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Encodings for Evolutionary Algorithms in Smart Buildings with Energy Management Systems

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***Abstract*—In energy systems, the transition from traditional, centralized architecture and controllable generation to an ever more decentralized and volatile generation due to an increasing use of renewable energy sources arises new challenges for the management and balancing of the electricity grid. These can be met through energy management systems (EMS) that enable flexible consumption and production of energy on the demand side of the grid. The EMS for smart buildings that is used within this paper allows for the integration of a multitude of devices through an architectural approach which is similar to "plug-and-play". These devices can then be optimized to a flexible load shape by an Evolutionary Algorithm (EA). The differentiated optimization capabilities of the devices require adequate encoding schemes. Such schemes are the major contribution of this paper. The aptitude of these encodings is shown and validated through the simulation of smart buildings with different configurations, both concerning quantitative and qualitative benefits to be achieved according to energy systems' transition and users' objectives.**

I. Introduction

Nowadays, societies heavily rely on permanent availability of different energy carriers. Additionally, the world-wide energy supply is in a phase of transition, which is not a uniform process all over the world, though the common similarity is the intensification of power generation from renewable energy sources. For instance, the German "Energiewende" ("energy transition") causes an increasing share of power generation from renewable sources and a steady reduction of nuclear based power generation, due to the phase-out of nuclear power generation scheduled by 2023. Ambitious targets are set to this transition: 35 % of electricity consumption in Germany shall be covered from renewable energy sources by 2020 and at least 80 % by 2050 [1].

Techniques that allow for flexible load shapes on the demand-side are a promising possibility to cope with the induced problems in grids and markets [2]. Buildings, both commercial and private, may contribute enormously to the flexibility of electricity consumption and production by using *energy management systems* (EMS) [3]. The heterogeneous structure and capabilities of these target scenarios with diverse setups of devices for energy consumption, storage, and generation call for a flexible approach towards configuration and optimization of an EMS.

The EMS used in this paper utilizes an architecture similar to the concept of "plug-and-play" to optimize shiftable or interruptible loads and flexible production. in different environments. Therefore, it provides different mechanisms that enable a flexible and ad-hoc integration of components.

Major contributions of this paper are the description and testing of encoding schemes for different types of devices. These schemes allow for a global, abstracted and generic optimization of the *energy management problem*. The optimization problem varies due to different environments, available devices, and user preferences. This results in varying search and solution spaces for the optimization algorithm at the run-time of the EMS and calls for a self-adaptive approach to the optimizer's configuration. First qualitative benefits of adapted parameters are presented in this paper.

In the following Section II, the energy management scenario in a smart building is described. Section III then introduces the EMS with its architecture and self-adaptive approach the paper is based upon. The encodings, enabling the EMS to integrate different types of components, are depicted in Section IV. These encoding schemes are validated in different experimental setups, which are described and discussed in Section V. The paper closes with a summary of findings and a further outlook to future work.

II. Energy Management Scenario

In this paper, the scenario for energy management focuses on EMS in modern smart buildings as visualized in Fig. 1. These buildings can be equipped with both energy consuming devices and decentralized energy resources like combined heat and power plants (CHP) and photovoltaic systems (PV). Moreover, storage systems for different energy carriers like hot water and electricity can be installed: Hot water storage tanks enable the operation of the CHP whenever capacity is left in the tank and battery storages enable partial independence from the electricity grid. Additionally, electric vehicles (EV), which can these days be found in more and more private, public and commercial buildings, may be connected to the building and thus their charging process is optimized by the EMS.

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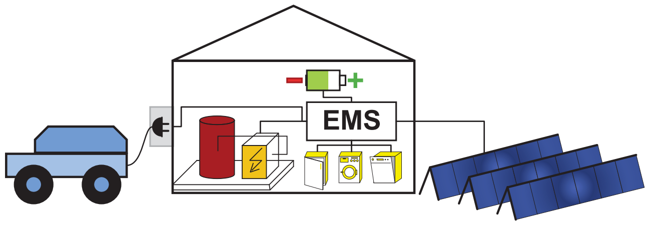


Fig. 1. Smart building scenario with EMS

The different devices installed in smart buildings offer distinct capabilities in terms of influencing their electrical load shape and the overall energy profile of the building. In case of the decentralized energy resources, this could be done by the decision to either feed power back into the electricity grid or to charge a battery storage. Other devices, such as household appliances or EVs, can be delayed in their operating or charging time. This causes a shift of the electrical load.

