Agent-Based Modelling of Electrical Load at Household Level

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Abstract. Regarding electrical systems as complex systems offers new approaches for analysing, modelling and simulating those systems. Using software engineering techniques like Model Driven Engineering, a disaggregated model for household electricity demand is created. The Tafat framework for simulating complex energy systems is presented, including the concepts of the metamodel, models and behaviours. A first case study simulating the load curve of 1000 households composed of five different social groups is discussed and compared with an aggregated curve. The model is able to represent the load curve of a sample of households using a bottom-up approach.

Keywords: agent based model, electrical system, domestic load curve simulation, residential demand, demand side management, appliances, model driven engineering, simulation framework, demand size management, complex system

1 Introduction

During recent years, an increasing interest in knowing more about electrical demand at low levels of the power grid can be observed. This is mainly due to the process of change the electrical system are undergoing, motivated by causes such as the introduction of renewable energy sources (RES) as well as distributed generation (DG). These changes require a better knowledge of the load curves at a distributed level, which involves different factors such as electrical equipment, user behaviour, environmental conditions, etc. that have a potential impact on the consumption. Aggregated data at substation level is no longer accurate enough to describe the consumption processes at the level of the distribution grid.

Modelling the consumption locally can help us to better understand the composition of aggregated load curves (also represented by load profiles) and analyse how local measures can have an effect on the global curve. Current aggregated models do not provide the possibility to model local measures on the grid, as for example punctual actions taken by individual consumers, like switching on a cooking stove or an oven. They can only be included by modelling their aggregated effect and integrating it at aggregated level, due to their resolution. When considering the proposed changes in the electricity system, for planning and control activities at distribution level, these curves are not suitable, as they only fit for a large number of consumers because they describe the average use of energy over time [12, 4].

Some approaches already exist found which considered these facts and implement a demand modelling at lower scale. In [10] a simplified demand model for domestic lightning is presented that provides estimating the aggregated demand or even the distributed loading for groups of households. In [4] a multi-use bottom-up domestic consumption modelling tool was developed and verified. [14] gathered and analysed high resolution domestic electrical data and found that logging at intervals of few minutes is necessary to capture the fine detail of load patterns for evaluating on-site generation. In [11], a high resolution stochastic approach, using heterogeneous Markov chains is chosen to model domestic electricity demand.

2 Electrical systems

The electric power system is composed of different electrical components that allow for the production, transmission and consumption of electric power. Production or generation of electric power is the process of converting energy in other forms (chemical, mechanical, nuclear, etc.) into electrical energy. For the transmission, different kinds of electrical networks are used. Generally, they are classified by their nominal voltage at each level. Long range transmissions over hundreds of kilometres are performed at high voltages of several hundreds of kilovolts (kV). These networks are called transmission systems. Transformer stations (substations), can reduce the voltage at a given point in order to feed electricity to the so called distribution system. The distribution system carries the electricity to the final consumers. These networks operate at medium voltage levels, usually between 1-50 kV. In a final stage, distribution transformers can convert from medium voltage into low voltage (less than 1 kV) which is the typical voltage level find at residential or tertiary customers. Some specific customers (such as industries) may have direct connections at medium voltage level, too.

In a *classical* energy system, generation is injected at high or medium voltage level and consumed in the distribution system. Following the trend of introduction of renewable energy sources and distributed generation, injections of energy at almost all levels of the system are possible. Also, and in order to better match the fluctuating production introduced to the system, Demand Side Management (DSM) mechanisms, which allow to manage the consumption are being developed. The electricity system can be seen as a complex system, being composed of a large number of interacting entities. The reproduction of the behaviour of the system is therefore not possible by modelling only individual objects or the system in a monolithic way. In this paper, we use a disaggregated method to model a part of the electricity system. A detailed model of low-voltage demand is constructed for simulating the load curve of individual households. This includes the loads of each household, representing the final end consumers of this electrical system. Simulating a large number of entities, the individual consumptions can be aggregated and a representation of a load curve at e.g. substation level is created.

