Changing the energy system towards sustainability. A co-simulation framework (ID 69)

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Abstract

This paper proposes a (conceptual) simulation framework for a collaborative management in power distribution grids. By combining insights from electrical engineering as well as sociology, this framework highlights the emergent, socio-technical character of the energy system. The interplay of social and technical aspects is further emphasised by referring to the “energy traffic light” concept as an exemplary case of application.

1 Introduction

The energy system is undergoing a paradigm shift. So far the grid was a centralized system, dominated by a few large power generation plants and a large-scale distribution of electricity to end-users. The load-flow was pre-determined, and the roles of producers and consumers were clearly defined. However, renewable energy sources (RES) and new low carbon electricity technologies seriously challenge this conventional energy supply system. On the one side, PV, wind and small-scale cogeneration plants are producing electricity and heat in a distributed way. On the other side, end-users are becoming more flexible and are producing their own electricity as well. This transition results in new uncertainties and risks, mainly because electricity generation and consumption will become harder to predict and unforeseen power fluctuations will become more likely. Especially power distribution grids will be facing these situations, since they host a large share of installed RES and constitute the connection point to the end-user [1].

A possible solution to cope with these challenges is the application of new types of collaborative (information) management and governance measures [2]. One important topic in this context is the use of local flexibilities from end-users for grid management issues. Since these flexibilities can also be used for market operations or for ancillary services, there is a need to design a proper framework to organize the use of flexibilities.

Here, if not before, it becomes apparent that the energy system constitutes a socio-technical system that encompasses technical as well as social elements and interactions: Social actors with variable rationality (e.g. transmission system operator – TSO, distribution network operator – DNO, energy retailers, and end-users) interact and collaborate within a technical infrastructure system (e.g. through energy purchase/sell, active and reactive power exchange or ancillary services).

This paper presents the first step in modelling an *interdisciplinary framework* for a collaborative information management, which is applied to a *power distribution grid* and pays particular attention to the *emergent, bottom-up behaviour* of the power grid. Furthermore, the framework aims at formulating *what-if scenarios* for future electrical distribution networks, conducting experiments with different system configurations and modes of governance.

The proposed framework is based on design principles of agent-based modelling and simulation (ABMS) as well as a sociological macro-micro-macro-model [3]: Governance measures do not necessarily have a direct impact on the dynamics of a socio-technical system, but rather influence decision-making of strategic actors at the micro-level (e.g. end-users), which then leads to emergent effects on the macro-level (e.g. power-surplus, power-shortage or even black-outs). Consequently, this paper aims to provide a conceptual framework for linking (technical and social) simulation models from electrical engineering and sociology in order to depict such an emergence. As far as the authors' knowledge is concerned, no previous work deals with collaborative management in power systems, with special focus on distribution grids and end-users, using a socio-technical approach.

The paper is organized as follows: Section 2 gives an overview of the proposed simulation framework and describes the involved models and their interdependencies. Section 3 elaborates on a practical problem within the context of the “energy traffic light” which can be addressed by the proposed simulation framework and serves as an exemplary case of application. In the end, the paper gives concluding remarks and provides insights into next steps.

2 Conceptualisation of the framework

As indicated previously, macro-micro-macro-models of socio-technical systems may help to understand the (bottom-up) dynamics of socio-technical systems and to detect emergent, unintended effects. We propose a (conceptual) simulation framework for the governance of a power distribution grid (**Figure 1**), consisting of the following six simulators.