The maximum delay is usually defined by the user, ipso facto, there is some point of time in the future when the appliance has to have finished its operation. The maximum possible delay is called *temporal Degree of Freedom* ($tDoF$). Appliances with $tDoF$ include dishwashers, washing machines, and tumble dryers with time preselection. Some of these appliances may also be interrupted or paused at certain defined points during their operation cycle. The EMS then optimizes the delays, interruptions and, if available in the scenario, the generation times and/or amounts with respect to constraints, the users' preferences and the optimization objectives.

Household appliances may also offer alternative load profiles for the same application, i.e., a certain program. For instance, appliances may internally shift or lengthen their energy consumption by extending the duration of heating phases. Additionally, the so called *hybrid* or *bivalent* appliances are able to utilize energy from different energy carriers alternatively. To name one example, a hybrid washing machine could use cold water and heat it up with its own electrical boiler or, alternatively, use hot water which is provided by a gas-fired central heating system. This offers the possibility to use gas instead of electricity and vice versa. Thus, these potentials are called *energy-related Degree of Freedom* ($eDoF$). Another example is the charging process of EVs at power levels that can be controlled by the EMS.

Accordingly, energy management of these devices has to consider different energy carriers as well as constraints and objectives: Electricity in terms of active power and reactive power, natural gas consumption, hot and chilled water consumption, emissions of greenhouse gases, user-defined objectives, physical constraints of the devices, and external signals, such as time and load variable energy tariffs. Therefore, the respective optimization algorithm is also confronted with the coordination of these energy flows, taking into account internal and external limitations. This challenges the flexibility, adaptivity and robustness of the EMS which is used to optimize the resulting energy management problem.

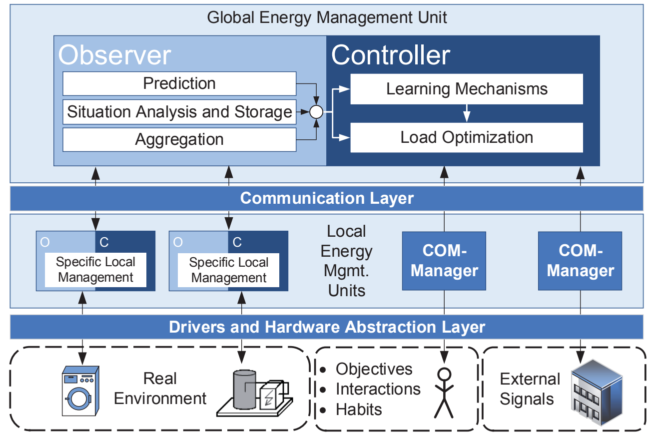


Fig. 2. Organic Smart Home – structural overview

III. Organic Smart Home

The *Organic Smart Home* (OSH) [4], the EMS used in this paper, is based on the generic *Observer/Controller Architecture* [5]. This architectural approach enables controlled self-organization in complex technical systems, such as modern smart buildings with energy consuming and producing devices.

The OSH (see Fig. 2) uses *Observer/Controller-units* (O/C-units), i.e., pairs of observers and controllers, to measure and influence the sensors and actuators available in the smart building's devices. This enables an adequate manipulation of the system's overall behavior through aggregation, prediction, and learning mechanisms. The hierarchically structured architecture of the OSH makes use of one *local* O/C-unit for each device taking part in the energy management. These local units encapsulate the knowledge about capabilities and limitations of their component, making it transparent for the global energy management situated in the *global* O/C-unit. There, the system and its behavior are monitored, analyzed, predicted, and optimized on a global level.

To enable a flexible load shape according to the situation on energy markets and in the local grid, external entities, e.g., grid operators or utilities, can communicate time-dependent price signals or load limit signals to the OSH via defined interfaces, called *COM-Managers*. These signals for electricity can then be considered as globally influencing factors in the optimization process, together with tariffs of other energy carriers.

The energy management problem varies with the availability and presence of devices, their local limitations as well as possible $eDoFs$, objectives as well as $tDoFs$ set by the user, and communicated external signals. Hence, the OSH utilizes a sub-problem based approach to optimization. This means, the energy management problem is not set up a priori in a closed form, but built up from *problem parts* at the run-time of the EMS. The problem parts are generated in the local O/C-units and communicated to the global O/C-unit. There, an EA operates on bit strings as described in [6] and pursues the actual optimization process. Therefore, the problem parts should be encoded in a homogeneous manner using suitable encoding schemes. That allows for an abstracted optimization.

