Modeling domestic housing loads for demand response

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Abstract— Increasing electricity demand and upcoming shortages of resources, make on-line energy management like peak-load reduction and control energy provision by the demand side of the electric power system a valuable method for keeping the grid stable and efficient. For developing the next generation if these methods, a simulation environment for studying demand response (DR) algorithms with large-scale and detailed grid simulations is currently developed. An important part of this is an accurate but computationally inexpensive dynamic model for domestic housing and small business loads. This paper presents the design of this model and the deduction of the model parameters. As a determining factor for domestic loads, the power consumption of heating, ventilation and air conditioning (HVAC) systems has been identified. The model is partly based on earlier proposals that simulate the state changes of thermostatically controlled processes, but the complexity is further reduced to an absolute minimum. The result can be used as one of the basic building blocks required to set up a comprehensive simulation of power consumption in electric power grids under DR conditions.

I. INTRODUCTION

Due to the increasing demand of electrical power on one hand, and shortage of resources (generation and transport) on the other, research in the area of demand response or demand side management in the electric power grid has been intensified in recent years. In situation of growing pressure on the power grid, it is worth to consider the potential contribution of the demand side in the power system. Here, large unutilized potentials for "virtual" energy storage (e.g. in inert thermal processes for refrigeration, air conditioning and heating) exist, that could help to maintain the power balance in a control area [1]. These demand side processes convert electrical energy in some other form of energy (thermal, chemical, mechanical, etc.) and probably even store the energy in this form, e. g. in a thermally isolated mass. Such virtual demand side storages cannot feed back energy into the grid, but they can store the energy needed by the end-user process so that the timing of energy consumption becomes more flexible. By extending control strategies to the demand side, more degrees of freedom are made available in the overall system, resulting in a more effective and efficient operation.

A number of different approaches for demand response algorithms have emerged (see e.g. [1], [2], [3], or [4]). This paper originates in the context of an integral approach that aims to simulate a variety of such algorithms for demand response, the DAVIC* platform [5]. Motivation of DAVIC is to provide a fast and reliable simulation platform that can simulate and compare different energy management algorithms like frequency-response algorithms and peak-demand reduction algorithms, etc. Fig. 1 shows the DAVIC modeling approach. The conventional part represents the power system modules that are usually considered during the simulation of any traditional power system problem. An additional module "environmental aspects" is also utilized in this block in order to integrate the possible effect of environment like climate conditions, special events or human behavior, etc. on the consumption patterns. It is evident that energy utilization is affect by the weather conditions etc.

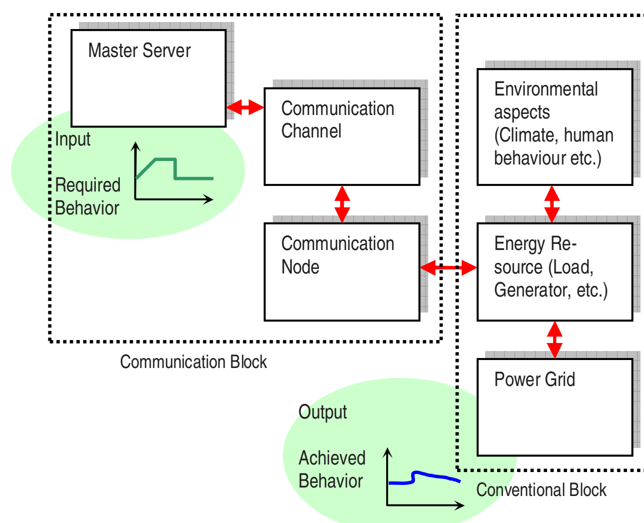

Fig. 1. DAVIC Modeling Approach. The internals of the "Energy Resource" block is the topic of this paper.

The communication block contains the management and communication modules, which are responsible for the interaction among the participants of a power system. The communication node is responsible of collecting local information from

* Distributed Automation Via Implicit Channels

the attached energy resource and takes some real-time decisions based on the control algorithm which is tested in the simulation. The algorithm itself might be distributed among the communication nodes (i.e. hosted on them) or reside on a central or hierarchical system of servers.

This paper focuses on the energy resources in the grid, more precisely on the modeling of domestic housing loads. Customer processes can be represented by simple state machines or Markov-chain models and are managed by local instances of a potentially distributed algorithm. In this paper, a strongly simplified Markov-chain state machine approach is presented, that is optimized for simulation of very large numbers of individual energy resources.

