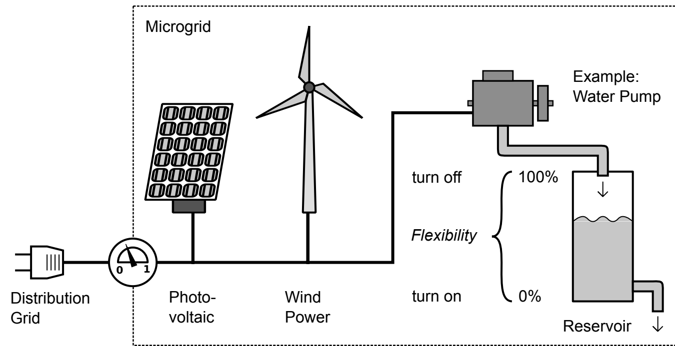

Figure 1. Basis scenario

For example, prosumers might be the members of a rural cooperative that wants to use wind- and biogas-power plants to operate agricultural machines, drainage pumps and cold warehouses as much as possible from renewable energies that are locally available at little costs. Prosumers also could be the co-tenants of a sustainable city quarter, wanting to fuel thermal heat pumps, air conditioning, hot-water boilers etc. from roof-top PV installations and a combined heat-and-power-plant. A third example are islands, which want to shift from diesel-generated electrical power to renewable energies without having to install expensive battery banks.

With our approach, the energy-consuming or generating prosumers can alleviate the impact of fluctuating energy sources. For example, one prosumer might operate a raw-water reservoir for flushing the toilet while another one provides a roof-top PV installation. If both prosumers synchronize so that the raw-water pump starts if (a) the sun shines and the reservoir is not filled entirely, or (b) the reservoir is empty and must be filled immediately, the total demand for the spinning reserve of the grid operator decreases. A smart grid approach for such a scenario must fulfil a number of specific requirements:

R1: Balance Energy Consumption and Generation The smart grid approach must be able to tell each prosumer in real-time if it is cost-efficient to start or stop energy generators or consumers.

R2: Clear Benefit The installation of such technologies must pay for itself, beginning from the first energy appliance to be installed and within a reasonable period of time.

R3: Interoperability It must be possible to mix appliances

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under control of a smart grid approach with energy appliances and infrastructures that already exist.

R4: Low Complexity Adding or removing smart grid appliances must be possible without having to inform or reconfigure other appliances. There should be no need for elaborate communication protocols.

R5: Robustness The approach should come with no single point of failures and must remain operative even if, say, the communication has been interrupted.

R6: Understandability The actions of each appliance under control of the smart grid approach must be directly comprehensible for the prosumer.

R7: Data Privacy The approach must do without any external instances that might learn in detail the energy appliances, preferences and habits of each prosumer.

In this paper, we propose SEAM, our approach for Swarm-based Energy Allocation in Microgrids on the prosumer level. We strive for a simple approach that can be installed on inexpensive off-the-shelf hardware and allows generation-side management and demand-side management for prosumers. That is, we assume that a grid operator exists, which balances over- and undersupply of energy, if this is beyond the capacities of the prosumers.

Our approach considers each energy appliance under control of SEAM as a swarm member. Thus, we want to obtain an emergent, complex swarm behavior as a result of the actions of many independent, distributed swarm members following simple rules without a central coordinator. In our case, each swarm member decides individually, based on a price signal and local information, if it should start or stop operating. The sum of the decisions of all swarm members converges to an emergent state where generation and consumption of energy is balanced as good as possible, which reduces the need for the spinning reserve at the site of the grid operator. From a business perspective, SEAM creates a distributed, privacy-aware platform for transactive energy management with low entry barriers for participants. In particular, we make the following contributions:

1) We describe the intuition behind SEAM, our approach for Swarm-based Energy Allocation in Microgrids.
2) We provide a formal framework for SEAM, which allows to assess its applicability to a given scenario, such as an insular grid or a urban microgrid.
3) We formally show under which conditions SEAM converges to a global state where energy consumption and generation is balanced.
4) We provide a description of a model prototype using SEAM.