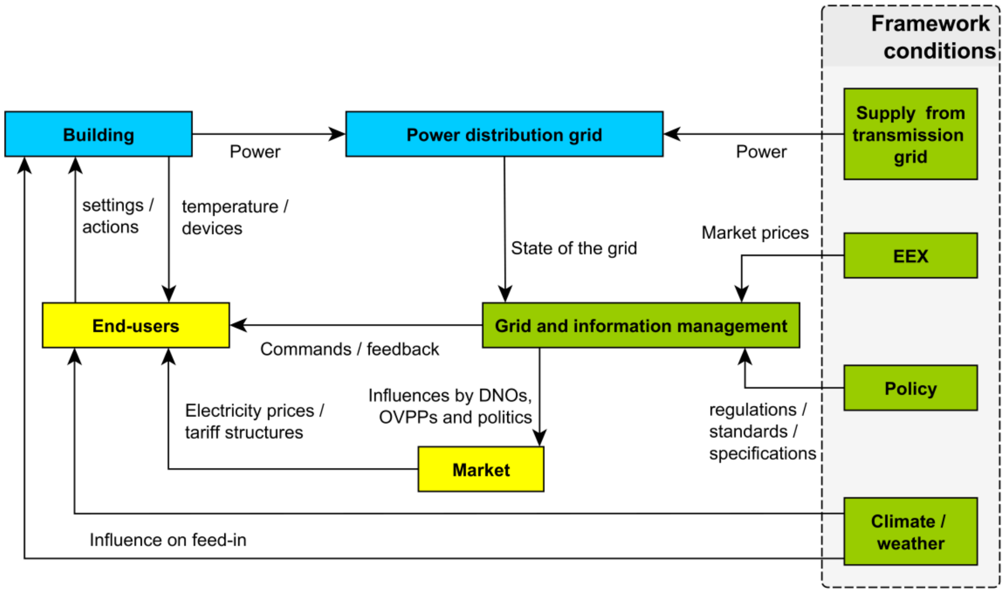

Figure 1: Concept of the overall framework

The *end-user* simulator describes the decision-making of consumers: Based on individual preferences and values, actors decide (habitually or rationally) to invest in technologies, switch tariffs, change their energy consumption behaviour or follow recommendations from energy-monitors (e.g. smart meters or mobile applications). These decisions are furthermore ‘translated’ into load values, which primarily serve as inputs for other modules (cf. *building* simulator).

The *grid and information management* simulator primarily represents controlling interventions on part of DNOs and therefore the standard ‘operating business’ of grid management. Controlling interventions require comprehensive knowledge of the grid, which is why this module also entails the flow of data and information between different actors. Relevant actors in this module are therefore DNOs, virtual power plant operators (VPPOs) and meter operators.

The simulator for the *power distribution grid* is used for load flow calculations, i.e. the current status of the grid. This status is the result of an equation system; values generated by end-users (i.e. loads), producers (i.e. decentral feed-in), feed-ins from the transmission grid and DNO commands are inputs for these equations. DNOs, in turn, use the output data from this module to 'interpret' and manage the grid's status.

A high potential for load shifting on end-user level can be found in the heat sector, making the precise modelling of space heating and hot water demand necessary. Therefore, we include a *building* simulator to represent the actual 'behaviour' of a heating system. Furthermore, this building module also has to depict different technological entities and characteristics, e.g. the energy management system (based on Model Predictive Control), the type of the building as well as the technological equipment (i.e. standard gas heating devices, photovoltaic plants, batteries, heat-pumps and micro co-generation plants).

The *market* simulator encompasses energy retailers' and VPPOs' portfolio of tariffs for end-users and does not represent a typical market simulation (i.e. pricing structures based on demand and supply).

Framework conditions are externally given and consequently not open to influences from other simulators. They encompass pre-parameterized values and trajectories, e.g. weather/temperature or electricity prices on the European Energy Exchange (EEX). Furthermore, political regulations or feed-in capacity from the transmission grid also represent external inputs. Consequently, framework conditions basically help to characterise scenarios. The emergence of framework conditions is, however, not subject of analysis here (i.e. political negotiations etc.).

Coupling multiple simulators, using the *mosaik* framework[1], allows us to combine insights from electric engineering and sociology rather easily while simultaneously keeping the framework flexible. Consequently, the key challenge is to define relevant information flows between the different simulators. In this paper, and for reasons of space, we will only describe three simulators here in detail: End-user, power grid and building.

2.1 Simulator 1: Power grid

The goal of the power grid simulator is to represent an electric distribution network within the simulation environment. It includes models of relevant electrical components of a power distribution grid such as busbars (nodes), transformers, and lines. Detailed models for loads, storage and generators are not handled in this simulator (see simulator building). It also contains information regarding grid topology i.e. how and through which lines different busbars are interconnected with each other, and which generators, loads and/or transformers are connected to each busbar. A set of nonlinear equations describes the relationship between electrical components in a compact way, and from now on,

[1] https://mosaik.offis.de

this is called the power grid model. Values of end-user consumption (loads), power feed-in from distributed generators and overlaying voltage networks, as well as control commands from the distribution network operator (DNO) serve as inputs for this power grid model. With this information, and based on some initial conditions, the power grid simulator computes a load-flow calculation and provides resulting power flows for each line, and respective voltage magnitudes at each busbar. The output of the simulator would allow to determine if, for the given initial conditions and inputs, voltage and loading values are within safety limits.

In the power grid model, it is assumed that only one reference node (slack busbar) exists, and that the remaining nodes are PQ nodes, i.e. nodes with known active and reactive power feed-in/consumption and unknown voltage magnitude and voltage phase. Active and reactive power values are coming from a different simulation instance: the building simulator. Accordingly, in the co-simulation framework the PQ nodes are the coupling points between the power grid simulator and the building simulator.