The remaining part of this paper is organized as follows: In Section II, related modeling approaches are discussed. The Markov model proposed in this work is presented in Section III. Simulation results basing on this model are demonstrated in Section IV. Finally, conclusions and outlooks are drawn in Section V.

II. Intelligent Buildings and the Grid – Problem and Related Work

Buildings, commercial as industrial and even domestic, are as significant player in the case of intelligent grids as they are a dominant sector of electricity consumption [6]. Building operations can be a viable contribution for grid optimization and reliability. The essential electric loads that allow for influence are

- heating, ventilation and air conditioning (HVAC)
- lighting
- pumps (water, etc.)

HVAC processes show thermal inertia (heated or cooled walls, etc.) and material flow latency (CO_2 concentration of the air) that can be used for achieving a virtual energy storage. HVAC even allows for real in-advance storage, when buildings are pre-cooled during the night or in the early morning hours. Lighting is often ignored, when load management options of buildings are evaluated. Surely, a 100% shed of lighting is typically not accepted, but dimming – supposing dimmable ballasts are available – is almost always possible. Pumps, if present show excellent automated DR capabilities, they can be scheduled, their process often offers some inertia and they can sometimes be duty cycled without noticeable effects.

Additionally to the loads, buildings try to more and more integrate local generation, most notably photo voltaic (PV), and more seldom wind power.

A third degree of flexibility comes when hybrid or battery operated cars are parked in the garage of the particular building. These explicit electricity storages can store and even supply energy, the right infrastructure assumed.

These three mechanisms, combined with the significant number and size of buildings, leads to their important future role of intelligent grid participants. Their typically very deterministic operation is another plus that can be leveraged with automated demand response systems.

The necessary ingredients for designing responsible buildings that are capable of reacting to grid situations are

- a model of the building (or typical buildings) that serves as designing optimization strategies,
- a communication/automation infrastructure to and within the building, and
- an algorithm that detects the current state and selects appropriate actions according to some strategy.

Models of buildings can get pretty complex, depending on how far one goes. One of the most complex and powerful examples is Energy+ of the US Department of Energy (DOE). Energy+ takes all structural matter of buildings into account (walls, etc.), their shape, zones, windows, weather data, etc. and calculates all energy flows in the building (heating, cooling, ventilation, lighting, etc.). It allows to model multi zone air-flow and other detailed aspects of buildings. The goal for developing Energy+ was, however, not to find optimal DR algorithms but rather to improve the structural building itself, to find problems in the architecture of the building and to improve the usage of modern construction material. According to the Energy+ developers, a simple individual simulation run takes several seconds up to minutes, depending on the number of zones. It is far too complex and powerful for this research and would consume too much computational power if used in a simulation of 10,000+ houses.

A more simple model is under development by B. Burke and D. Auslander at UC Berkeley (not published yet), where the building model is reduced to 5 elements (walls, air, sunlight, heating, cooling) and the primary subject of research was a network of PCTs (programmable, communicating thermostats) that get load shed commands via RF signals. It is the plan to use such PCTs throughout California. The model uses a DE solver and dynamic simulations.

An even easier model of thermostat controlled appliances (TCAs) was proposed by Lu in [7], where a 20-stage Markov-chain state machine is gradually improved and tuned to match the real behavior of TCAs. This model is especially suitable for very effectively calculating many statistically disjunct processes. In our case, where DR events are broadcast to all customer processes, this statistical model does not really fit and must be modified.

The DAVIC project took Lu's model as a conceptual basis for its TCA models and massively simplified it before enhancing it with the characteristics of remote automatic DR (see later in this paper).

Having a good-enough and computationally easy building model, the second step is to set up the necessary remote instrumentation and control infrastructure. Electric aggregators (companies that purchase energy at wholesale prices and resell it to their customers) like Enernoc in California and others typically install their own, proprietary systems to perform load shedding to optimize their energy purchases. Auto-DR with its DR Automation Server (DRAS) is the first attempt to standardize the IT interfaces in such a system [3]. Using established technologies like web services and XML as a basis for an open and freely available specification, interoperable and interchangeable infrastructure comes one step closer to reality.

Communication with and among buildings can (in this context) therefore be considered solved, although there are still serious open points like IT security, reliability and availability. As with so many machine-to-machine communication systems, the problem of IT security in automated demand response lays in key distribution and commissioning scenarios.