2.1 Complexity and intelligence in electrical systems

Classically, the electrical system management has been done based on the aggregated consumption data at a global level. The nature of this management is has been centralised since the system was considered as an indivisible unit. When new devices that apply demand side management strategies are introduced in real electrical systems, new management conceptions must be considered. So, the management of the future electrical system must overcome the restrictions that are introduced now and start analysing the electrical system as a distributed system.

This conception of the electrical system shows analogies with other living complex systems, such as ants or bees colonies, in which there are several agents that are taking decisions and acting locally. Actions that each agent are executing locally are aggregated, and these actions can lead to emergent phenomena.

From our perspective, in the electrical systems, people living in the household are agents [13]. They can be considered as intelligent [3] since they are self interested units and exhibit an adaptive behaviour to their environment. These agents are able to take decisions and coordinate their actions with other agents. The main difference with the study of living complex systems is that in the electrical system, we are not interested in the study of the emergent behaviour starting from the local actions, but the modification of local behaviours to get the desired emergent behaviour [9]. However, in a second point of view, a complex system simulation model can serve to observe unwanted emergent phenomena and study these effects on the system. An approach to analyse complex systems from this point of view, at the very bottom, can be seen in [6].

2.2 Analysing electrical systems

From an analytical point of view, in electrical systems, we can classify objects according to their behaviour in three categories: first entities that can be described in term of their physics such as a building that exhibits a thermodynamical behaviour, second entities that can be described with a mechanistic model such as a washing machine and third agents that can be described with a intentional model such as people living in a household or smart meters.

This behaviour separation match perfectly with the differentiation proposed in [2]. In this work, the author proposes the following three behaviour categories from a observer point of view:

- **Physics Stance:** at the level of physics and chemistry. It is concerned with things such as mass, energy, temperature, velocity, and chemical composition.

- **Design Stance:** at the level of biology and engineering. It is concerned with things such as the function of a living system or the design of a system.
- **Intentional Stance:** at the level of software and minds. It is concerned with things such as belief, thinking and intention.

3 Simulation of electrical systems

Like other complex systems, electrical system simulations involve the behaviour execution of the many elements that exists in a real grid.

The process starts by modelling the electrical system using Tafat. Tafat is a framework for building simulation through Model Driven Engineering which is currently under development by SIANI and EIFER. It is currently implemented in JAVA, but designed to be language-independent. Tafat uses an object oriented and agent-based approach. In this framework, each element of the system is represented including a behaviour that explains how it changes over time. Then, a simulation is run by executing all the behaviours concurrently. During the simulation, behaviours can modify the attributes of these entities. One entity can have different kinds of behaviours, that are stored in a repository. The separation of structural and behavioural elements (entities, defined in the metamodel; and behaviours, stored in a repository) should be underlined here.

However, since the electrical system is locally and massively affected by the human interventions, it is also required to model this behaviour along with other entities that belong to the electrical system architecture. Representing the human behaviour means that it is required to define what people do during a time period, which electrical devices they have and how they use them.

Until now, the human behaviour has not been analysed and electrical companies only have historic aggregated data of the consumption at global level. From now, it is quite important to have data at the household level to be able to model households and simulate the behaviour of people inside. So, the main challenge in modelling electrical systems is to describe all the electrical appliances in the households and the behaviour profiles whose actions generate electrical consumption.

3.1 Software engineering approach

It is needed to approach the software engineering of the simulator with a methodology that supports the modelling of a large number of entities. The goal is to make the simulator development and maintenance easier.

The approach that has been taken is based on a software engineering paradigm called Model Driven Engineering (MDE) in which systems are developed at an abstraction level close to the problem domain. In this approach, models are the artifacts that drive the development process. From an evolutionary point of view, development methods have been trying to get more abstractions in order to reduce the gap between the programming semantic and domain semantic.

MDE is the result of the combination of technologies such as Domain Specific modelling Languages (DSML) and engines that analyses models for synthetising software artifacts. This paradigm allows to improve productivity and flexibility at developing a simulator, since the application is developed and modified just by changing the model [8].

3.2 Metamodel and models

To model the electrical system, a metamodel for this domain has been developed. The metamodel is a formal representation that supports the description of an electrical system with a semantic that is closer to the domain expert. The metamodel can be understood as a representation language for modelling electrical systems.