2.2 Simulator 2: Building

The building simulator involves models of flexible and non-flexible residential appliances, as well as models for distributed generators. These models can be static models – no dependency with previous states, or dynamic models – there is a dependency between actual state and previous state, e.g. a storage unit. Hence, the task of the building simulator is to solve local residential electrical and thermal power flow equations, to give the total electrical power consumed or injected at a specific node, and to compute the resulting state of the dynamic elements (for example state of charge of a thermal energy storage or room temperature of the building). These set of equations describing the behaviour of corresponding building appliances is called the building model.

Because of their flexible operation to balance intermittent power from renewables, residential heating systems play an important role in the current work. Therefore, heating demand and heating supply in residential systems requires detailed modelling. For accounting the demand, the building model uses some dynamic equations to represent the thermal dynamic behaviour of a residential building. This helps to consider building storage capacities as well. Residential buildings imply two types of objects: single-family houses, and multi-family houses. Clearly, buildings must contain not just thermal, but also electrical appliances. For example, a single-family house can embrace two energy sectors. In the electrical sector, there can be a rooftop photovoltaic plant, and the normal inflexible residential loads – lights, refrigerator, washing machine, stove, etc. In the heating sector, an example will be a heat pump with respective thermal energy storage. Here, the heat pump will be the coupling element between the electrical and the heating sector. **Figure 2** presents one possible residential configuration [11]. The power generated by the PV plant can flow into the grid (up) through the point of common coupling (PCC), or can flow to the household load and the heat pump (down). The heat pump is directly connected to the thermal energy storage (TES). The stored energy can be used for hot water or for space heating purposes.

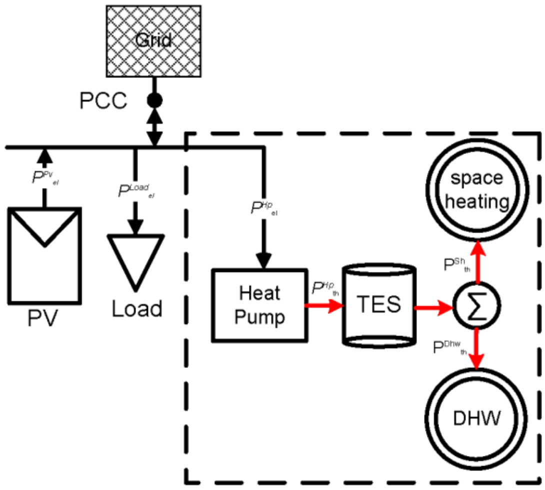

Figure 2: Residential setting with PV-Heat pump [11]

As residential units can follow different operation schedules, there is an energy management system (EMS), whose task is to compute such operation schedules. Different approaches have been proposed to perform this task, being optimization-based approaches the most widely accepted. Particularly model predictive control (MPC) is gaining relevance because of its prediction nature and robustness against uncertainties [4–9]. MPC is a concept from the control theory, which consists in optimizing the future operation of a system by computing optimal trajectories for its inputs taking into account impact of future disturbances. This optimization is performed over a finite time window by applying suitable numerical optimization and forecast methods within a receding horizon control scheme [10]. Therefore, the EMS contains one MPC unit.

Figure 3 shows an MPC based energy management system schematic structure for buildings.