Our prototype shows that the behavior of SEAM is in line with the properties derived from our formal framework. Furthermore, SEAM copes very well with fluctuating energy sources and unpredictable energy consumers.

Paper structure: The next section reviews related work. In Sections III and IV, we provide an intuitive and a formal description of SEAM. Section V analyzes the stability of SEAM, followed by a description of our prototype in Section VI. Section VII concludes.

II. Related Work

In this section we outline and compare general strategies for energy allocation in smart microgrids.

A. Smart Microgrids

Microgrids [1] are collections of energy consumers, energy sources and perhaps facilities for energy storage, functioning as a single system. A microgrid can be connected to a wide-area transmission grid. It also can be an autonomous system, using its own resources for energy generation and grid stabilization. Microgrids show their strengths in areas with heterogeneous loads, varying energy sources and long distances/few options to store energy locally [2]. One of the core objectives of today's microgrids and the focus of this work is to balance supply and demand in order to foster the integration of renewable energy sources. For this purpose, a number of alternatives exist:

Centralized forecasting approaches let a centralized coordinator compute a forecast of energy consumption and supply, based on a wide range of information. A typical example is a microgrid in Chile [7], which uses a neuronal network to continuously calculate a two-day forecast. The microgrid uses a rolling-horizon strategy to control battery banks, diesel generators and loads like water pumps. Another typical example [8] uses a genetic algorithm for forecasting. A characteristic feature of this example is that it uses not only weather information and load profiles, but also economic models and the energy price to produce an optimal schedule for all connected appliances. A novel high-frequency microgrid is shown in [9]. The advantage of high-frequency (500Hz) is the reduction of the transformation and transportation costs at smaller networks. The system works also with a two day forecast, optimization of loads like water pumps and optimization of storage systems like battery banks.

Multiagent systems allow to build decentralized microgrid coordinators. Each agent is free to implement its own scheduling strategy to, e.g., build a smart city grid [10], charge electrical vehicles [11] or route energy between grid segments [12]. Since the agents are autonomous to some extent, this approach allows flexible microgrids with low entry barriers that do not need to transfer sensitive personal information to a third party. As a disadvantage, the agent run-time environment is a critical infrastructure.

Hybrid approaches combine two or more different energy sources, such as PV and Diesel generators [13], Wind-PV-Diesel [14] or solar thermal-geothermal power [15] into an integrated energy appliance. The appliance uses a controllable energy source when a flexible one cannot meet the energy demand. Because the vendor ensures that both energy sources complement each other, this approach allows to build low-complexity microgrids. However, this approach does not support the integration of other prosumers.

Transactive energy focuses on the active participation of prosumers via market mechanisms [16]. That is, the grid operator calculates a net-metering price for energy at real-time, which includes the costs of consuming and generating energy as well as the costs of stabilizing the grid. Each prosumer can decide individually if he is willing to generate or consume energy to the given price. As experience shows [17], the technology works as intended, but the calculation of a good net-metering price heavily depends on big-data analytics, including weather forecasts, marginal costs at different generation plants, congestion data of the transmission grid and various factors related to grid stabilization.

Energy auction approaches transform supply and demand of energy into bids that are placed on a centralized auction platform. This platform performs double-sided continuous auc-

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tions to obtain the optimal market price and energy allocation for any point in time. PowerMatcher [18] is a well-known implementation of such an auction platform. Similarly to multiagent systems, each participant is free to implement its own scheduling strategy. Extensions of PowerMatcher even have been developed to run hybrid systems [19]. However, it is difficult to derive reasonable bids [20], e.g., for renewables that generate energy nearly without marginal costs, or for heating systems where the user does not want to gamble a convenient temperature. Thus, the complexity of the system is high for prosumers that do possess detailed background knowledge. Furthermore, the bids reveal many personal details.