The optimization algorithms for this system are still under research. First attempts were done in [2] and more specific in [8]. Further research will show which topology is suited for which type of algorithm, and if hierarchical, centralized, distributed or hybrid algorithms show the best performance and stability.

III. Model Description

The requirement for the proposed model is that it has to be accurate enough for a realistic dynamic simulation of the electric power grid. Also, it has to be computationally undemanding so that it can be used for a large-scale simulation of power grid sections, where each single resource (generator, load, lines etc.) is simulated.

Therefore, two design decisions are taken: First, the housing load is assumed to be dominated by the power consumption of HVAC (Heating, Ventilation and Air Conditioning) systems [7]. The trend of HVAC usage in the domestic field will even be increasing in many parts of the world in the near future either due to climate change or simply the broader availability and affordability of these systems. Other loads are decreasing (e.g. due to usage of high-efficiency light bulbs in the lighting sector). Second, for modeling the HVAC power consumption, essentially a three-state Markov-chain model is defined, which is motivated by the behavior of thermostat controllers. This is depicted in Fig 2. If there are more than one significant processes at the load side, 2 independent (or more) state machines can be combined in one demand node (e.g. one for hot water and a second one for air conditioning).

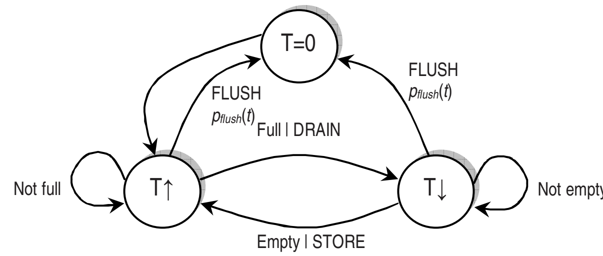

Fig. 2. State machine view of the model. The FLUSH state change happens with the probabiliy $p_{flush}(t)$.

The task of such a controller is to maintain a temperature difference ΔT between ambient and internal temperature (e.g. of the air-conditioned room), keeping this internal temperature in a specific band. It does this by duty-cycling the thermal converter unit, which changes electrical energy into thermal energy (see Fig. 3). The temperature curve obeys the laws of thermal conductance. A first approximation of this is an exponential function [8], but here for the sake of simplicity of the model a linear approximation is used as shown in Fig. 3. The parameters of this model are:

- ΔT_{high}, ΔT_{low} defining the temperature band
- t_{on}, t_{off} defining on and off time of the duty-cycle operation [7][9].

In addition to this basic on-off behavior, three dedicated events, which can happen at any time, are defined as follows:

- **The DRAIN event**, which can be issued by an external demand response controller, causes the HVAC process to immediately turn off and let the temperature difference (slowly) fall to the lower limit, from where the process resumes working normally. If the HVAC process was already off, no change takes place. The DRAIN command can be used for immediate electrical load release. Still, the temperature stays only within the working band. After the DRAIN command has been issued, energy is "drained" from the demand side. The effect of the DRAIN command is depicted in Fig. 4.
- **The STORE event**, which also can be issued by an external demand response controller, causes the HVAC process to immediately turn on and let the temperature difference increase to the upper limit, from where the process resumes working normally. If the HVAC process was already on, no change takes place. The STORE command can be used for immediate electrical load increase, e.g. for providing control energy to the grid. Again, the temperature stays only within the working band. The STORE command urges the process to store thermal energy. The STORE reaction of the process is depicted in Fig. 5.

- **The FLUSH event**. In contrast to the former two external commands, FLUSH is an internal event which occurs depending on the FLUSH probability $p_{flush}(t)$. The FLUSH event – in a simplified manner – models the irreversible consumption of the energy stored in the process. For a refrigeration process, FLUSH means the opening of the door, or storing warm goods etc. For a water heating process, FLUSH indicates the usage of the warm water and replacement by cold water. For an air conditioning process, FLUSH refers to opening of windows or doors causing air exchange. As illustrated in Fig. 6, this is modeled by an instant temperature drop to the lower limit. There are – in this simplified example – no “partial Flushes” considered, the energy storage is always completely emptied. The authors plan to introduce partial flushes soon, as they represent the more likely behavior of thermal masses.