This metamodel comprises the classes of entities that have been identified in the real world. So, the metamodel defines what kind of elements can be represented in the model and provides a standardised way of representing elements. Classes are represented in a model by means of context, features, variables and behaviour (Figure 1). Context defines where elements can be placed in the scene. Features are defined as static data of an element; while variables are defined as dynamic data. The behaviour is the logic that updates the dynamic data.

In the metamodel, we distinguish different types of model elements: entities, static objects that belong to the scenario (e.g. refrigerator); agents, intentional objects that interact with entities and communicate with other agents (e.g. person); connections that define relations between entities or agents (Figure 2).

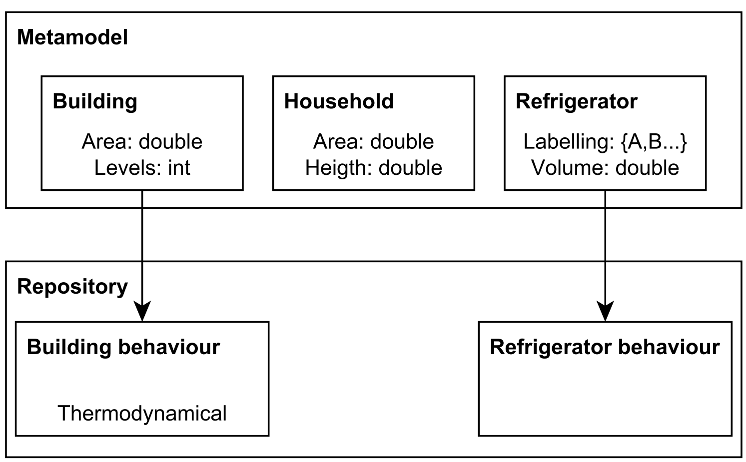

Fig. 1. Structure of the metamodel where the element definitions are exposed.

A model is a representation of a specific electrical system using the metamodel classes. Elements that are going to be simulated are instantiated from the metamodel in the model. Both, models and the metamodel, are represented using XML.

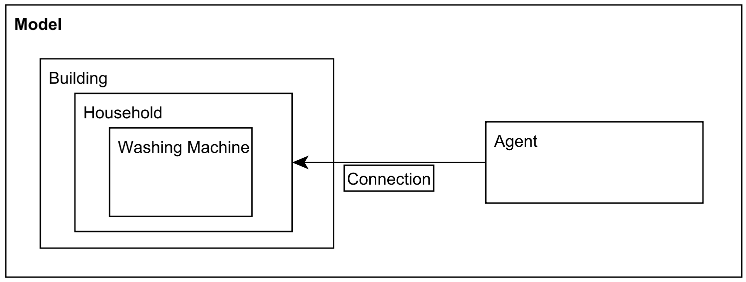

Fig. 2. Structure of the model shown by an example including behaviours

3.3 Programming behaviours

To simulate the electrical system, all the metamodel classes have to include behaviours that must be programmed.

A separation between the different types of behaviours must be done according to the discussion exposed in the section 2.2. In this section, an example of each kind of behaviour will be exposed.

Environmental behaviour Environmental behaviours represent the change over time of some environmental variables. Environmental variables are normally common to a group of entities or devices and describe the surroundings or "outdoor". These can be for example solar radiation models, which represent the insolation and can be used for calculation of the thermal gains of a building, or further for energy production (photovoltaics, solarthermal use, etc.). These behaviours do not directly change the attributes of a device or agents, but rather allow some interactions in an indirect way (e.g. through heat exchanges, etc.).