B. Swarm Approaches

Our approach has been inspired by collective swarm intelligence, as seen by ants, bees or birds. The common factor of collective intelligence is that a complex, "smart" swarm behavior emerges from individuals who compete for resources based on straightforward rules and local ad-hoc information. Note that other definitions of swarm behavior additionally require interactions between neighboring swarm members. In our case, the resource is the price signal and the rules consider the valuation for energy. It is appealing to apply swarm concepts to microgrids. For instance, particle swarm algorithms (running on a central instance) can be used to optimize microgrid parameters [21], [22]. However, existing swarm algorithms (cf. [23], [24]) are difficult to distribute over a microgrid. One approach [25] allows a distributed architecture by modeling energy generation and consumption as a system of coupled oscillators. Since this model comes with a high complexity and binds the prosumers to a predefined scheduling strategy, this approach does not meet our requirements. Furthermore, some enterprises, e.g., Encycle, Easy Smart Grid, LichtBlick, GridSense and Siemens, are developing swarm approaches, with different directions of impact. Finally, a preliminary simulation study of our approach can be found at [26].

III. SEAM

Without loss of generality, assume a scenario as shown in Figure 1: A microgrid contains a PV site and a wind power plant, which feed energy into the microgrid at variable and less predictable rates. The major energy consumer in the microgrid is a raw-water pump, which fills a water reservoir. The pump has some demand-side flexibility: If the reservoir is full, the pump must be turned off. If the reservoir is empty, the pump must be turned on. In between, the pump may or may not be activated. The microgrid is connected with a distribution grid. The grid operator (a) provides energy if the local renewables do not provide enough energy to match the demand and (b) connects to spinning-, non-spinning- and frequency-response reserve power to ensure grid stability. In comparison to the normal energy supply, using reserve power is more expensive by some orders of magnitude. Furthermore, the transmission grid comes with transmission losses. Thus, the most efficient mode of operation is to consume the energy provided in the microgrid locally, i.e., to minimize the energy flow to and from the grid operator.

Now assume four pumps and an amount of energy provided over time as shown in the graph in Figure 2. Intuitively, an *optimal schedule* as shown in the figure would activate pumps in a way that their reservoirs never run empty. Furthermore, the schedule would activate many pumps in parallel if there

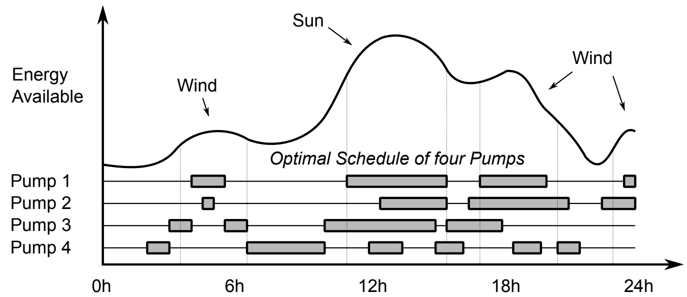

Figure 2. Example schedule

is a surplus of energy and deactivates pumps in case of an undersupply. Note that we do not make any restrictive assumptions on the kind of flexibility of the energy appliances. For example, an owner of an electrical vehicle might want to charge the battery to 30% immediately after coming home for spontaneous drivings. He might be willing to deliver energy to the microgrid if the battery is charged above 80%, and he might want the car to be charged to at least 60% at 7am each week day for commuting.