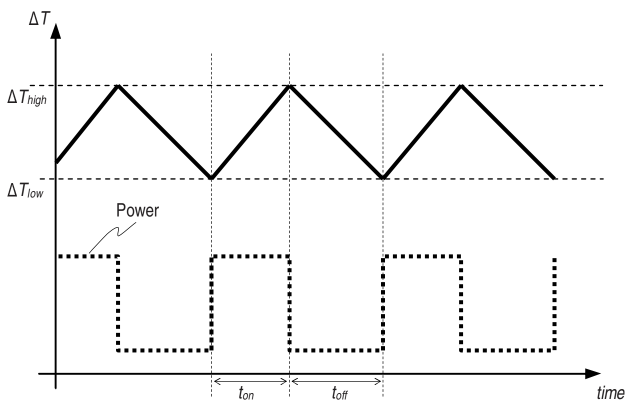

Fig. 3. Normal operation of the HVAC load (linear model)

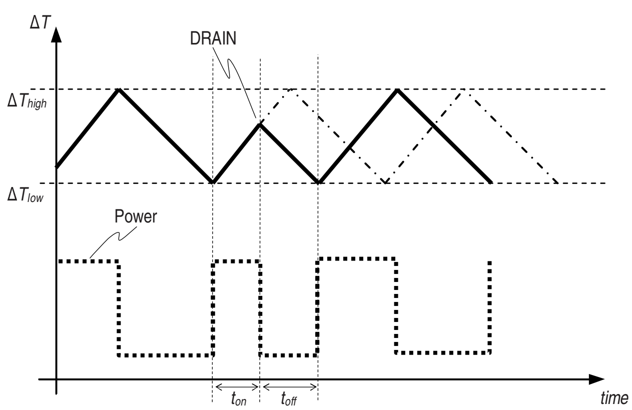

Fig. 4. Reaction of HVAC load on external DRAIN command (generated by demand response controller).

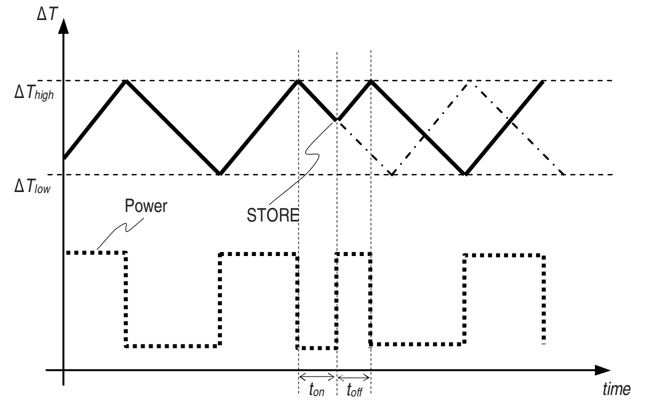

Fig. 5. Reaction of HVAC load on external STORE command (generated by demand response controller).

The two commands DRAIN and STORE are designed to be used by any demand response algorithm, which is out of the scope of this paper. The remaining question is, how to determine the probability function $p_{flush}(t)$. This is in the focus of the next section.

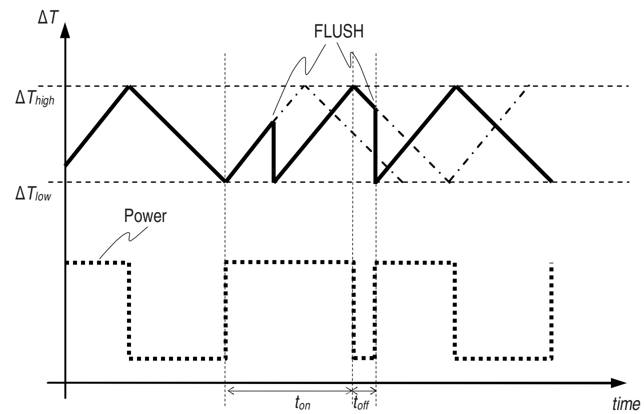

Fig. 6. The FLUSH event used for modeling disturbances of the process like opening freezer door, using hot water etc.

IV. SIMULATION

For finding appropriate values of the FLUSH probability, there are two possible approaches, a constructive and a deductive method. While the constructive option describes all sources of external influences on the process (such as human behavior, weather etc.) and then synthesizes the probability from this, the deductive option uses data gained from observations and maps it to the probability function. Here, the second option is used. The observation data utilized are synthetic load profiles (for central Europe) [10]. Synthetic load profiles are mainly used (and were initiated) by the power supplying industry and serve as reference load profiles for consumers who do not have on-site load management. Synthetic load profiles are the result of a statistical analysis based on representative samples from different consumer groups: households, shops (different groups for different opening hours) and industry (different groups for different working hours). Here, the household profile "H0" is used as shown in Fig. 7 (solid line). The following discussions are valid for a summer working day, but can easily be transferred to any other profile.