Device behaviour Most of the electrical devices used in a household are major appliances such as washing machines, refrigerators, etc. There are also some other, smaller appliances, such as CD players, TVs, HiFi Audio equipment, etc. Usually, the major appliances cause a larger part of the electrical consumption. In order to recreate the individual load curves, EIFER (European Institute for Energy Research, a common research institute by KIT and EDF) has developed individual models for the behaviours of electrical appliances, which were integrated into Tafat. Simplified technical models are used, which take into consideration different technical parameters of a specific appliance. So, for example, the load curve a TV will be characterised by the size and technology (CRT, LCD, Plasma, etc.). Major appliances also are modelled using the EU Energy Label

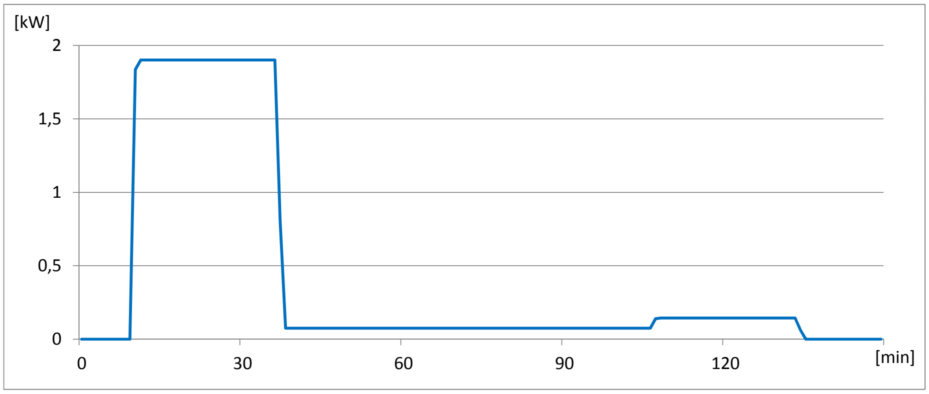

Fig. 3. Simulated load curve of a washing machine

as an input parameter, which is an indicator for the energy consumption of a device and is compulsory for appliance sold in the EU. Different releases for the behaviours of the electrical devices were created. Using this modular approach, a behaviour of a single device can be *exchanged* in a simple way. The different releases include simplified technical models with varying degrees of accuracy, thus allowing for an optimisation of execution time vs. accuracy of the model. In Figure 3 an example of the load curve generated by the behaviour of a washing machine can be seen. This load curve is created by a simplified technical model of this appliance.

Social behaviour A flexible architecture is proposed to carry out a social behaviour. As described in section 2.2, intentional stances are the most complex behaviours. For this reason, the architecture must be flexible to allow a range of behaviours from simple behaviour based on a list of tasks to a complex behaviour implemented as a neural network.

The mission maker is the intention launcher, the decision maker is in charge of choosing a recipe to accomplish the mission launched and the action maker is the executor of the recipe. The recipe is a list of actions that executes to accomplish a mission. With this architecture, a simple behaviour can be developed by creating a big recipe in which all the tasks are described and having a mission and decision maker very simple. Otherwise, in a complex social behaviour, the task can be launched by the mission maker according to several parameters of its own agent or the environment, having a hard process to choose a recipe in the decision maker, but easier recipes that only describe how to arrange a task as, for example eat.

3.4 Simulation

The main problem for developing good models that represents accurately a place (town) as the lack of data. Often, it is quite difficult to gather the needed data.

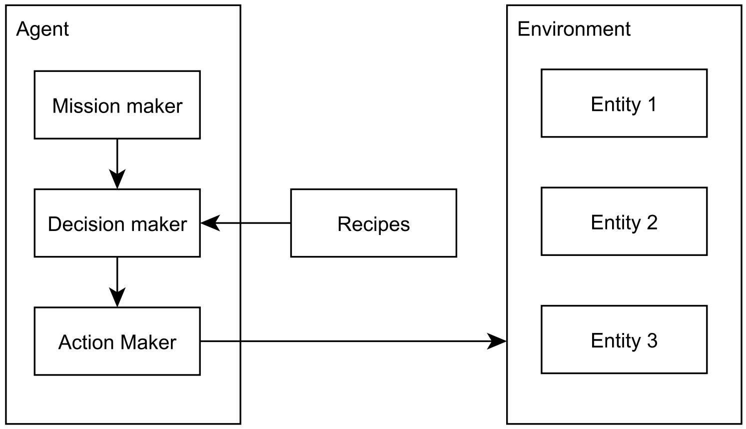

Fig. 4. Agent architecture composed by a mission maker (intentions), decision maker (recipe selector) and action maker (recipe executor)

Ideally, models should be built using real data, since the simulation will help to understand what happens in the electrical system. However, since data is not available at all, a model approximation is done. A tool called profiler has been developed (Figure 5), which helps to carry out this task. Using a high-level description of a place (for example, amount of buildings and population), Profiler automatically generates an electrical system model that can be simulated directly. The profiler is part of Tafat, a MDE platform that supports the development of simulations.