A. Scheduling Energy Appliances

Obviously, in reality an optimal schedule is impossible for supply- and demand-side management, since it would require a perfect forecast of the states of any energy appliance in the microgrid at any time in the future. With large grid installations, the law of large numbers mitigates the effect of local fluctuations in the energy supply and demand. In a microgrid, several alternatives already exist to obtain a *reasonable schedule*:

- A straightforward way would be to use a *timer switch*. The timer can be programmed so that the activity times of the pumps correspond with the typical hours of sunlight and wind. The effectivity of such a schedule is limited, but this approach is feasible for each prosumer without invoking third parties or installing sophisticated hardware.
- A *central coordinator* can do forecasting or implement an environment for a multi-agent system, as described in Section II. However, the coordinator puts the privacy of the prosumers at risk, comes with high total costs of ownership and requires a high overhead for installation, maintenance, configuration and communication.
- The third option is to implement a real-time market for energy, e.g., with transactive energy approaches or by using energy auctions. While such an approach comes with much lesser entry barriers for prosumers than a global coordinator, it still requires a trusted third party knowing personal details regarding the energy consumption of the prosumers. Furthermore, it known from economics that the efficiency of markets depend on perfect information.

B. The SEAM Approach

We have developed SEAM, a different approach based on swarm mechanics, as shown in Figure 3: An energy meter measures the amount of energy that is imported from the distribution grid into the microgrid. Based on this information, the energy meter calculates a price signal. The more energy is imported, the higher the price to consume energy and vice versa (left side of Figure 4). With SEAM, the price signal helps to shepherd the swarm of energy appliances similarly

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to pheromone trails of ant colonies. Thus, the semantics of the price signal differs from net metering prices as used with transactive energy approaches or energy auctions.

Our price signal is broadcasted periodically to a number of smart controllers. A smart controller can be a standalone device, but it can also be implemented in the firmware of any device containing a micro-controller. Each smart controller is responsible for controlling an individual energy appliance, i.e., an energy storage, a consumer or a generator. In particular, the smart controller uses the price signal and local information about the flexibility of the appliance. Such local information can be the allowed tolerance for the temperature of a cooling house, it can be the charging status and desired charge of a electrical vehicle or it can be the heating demand of a combined-heat-and-power plant. If the flexibility is high, e.g., if there is plenty of time until a water pump must be activated to ensure that the reservoir does not run empty, the controller is unwilling to pay much for activating the pump. On the other hand, if the reservoir is about to drain, the controller must accept any price for energy.

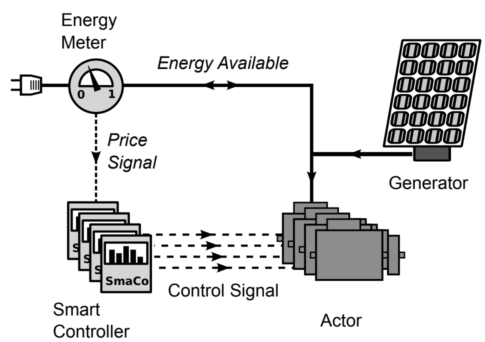

Figure 3. SEAM swarm

A straightforward approach to implement such a strategy would be a linear regression model. In this case, a straight function describes the relationship between the flexibility and the price signal (right side of Figure 4). Thus, each controller would implement the following swarm algorithm, which is continuously evaluated:

Switch on if: *The device is off, local properties allow that it can be switched on, and the local flexibility results in a valuation of energy that is higher than the price signal.*

Switch off if: *The device is on, local properties allow that it can be switched off, and the local flexibility results in a valuation of energy that is lower than the price signal.*

A more sophisticated strategy could solve an optimization problem on a forecast of the energy price (see Section IV).

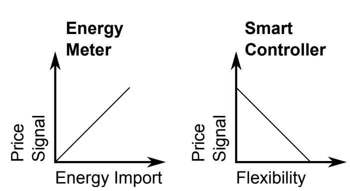

Figure 4. Balancing supply and demand

The decision about turning an energy appliance on or off is based solely on the broadcasted price signal and local data, i.e., there is no global optimizer and no communication with other controllers involved. The decisions of the swarm of smart controllers have an effect on the energy generated and consumed. This is measured by the energy meter and transformed into a new price signal, which is broadcasted again. Thus, a closed-loop feedback control circuit is established with the energy consumption as a feedback channel. If one appliance has an urgent need for energy and turns on, others might decide that the price is too high and switch off. Similarly, if the PV power plant delivers more energy, some appliances might decide that the energy now is inexpensive enough to be used even if, say, the tolerance limit of a cooling warehouse is not reached yet.