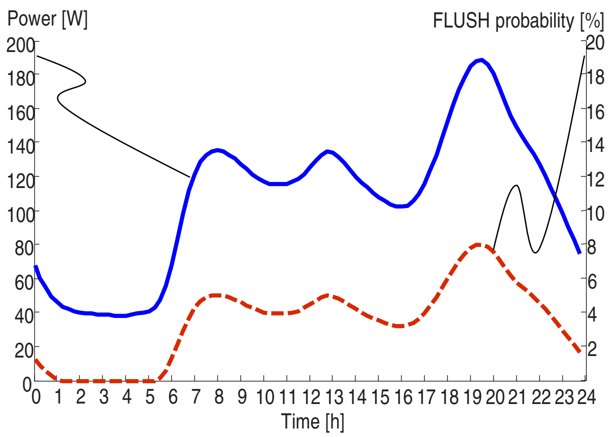

Fig. 7. Synthetic load profile for domestic load (solid line) and resulting propabilities for the FLUSH event (dashed line).

The simulation setup is as follows: A set of electrical load resources according to the described model with is created, parameterized with ΔT_{high}, ΔT_{low}, t_{on}, t_{off} and P_{el}, which is the power consumption in on-mode. These parameters are randomized within ±5% at the initialization step of the simulation. The set size was chosen to be 1000. Larger set sizes can also be chosen, but a larger set does not have any significant influence on the result of this specific simulation, rather increase simulation time.

The probability function $p_{flush}(t)$, which is the same for all resources, is determined in such a way that the sum consumption of all 1000 processes matches the power consumption predicted by the synthetic load profile. In each simulation time step (set size is 5 s), it is decided upon this probability whether a FLUSH event happens or not. Consequently, the probability values depend in the time step size. The result for the probability function is shown in Fig. 7 (dashed line). The resulting net power consumption is shown in Fig. 8. By ensuring a close reproduction of the synthetic load profile by the proposed domestic housing load model, the probability function $p_{flush}(t)$ was found to be accurate and can be confidently used in future.

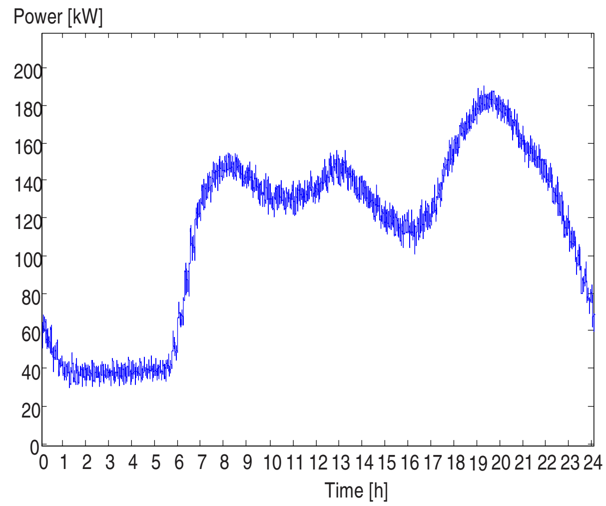

Fig. 8. Simulation result achieved by using the described domestic load model (1000 resources).

V. Conclusion and Outlook

A simplified two-state Markov based model for HVAC is presented in this paper in order to reduce the computational over-heads of large-scale simulation of power grids. Three state-changing events are introduced into the HVAC model in terms of the most common behaviors of the modeled real energy resources. Two of these events are centrally controlled, while the third one is a statistical parameter with a certain time-dependent probability. The probability function has been obtained using deduction from synthetic load profiles. We consider extending the mechanisms of the events so that they reflect other environmental influences.

The proposed model will be utilized for simulations within the DAVIC platform in future. The envisioned usage of DAVIC is the analysis of existing and new demand response algorithms in regard to performance (timing, costs, stability, etc.). All performance parameters will be evaluated by a set of standard tests that expose the algorithm to a variety of challenges or stimuli. These can be grid failure, grid overload, and communication failure in the demand response system or even oscillating demand. In this context, the model for domestic housing and small business loads has to make a significant contribution.

VI. Acknowledgements

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