Electrical models can be created to represent the load accurately but lightweight enough for use in large scale simulations, and handle demand side management mechanisms through the use of an agent-based approach.

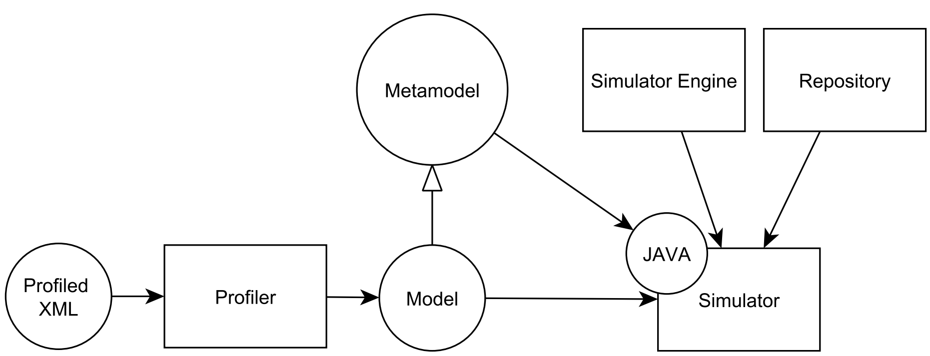

Fig. 5. Tafat architecture

4 Case Study

4.1 Modeled scene

The case study proposed is an analysis of the electrical load of households according to social group characteristics. The following five different social groups have been taken into account to develop the case study:

1. junior single,
2. senior single,
3. junior couple,
4. senior couple and
5. family with children.

These groups were taken as a part which represents about 70% of the population of Germany, being the most numerous groups identified by the German Socio-Economic Panel Study (SOEP). The constitution of this sample is shown in Figure 6.

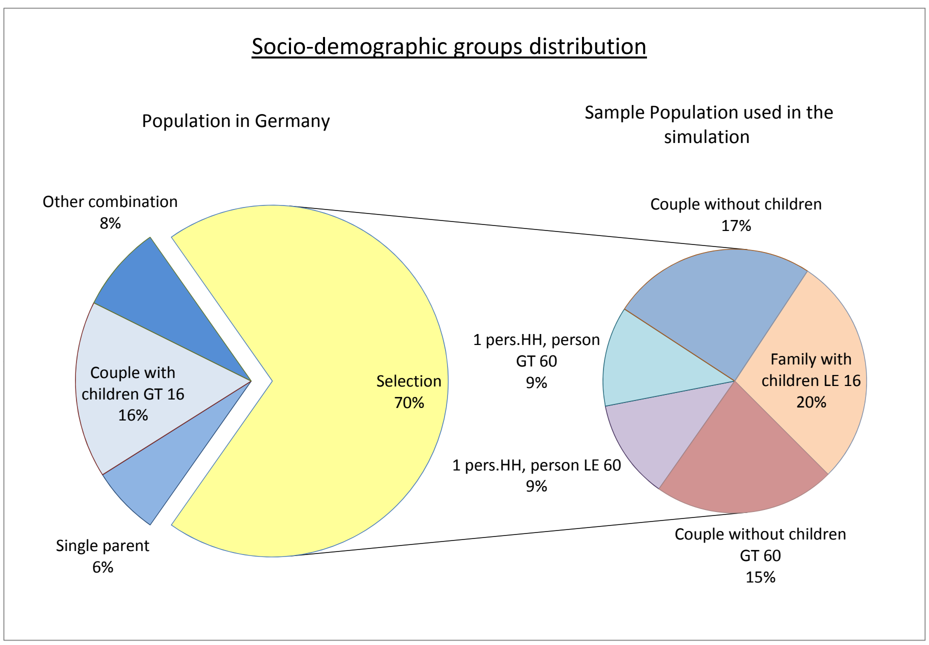

Fig. 6. Socio-demographic groups used in the case study. Source: SOEP.