Because the price signal is obtained by measuring the available energy, it is possible operate SEAM-controlled appliances together with existing ones, and controllers can enter and leave the swarm at any time without having to reconfigure any grid component. Since there is no outgoing communication, the privacy of the prosumers is not an issue. It is simple to understand the decisions of the smart controller by observing the local demand and the price signal. Finally, if the broadcasted price signal fails, the energy appliances can simply return to a mode of operations that is identical to a non-smart grid. Thus, SEAM fulfils the Requirements R3–R7 named in Section I.

Observe that the price signal is just a representation of the balance between supply and demand. Thus, it is possible to realize SEAM without modifying business cases of the grid operator – instead of a price, a normalized factor in the interval $(0, 1)$ would serve the same purpose. Furthermore, the price signal contains the marginal fee for energy. In other words, it is the price of consuming an infinitesimally small amount of energy at a certain time. Thus, the price signal represents the balance between demand and supply of energy, which allows us to develop swarm algorithms that allocate energy, but it cannot be directly used for net metering.

IV. A Formal Framework for SEAM

In order to show that SEAM converges to a state where energy consumption and energy generation is in balance (Requirement R1), we now describe a formal framework that describes the optimal point in time to turn on or off a device, given the local information and a time series of past energy prices in the possession of each smart controller. To ease our presentation, we model consumers as loads that are active for a predefined time interval, once they have been turned on. Our framework can be extended to more elaborate models easily.

A. Basic Properties

Without loss of generality, assume an electrical device $d \in D$ must be active for a certain time Δt^d within a time interval ΔT^d. This is typical for many devices, e.g., anything that operates cold or heat and fills or drains a reservoir that is continuously in use.

$d \in D$	Electrical device with flexibility
ΔT^d	Flexibility to shift the consumption of d
Δt^d	Minimal time span d must be running in ΔT^d
s^d	Start time of d
l^d	Electrical load of d
p_i	Price signal at time i
c_i	Forecast of the price at time i

TABLE I. Important symbols

Assume a cold warehouse must hold a temperature between 4 and 6°C. The cooler consumes $l = 800$ Watt. The warehouse warms up in 20 Minutes from 4 to 6°C, and it cools down from 6 to 4°C within two minutes. Thus, $\Delta t = 2$ min. To ensure a temperature below 6°C, the last point in time s' the cooler must start for $\Delta T = 22$ min is after 20 minutes. Thus, $0 < s' < (\Delta T - \Delta t)$. Table I lists the most important symbols used. Our model comes with three assumptions:

Assumption 1. *$|D|$ is large, i.e., there are many individual devices.*

Assumption 2. *The distribution of the loads l_d of any device $d \in D$ follows a Gauss Distribution, i.e., there are few devices with a very high energy consumption and a long tail of devices with a small consumption. This models a difficult case: Our framework will show that the energy allocation is easier if all devices have the same load l.*

Assumption 3. *The inaccuracy of the forecast c_i for the price signal at time i increases with increasing i. Let $\Delta c_i = c_i - p_i$ the difference between the exact price and its forecast at time i: For any two points in time $\forall i, j \in \Delta T$ with $i < j$, $|c_i - p_i| \leq |c_j - p_j|$. Thus, Δc_i increases with i: $|c_i - p_i| \sim i$*

This is natural. At the current point in time the price is exactly known. It might be possible to guess the energy supply and demand in a local microgrid for some minutes in the future with high accuracy. But it is hard to tell the weather and the devices that are active for some hours or days in the future.

Obviously, it is impossible to shift the starting time s^d of a device d into the past. If a smart controller thinks there will be a better price in the future and the demand can be shifted to the end of the flexibility interval, but the price is higher then, the device must be activated anyway.