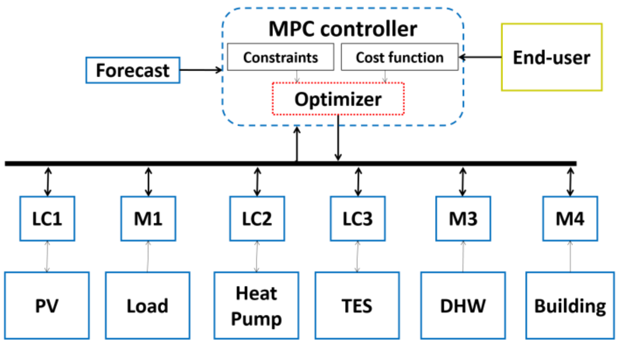

Figure 3: MPC based energy management system

Setting of the simulation parameters for the building model, such as type of appliances present in the building, technical characteristics of the appliances, MPC prediction horizon, MPC sample time, etc., happens just once at the beginning of the simulation. The building model gets weather input data from the external conditions module, and additionally, data from the end-user simulator serve as input for the model. Specifically, these input data contain information regarding end-user building operation preference (self-consumption or energy costs minimization), and comfort limits (temperature set-points for the heating appliances). With this information, the MPC starts the optimization and concludes by giving the resulting optimal values for electrical consumption of the flexible loads, power generation for the distribution generation units, and charging and discharging power for the storage systems. After balancing electrical power flows within the residential system, the output of the building simulator is the total power consumption/injection of the considered residential setting. This is treated as a single variable, which denotes consumption if the variable is larger than zero, or generation if the variable is negative. This variable is then forwarded to the power grid simulator, which reads the variable as the power at the specific node, where the instance of the building simulator is connected. Once all the solutions from all building simulator instances are available, the power grid simulator can start with its power flow calculation, and a new simulation cycle starts. To sum up building appliances' operation mode may change over time depending on end-user preferences. For instance, end-users may decide to respond to an incentive from the DNO, or change comfort settings. These kinds of actions are computed in the end-user simulator, and are the coupling points between end-user simulator and building simulator.

2.3 Simulator 3: End-user

The purpose of this simulator is to represent energy consumption behaviour by applying sociological theory of action. By doing this, we firstly aim at obtaining a more detailed representation of individual load curves: Heterogeneous end-users take decisions, generate local loads and affect the state of the power distribution grid. Secondly, this simulator is needed to depict consumers' reactions to different types of feedback, e.g. information and incentives.

Models of this simulator are end-user agents, i.e. private households.[2] The main issue of modelling energy consumption behaviour is its high complexity: Electricity is a hidden good, deeply embedded in daily energy services [12]; its use is furthermore strongly influenced by an individual's norms, practices, available devices and contextual factors [13]. Consequently, when looking at energy consumption and environmental behaviour, "people move between […] two extremes, from simple heuristics to complex cognitive strategies, depending on the significance of the decision that they have to make […]" [14, p. 14] – which indicates some sort of variable rationality.

2.3.1 The Model of Frame-Selection

For our purposes, we decided to use and adapt the model of frame selection (MFS) [15]. The main benefit of this model is its ability to implement actors'

[2] Industrial end-users, however, are also of major importance here and will be implemented in the future.

definition of a situation as well as their *variable rationality*. In our opinion, these two (sociological) ideas are highly relevant for understanding energy consumption behaviour and furthermore compatible with insights from other disciplines, like social-psychology.

According to our adaption of the MFS, the decision-making process of end-users is divided into three sequential stages: frame-selection ("What kind of situation is this?"), script-selection ("How am I expected to behave?") and action-selection ("What am I going to do?"). In the frame-selection, agents define their current situation, which results in the formulation of a perceived need to act (in short, medium or long-term; or not at all). In the script-selection, end-users choose programs of action that are perceived as relevant or suitable in the respective situation / frame (like investing or changing / maintaining behaviour). Lastly, in the action-selection, the agent performs an actual activity that has direct impact on his performance and load curve (e.g. buy a more energy-efficient device, turn off devices or do nothing). Those changes serve as input for the building simulator.

The variable rationality of actors is represented by taking two different modes of decision-making into account [15, p. 99]: The habitual, *automatic-spontaneous* mode (AS-mode) and the rational, *reflecting-calculating* mode (RC-mode). Each of the three selection-processes above is carried out in one of these two modes. When deciding in AS-mode, agents primarily refer to internalised values and spontaneous situational awareness, i.e. fixed mental models, which are defined as expectations about people, social roles, events or behaviours and thus include "moral norms, conventions, routines, and emotional or cultural reaction schemes held by the actor" [15, p. 99]. In RC-mode, agents consciously and systematically process available sources of information in order to assess and select a suitable behaviour. Consequently, this mode can refer to any rational-choice theory: We apply Esser's model of subjective expected utility (SEU) here [16].

In sum, the MFS assumes that each actor interprets a specific situation differently and chooses from several behavioural alternatives, which he assumes to be appropriate for the given situation. By parametrization of the MFS variables, different types of agents – characterized based on literature review or surveys – can be implemented, e.g.: "eco-conscious", "careless spendthrift", or "hesitating technophobes" [17].

As standard behaviour, end-users act in the habitual AS-mode and select a 'default' frame, script and action (i.e. no perceived need to act and doing nothing): Although this constitutes a deviation from the original MFS, where no default choices exist, we wanted to emphasize that people tend to "anchor" on the status quo rather than processing all relevant information [18].

An end-user changes his behaviour, however, when one of the following two conditions applies. An agent may *select another frame, script or action in AS-mode*, when he is intuitively certain that a specific behaviour is suitable. This is determined by calculating a "match" for each respective frame, script or action option: If the actor's frame, script or action match exceeds a certain threshold or is sufficiently higher than other matches, the option with the highest match is chosen.