A survey[3] has provided the information about the timetables and appliance usage of a household according to the social group. Based on this information the

[3] The survey consisted in local interviews with around 20 persons in Karlsruhe, Germany in order to obtain data like usage times and durations of specific socio-

agent behaviour which is related to the household is implemented. The electrical usage behaviour data employed for this study was obtained through a local survey. Thus the gathered data from a small sampling was used as input parameter in the Tafat model. Hence, 20 different social behaviours (i.e. 20 different model recipes) are been used to simulated the five socio-demographic groups. Each of these recipes includes some randomness through the definition of intervals at which devices are switched on or off. The exact time instant of time is obtained as a uniformly distributed random variable over this interval.

To arrange this study, an important utility of Tafat to build automatically a scene has been used. This utility uses statistical data from the SOEP and the survey to create a model scene in which the social groups are distributed in the households. Those households contain the electrical devices, and their amount, according to the social group.

4.2 Simulation and results

In the simulation, the device load curves within a household are generated. The curves were aggregated using an individual behaviour for each household taking into account some randomness (variation of the duration and use time in a defined range of the different electrical devices).

The simulation results show the load curve of a day of 1000 households with around 12 appliances each, composing thus an amount of approximately 12000 simulation elements. This type of simulation can provide the relevance of a determined power consumer in the household consumption as well as the influence of a specific type of consumer on the global load. The number of 1000 entities was chosen, as it was determined that larger amounts did not change substantially the results and only increased the execution time of the simulation. This is probably due to the use of a limited number of recipes (taken from the number of surveyed persons). In this case, the execution time was around 20 minutes on a standard desktop PC for the simulation of a period of 24 hours.

The 1000 household sample is composed of a distribution of the different social groups according to real statistical data, in order to obtain a sample of households that is as close as possible to reality. In Figure 7, the simulated load curve for one day can be seen. The simulation is run in a high time resolution, being the time step one minute. This allows observing effects which are neglected in simulations at lower resolutions, provided by 15 minute or hourly models. Some sharp peaks can be observed, which are caused by the use of high power consuming devices in the household. A general trend to use more power during the day is clearly visible. During the night, the base load (devices that are constantly running, such as refrigerators and other permanent loads) cause a consumption that is only around a third part of the daily peak load. The configuration of the simulation can be seen in Figure 8.

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demographic groups. It has to be noted that the survey is not representative but rather a sample of the user behaviours of those groups.