Proposition 1. *The valuation for energy z^d increases with decreasing flexibility. If the flexibility in time is large, i.e., there are many options to turn on the device at a later point in time without violating the user's settings, the controller will accept low energy prices only. In contrast, if the time is near when the device must be turned on, the smart controller is willing to pay a higher fee. Thus, $z^d \sim i$.*

B. Optimal time for turning on the device

After having shown the assumptions and basic properties of our model, we now describe how each controller might identify the optimal point in time to activate its electrical device.

Proposition 2. *All smart controllers try to minimize the total costs for consuming energy. To this end, the controllers compute a forecast c_i for the price in the future at time i. Thus, for each device d there is a smart controller solving at any point in time i an optimization problem: Find a starting time s_d so that the costs for consuming l^d over the time Δt^d will be minimal.*

$$\underset{0 \leq s^d \leq \Delta T^d - \Delta t^d}{\arg\min} \int_{s^d}^{s^d + \Delta t^d} c_i \cdot l^d \, di \tag{1}$$

A simple forecasting approach would be to interpolate the current price to the future. Another simple approach might use the time series of the prices from the day before. Our prototype (see Section VI) shows that even simple approaches work well. However, the price k^d paid by any device d is not the forecast, but the price that is valid at the respective time, i.e.,

$$k^d = \int_{s^d}^{s^d + \Delta t^d} p_i \cdot l^d \, di \tag{2}$$

Recall that the smart controllers rely on local information and do not communicate with each other. Each controller derives the optimal starting point in isolation. Furthermore, it can be assumed that the energy prognosis is similar on each controller. Proposition 1 tells us that controllers with a high flexibility use their forecast to avoid high prices and favor low prices in the future. However, if many controllers turn on their devices at the same time, the price will increase and vice versa. This multiplicates the effect of Assumption 3, i.e., the inaccuracy of the forecast increases with the increasing forecasting time.

Proposition 3. *From Assumption 3 it follows that the optimal starting point must be closer to the present time than obtained by Equation 1. Otherwise, the increasing risk for an inaccurate prognosis would result in a suboptimal starting point.*

We model the optimal point in time for switching on by considering a risk premium for the optimization problem in Equation 1.

Proposition 4. *The risk premium is the sum of the entry probability multiplied with the costs. With SEAM, the costs are the differences between prognosis and real price $(p_i - c_i)$ paid at time i. The entry probability can be described as a probability density function. Without loss of generality, we denote the risk premium at time i as r_i. Our optimization problem to find the optimal point in time to turn on a device now is as follows:*

$$\underset{0 \leq s^d \leq \Delta T^d - \Delta t^d}{\arg\min} \int_{s^d}^{s^d + \Delta t^d} c_i \cdot l^d \cdot r_i \, di \tag{3}$$

The choice of the probability density function allows to model participants that might be risk-averse, risk-neutral or risk-aware. Another option would be to learn the probability density by observing the difference between price and forecast.

Considering a risk premium results in a swarm behavior where the participants consume energy if the price is "good enough" instead of hoping for a better price in the future by risking inaccurate forecasts. Thus, for a sufficient number of swarm participants (cf. Assumption 1), Requirement R1 is fulfilled. Observe that we can say that without specifying an algorithm to compute the forecast or the probability density function. With our preliminary tests, using a time series of the price signal from the past as a forecast and a linear regression as probability density function turned out to perform well. Thus, our approach comes with a low complexity (Requirement R4).

V. On Swarm Stability

At the first glance, SEAM could produce an oscillating behavior: All or a large share of the devices turn on. Thus, the energy consumption increases and the price signal rises as well. The next time the devices receive the price signal, all or a large share of the energy consumers are unwilling to accept a high price for energy and turn off. In consequence, the consumption and the price signal decreases. The next time the price signal

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is received, all devices are turned on again and the procedure is repeated indefinitely. To ensure that this behavior does not materialize in a real installation, two research questions must be considered:

1) Under which conditions is it possible to provoke an oscillating behavior of a large share of all swarm members?
2) How must the swarm be constructed to ensure that oscillations do not occur normally and oscillations provoked by external events fade away?