Furthermore, an agent may *switch from AS- to RC-mode*, when he is not certain which behaviour is appropriate. If an actor's match for frame, script or action in AS-mode is not sufficiently high and an actor is 'dissatisfied', he switches to RC-mode and starts to deliberately reflect upon his behavioural options.

2.3.2 Dissatisfaction and learning

The presence of 'dissatisfaction' constitutes another addition to the standard MFS: We share the assumption of Davoudi et al. that changes in energy consumption behaviour are triggered when routines are perturbed [14]; and that *feedback mechanisms* may help to facilitate such a disruption by making energy-related routines visible, for example through information given by energy monitors. Feedback mechanisms thus help to reveal a "feedback-standard gap" [12], which represents a mismatch between current practices (e.g. actual electricity usage of a household) and pre-existing aspirations (e.g. saving electricity). Consequently, this mismatch "[…] may indicate a *level of dissatisfaction* with current practices […], and may act as the springboard for change [...]" [13, p.119]; own emphasis in italics]. Dissatisfaction is hence a result of dynamic learning processes that facilitate behavioural changes, which is not explicitly included in the standard MFS.

In order to determine a level of dissatisfaction, a range of feedback information, provided by energy monitors or electricity bills, are compared [12]: for example the comparison between data on current electricity usage and (1) personal historical usage data or (2) average consumption of neighbours ("social comparison") [19]. Deviations are then actor-specifically weighted and, if high enough, result in dissatisfaction.

A graphical representation of our adapted MFS can be found in **Figure 4**.

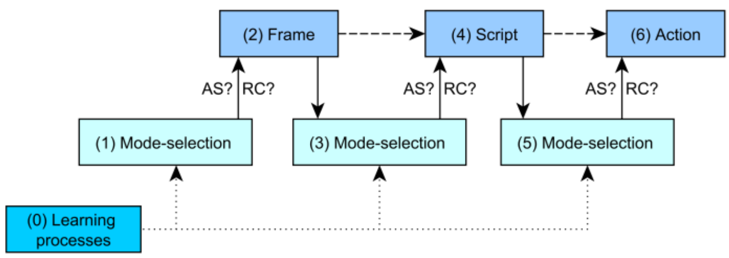

Figure 4: Adapted Model of Frame-Selection

3 Exemplary case of application: Energy traffic light

An important topic within the context of the energy transition is the use of local flexibilities (provided by end-users) for grid management issues. Since these flexibilities can also be used for market operations or for ancillary services, there is a need to design a proper framework to organize the use of flexibilities regarding grid situation. One suggestion is to organize grid operation in different phases, following a “traffic light” principle [20]. The green phase (i.e. mode of market competition) and the red phase (i.e. mode of strong control to prevent critical collapses) are more or less well defined and are not relevant for the purpose of this paper.

In the yellow stage, more interestingly, DNOs have to interact with providers of local flexibilities in order to avoid the red stage, for example by offering (financial) incentives or by restricting market activities and the provision of ancillary services.

It is in this phase, where a socio-technical analysis may provide new insights on how the DNO has to interact with end-users and other entities. Therefore, the energy traffic light concept serves as an exemplary case of application in order to show the functionality of the proposed socio-technical simulation framework.

In the *end-user simulator*, the three phases or signals are represented as different sources of feedback or information: The signals are visible through energy-monitors (smart-meters or mobile applications) and may include electricity pricing, usage data or recommendations of actions for end-users. Consequently, the phases may not only *trigger* actions of end-users, but also *inform* end-users in their decision-making. With the help of the MFS, it is possible to capture heterogeneous behaviours, because each (type of) end-user interprets a specific situation (i.e. a phase) differently and reacts accordingly.

Finally, building and grid simulation are influenced by those decisions, potentially resulting in a new grid state. Consequently, the DNO has to react to this emergent situation, and determine whether the intended goal, i.e. avoiding the red phase, was achieved.

4 Discussion and conclusion

The paper at hand presented a conceptual simulation framework for a collaborative management in power distribution grids, emphasizing the interaction between DNOs and end-users. By combining insights from electrical engineering as well as sociology, this framework highlights the emergent, socio-technical character of the energy system. The interplay of social and technical aspects is further emphasised by referring to the “energy traffic light” concept as an exemplary case of application: DNO’s interventions in the yellow phase do not necessarily have a *direct* impact on the grid state, but rather influence decision making of heterogeneous actors at the micro-level (e.g. end-users), which then leads to emergent effects on the macro-level (e.g. power surplus or shortage).

Next steps will include the definition of simulation scenarios, the technical description of co-simulation features and the conduction of experiments. The results will provide insights into future modes of governance and operation of distribution grids, including the end-user as an active participant in the energy system.

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