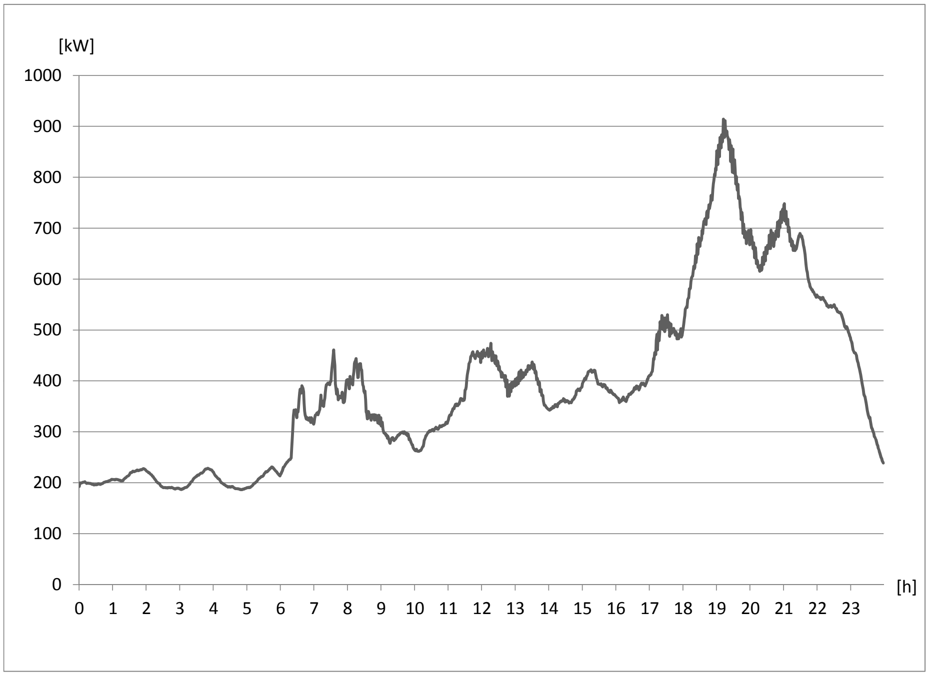

Fig. 7. Simulated load curve of 1000 households for one day

In Figure 9 the curve is compared to a standard load profile of Germany for a winter weekday (according to [1] and made public by [7]) for household demand. The profile is provided in a normalised form in order to be weighted with a given number of energy. In this case, and for comparison purposes, the profile was weighted with the same amount of energy as the simulation curve, i.e. that the daily consumed energy [kWh] is the same in both cases. The load profile is a smooth curve, representing an aggregated load behaviour at high levels of the electricity system for large number of consumers. The are the result of a statistical analysis based on representative samples from different consumer groups [5].

The simulated curve represents the total power consumed by a sample of 1000 households, modelled individually and with an autonomous behaviour for each of them. The curve has been adapted by averaging periods of 15 minutes in order to match the same time granularity as given by the standard load profile. The curve is more peak shaped, which is probably due to the relatively small amount of households (in comparison to the statistical samples taken to obtain a profile, which are representative) and the reduced number of behaviours (in total, only 20 different behaviours have been used). Furthermore, only 70% of the household population is modelled, neglecting other social groups which may change the curve.

Entity	Attributes	Components	Behavior
Building		Household: n=1	-
Household	sg = montecarlo[0] Households are classified into one of the 5 social groups (sg) using montecarlo method area = $f_{area}(sg)$ Area is variable depending on the social group	PowerConsumers CookingStove n=4 Microwave n=1 Oven: n =1 Dishwasher: n = 1 Refrigerator: n = 1 AudioHifi: n = 1 TV: n = f_{tv}(sg) Ligthing: n = 1 Washing Machine: n = 1 Computer: n=$f_{computer}$(sg) Waterboiler: n = 1 Hairdryer: n = 1 Vacuum: n = 1 Iron: n = 1 Console: n = $f_{console}$(sg) PowerBus	Sociological Behavior Each social group has 4 different recipes. A recipe is randomly selected. The recipe defines how the power consumers **mode** is changing
PowerConsumer	mode power		DeviceBehavior Power is calculated depending on the device mode and on its technical characteristics
PowerBus	power		DeviceBehavior power is calculated by aggregating the consumption of Household PowerConsumers

Fig. 8. Configuration of the entities used in the simulation.

Even though the selected samples in the survey are not representative for all Germany nor society as a whole (only five social groups were used), the general trend of both curves are similar. Three peaks can be observed, which are closely synchronised in time and correspond to morning, noon and evening peaks. These peaks are correlated with a large and concurrent usage of high power devices, such as cooking plates, ovens, microwaves, etc. due to alimentation habits, as well as lightning use in the evening hours. The morning and noon peaks are lower in the simulation than in the profile, whereas the evening peak is higher. The timely synchronisation of the ramps of the peaks matches quite well; this indicates that the activities (having breakfast, lunch, returning home, etc.) were modelled according to the average German user behaviour. Even though, some differences can be observed at the evening drop (21-23h), as well as a small second peak that cannot be found in the profile.