Assume a subset $M \subseteq D$ of the set of all devices D. All devices $m \in M$ switch on and off at the same time, i.e., all smart controllers responsible for those devices solve the optimization problem from Proposition 4 with the result that the optimal point in time to start consuming energy is the current point in time. For example, such an behavior could be provoked by a very high risk premium or by having many identical devices. Formally,

$$\forall m \in M : s^m = 0 \tag{4}$$

Equation 4 allows us to derive three of properties that must be fulfilled altogether to obtain an oscillating swarm behavior.

Proposition 5. *The sum of the energy consumptions of all devices in M must be larger than the sum of the energy consumptions of all other devices that are able to counteract the sudden increase in the total energy consumption by turning off.*

$$\sum_{m \in M} l^m > \sum_{d \in (D \setminus M)} l^m \tag{5}$$

Assumption 2 allows to derive for any real setting the share of devices that must be in M.

Proposition 6. *The run-times Δt^m of all devices in M must have a common divider. Otherwise, there would be no stable oscillation.*

$$\forall p, q \in M : \frac{\Delta t^p}{x} = a \wedge \frac{\Delta t^q}{x} = b \text{ with } a, b, x \in \mathbb{Z} \tag{6}$$

Proposition 7. *All devices in M must be turned on before an update of the price signal arrives that tells them to re-evaluate the optimization problem in Equation 3. I.e., the system must have some delay δ between two consecutive updates of the price signal:*

$$\delta = |i_1 - i_0| \tag{7}$$

From Proposition 5 to Proposition 7 it follows that it must be simple to design a microgrid based on SEAM, which cannot produce oscillations, either by ensuring a heterogeneous set of devices, well-distributed loads and/or updating the price signal with a low or random delay. If this is not possible, another feasible strategy would be to allow an operator to manually override the switching decisions of the largest loads in the microgrid.

VI. Prototype

We have build a prototype (see Figure 5) to confirm that SEAM operates on inexpensive off-the-shelf hardware (see Requirement R2), and that our formal framework as well as our assumptions can be applied to real settings.

From the algorithmic perspective, it does not make a difference if we connect real energy consumers with SEAM or a model. For practical reasons, we have decided for components from educational experimentation boxes (Franzis "'50 Experimente mit erneuerbaren Energien"' and Franzis "'Solarenergie"'). Our prototype provides two low-current LEDs and two motors as energy consumers (f). A lamp (a) shines on two PV modules (b) to provide renewable energy sources. A battery and two 1000μF capacitors (g) mimic a grid operator who provides a conventional energy source and grid stabilization. A display unit (e) allows us to monitor the state of the microgrid, the energy intake from the energy sources and the activities of the energy consumers. We have implemented SEAM in Java on a Raspberry Pi Model B+ in a DIN-Rail housing (c), which operates the energy consumers via a multi-channel potential free actor relais (d). Both the display unit and the energy meter makes use of MCP3426 16-bit multichannel $\Delta\Sigma$ analog-to-digital converters with I^2C interface and onboard reference. Observe that this setting stresses the Assumptions 1 and 2 requiring many devices with different loads.

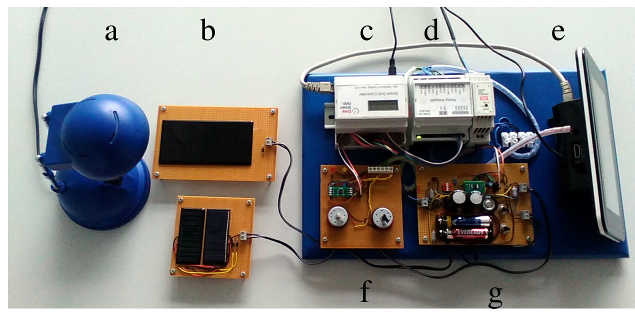

Figure 5. SEAM Prototype

The computational resources of the Raspberry PI model B+ are sufficient to run the energy meter service and four instances of a smart controller in parallel. Thus, the price signal can be transferred via inter-process communication. With our model prototype, we have defined a voltage between 2.7V and 3.3V as normal, i.e., below 2.7V, our conventional energy source steps in, and above 3.3V a Z diode has to consume surplus energy. In order to balance supply and demand, we have implemented the straightforward strategy denoted in Figure 4: Our forecast is an interpolation of the current price signal. The price signal is 1 at 2.7V and 0 at 3.3V. Any smart controller accepts a price of 0 if the flexibility (i.e., the time remaining until the the device must be turned on) is maximal, and a price of 1 if the flexibility is 0. The prototype allows us to configure a wide range of different flexibilities. Furthermore, by moving the lamp we can vary the generation of renewable energies easily. Switches allow us to manually activate and deactivate the conventional energy source and grid stabilization.

Our prototype provides a challenging scenario for SEAM: The energy consumption of a motor exceeds the consumption of a LED by an order of magnitude, we have only four energy consumers in total, and only one source of renewable energies. Furthermore, the energy sources are not under control of SEAM, and SEAM uses a straightforward approach to balance supply and demand.

Nevertheless, our prototype confirms that SEAM works well even in extreme situations. We have ran a number of experiments with two settings: (A) all devices are operated without SEAM, i.e., the devices are turned on if the flexibility is 0 and turned off after Δt. (B) SEAM controls the devices as described. With our experiments, we have moved

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the lamp in different positions and we have measured the energy drawn from the battery. Our experiments with setting B show that typically, our independent smart controllers organize themselves into a regular swarm behavior where one energy consumer is turned on after another one has been switched off. With this switching pattern, the energy produced by renewable sources is optimally consumed. If the pattern is disturbed, e.g., by moving the lamp, the controllers quickly find to another pattern. In comparison to setting (A), setting (B) typically consumes 30% less conventional energy. If the flexibilities are sufficient to compensate fluctuations in the generation of renewable energies, the conventional energy source can be removed.

We have tried to force our swarm of energy consumers into an oscillation where any device turns on and off periodically, as described in Section V. In fact, we can confirm Proposition 5 to Proposition 7: It needs a carefully designed artificial setup where the energy consumers are forced to start at the same time and must have identical run-times. Furthermore, we had to delay the update of the price signal. If we do not enforce this artificial setting, an oscillation will not materialize.

Finally, our prototype confirms that SEAM can be realized with inexpensive off-the-shelf components (Requirement R2). An industry-grade installation with a insulation level IP20 according DIN 40050 can be realized with modules that are readily available from manufacturers, such as Wago or Phoenix Contact. The computational resources needed to operate a smart controller can be provided even by a micro controller.

VII. Summary

Microgrids are a promising approach to foster the transition to renewable energy sources by balancing energy consumption and supply locally. However, existing approaches to schedule energy appliances cannot be readily applied to small-scale producers and consumers of energy, for various reasons.

In this paper, we have proposed SEAM, a distributed approach for Swarm-based Energy Allocation in Microgrids. SEAM makes use of swarm intelligence to let energy producers and consumers adapt to the availability of energy. SEAM maps the availability of energy to a price signal, which is broadcasted to all swarm members in real-time. We have shown that the individual decisions of all swarm members let the microgrid converge to a state where renewable energy sources are utilized as good as possible, given the individual flexibility of the energy appliances. We have described both a formal framework and a model prototype for SEAM, showing that the formally derived properties of SEAM can be observed in a real system. Given that SEAM does not rely on complex infrastructures, expensive hardware components or elaborate algorithms, it copes very well with fluctuating energy sources. As part of our future work, we will focus on the response times, i.e., we strive to provide optimizations and guarantees for the time the SEAM swarm needs to adapt to fluctuations in the energy generation or consumption.

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