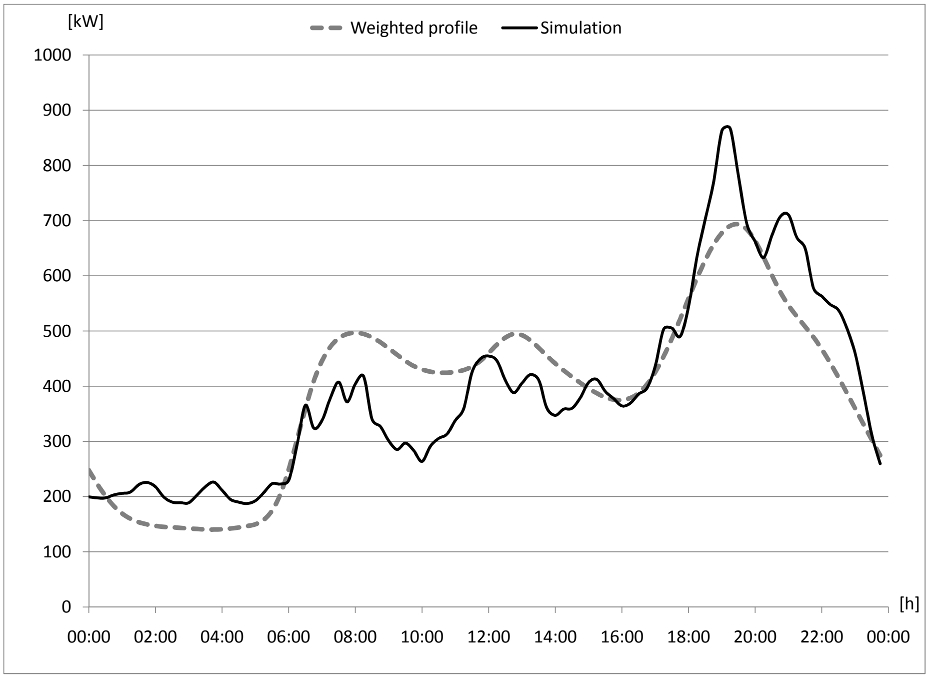

Fig. 9. Simulated load curve vs. standardised residential load profile

4.3 Discussion

Even using a relatively small sample of households and reduced number of behaviours, a curve that represents the major characteristics (peaks and troughs, as well as their timely synchronisation) is generated. Concerning the differences in the height of the peaks, the model could be reviewed in order to check the individual power curves of each electrical device. This seems to be quite hard as almost no data is available for such a validation (at a representative sample). However, the differences could also be related to the use of only 70% of the socio-demographic population share. Further, behaviour itself is another factor to consider, as a largely simplified and almost static model was used. Some specific characteristics of the model create peaks, which could be explained by a rather homogeneous behaviour of the groups. For example the second evening peak (around 21:30h) is possibly caused by some activities (watching TV, other evening activities) which start and end at similar times, because of the relatively small sample. Using data from a more representative survey or a more stochastic-based social behaviour, this could be avoided, though.

5 Conclusions and outlook

In this paper, a vision of the electrical system as a complex system has been introduced. This is necessary as the future grid behaviour becomes more distributed. Furthermore, the simulation of the electrical system at a household level as a complex system has been addressed.

The case study demonstrates that a bottom-up simulation of the residential consumption using an agent-based approach has been successful since the result curves show similarities to aggregated load curves. A comparison with a national aggregated profile shows similarities in the main characteristics of the curve. Moreover, due to the high resolution of the model, a large number of parameters (individual appliances types and models, socio-technical behaviours, etc.) is available for variation.

From now, the simulation that has been developed will allow us to experiment and study new algorithm and strategies for electrical system management. New scenarios, new problems and new challenges will arise in the near future with the introduction of renewables and a distributed production in the electrical system. Simulation is particularly necessary to design a new management approach.

The simulation will allow us with further work to study the integration of demand side management strategies. Strategies, such as adaptive or reactive technologies, incentives or campaigns, can be addressed for studying their impact at load curve level.

However, social behaviours need to be validated and improved. This validation is necessary for studying the emergent behaviours and for identifying the local actions of agents which provokes the desired emergent behaviour. Moreover, social behaviours must be improved in order to introduce a higher degree of heterogeneity to the models. Due to the high resolution of the household model, individual actions such as changing specific parameters on a device can be performed.

Furthermore, the model developed could be expanded in order to simulate not only the demand side, by including distributed generation or other injections to the grid (like storage), which could interact with the existing elements. This is already contemplated within Tafat, and would allow a disaggregated analysis of offer-demand balance and the possibility to estimate the impact of those measures at a system level.

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