IV. Encodings for Scheduling

Given the possibilities of the OSH together with the energy management scenario, the overall issue of the optimization process is to coordinate energy flows in a smart building according to the objectives of the users and compliant to external circumstances, e.g., situation in the electricity grid that are communicated through the load limit signals. These globally effective factors are taken into account by the global load optimization, which uses an EA that is based on a refined version of the *generic Genetic Algorithm* from the *Java-based framework for multiobjective optimization using metaheuristics (jMetal)* [7], [8]. The operators and parameter values that have been used in this paper can be found in Section V.

The observance of technical limitations and constraints of devices integrated into the EMS are achieved by the encodings of the problem parts in the dedicated local O/C-units. Therefore, the $DoFs$, which may be the $tDoFs$ or $eDoFs$ mentioned before, are encoded in different ways. The encodings enable a precise scheduling of the devices' operating times or modes of operation, and thus energy usage. To allow for the desired abstracted and generic "plug-and-play"-optimization, all encodings are bit string representations. Consequently, they can be combined to a comprehensive bit string representing the energy management problem at stake, providing good performance and solution quality as depicted in [9].

A. Encoding of delayable devices

Delayable devices have a $tDoF$, which is specified by the user's preferences by providing a latest finishing time f_j for the device j. Thus, it enables the optimizer to shift the starting time within a predefined period, beginning at the release time r_j, when the problem part is formulated in the dedicated O/C-unit:

$$tDoF_j = f_j - r_j - d_j$$

f_j	latest time by which the device j must have finished
r_j	release time of device j
d_j	duration of the planned operating time of device j

The delay until the time-shifted starting time is a *gray*-encoded bit string as shown in Fig. 3, enabling a planning accuracy to second basis and overcoming the *Hamming Cliff* [10]. The function *gray()* returns a gray-encoded bit string of a given integer value. The bit string $b_{j,1}$ in *gray-encoding* has a variable length $l_{j,1}$, which depends on the duration $tDoF_j$ in seconds:

$$l_{j,1} = \lceil \log_2 tDoF_j \rceil$$

The actual bit string $b_{j,1}$ may now be defined as follows:

$$b_{j,1} = gray(\lceil 2^{l_{j,1}} \ / \ tDoF_j \rceil \cdot \ p_{j,1})$$

The duration of the delay $p_{j,1}$ is then interpreted by the device's dedicated O/C-unit as follows:

$$p_{j,1} = gray^{-1}(b_{j,1}) \ / \ \lceil 2^{l_{j,1}} \cdot tDoF_j \rceil$$

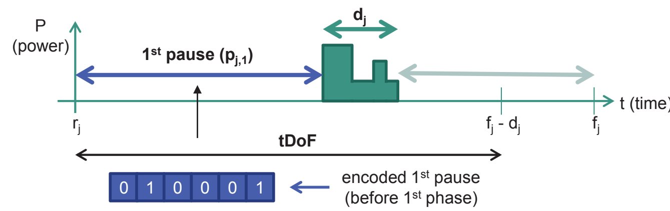


Fig. 3. Encoding scheme of a delayable load

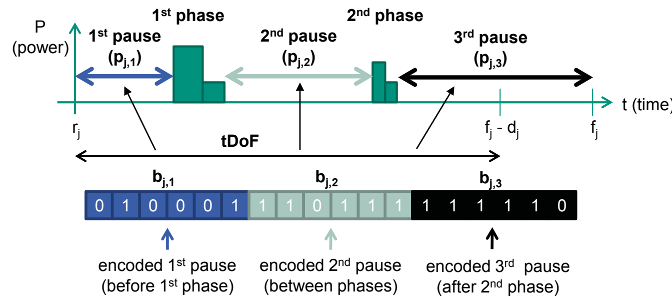


Fig. 4. Encoding scheme of an interruptible load

B. Encoding of interruptible devices

Nevertheless, the first encoding is not sufficient when considering devices which may not only be delayed but also interrupted at certain predefined points in their operation cycle. This second encoding is illustrated in Fig. 4. Instead of encoding only a single pause, this encoding utilizes multiple pauses to define the initial delay and the pauses in between the phases of operation, which are predefined by the points when the operation cycle is interruptible. If there are n phases, due to $n-1$ points of interruption, the encoding defines $n+1$ sub-strings for pauses. The length l_j of the total bit string b_j is now calculated as follows:

$$l_j = (n+1) \cdot \lceil \log_2 tDoF_j \rceil$$

Every sub-string $b_{j,k}$ for a pause k with $k = 1, ..., n+1$ has therefore the length $l_{j,k} = \lceil \log_2 d_j \rceil$. The duration of the delays for the pause k of device j can be interpreted as follows:

$$p_{j,k} = \frac{gray^{-1}(b_{j,k}) \ / \ \lceil 2^{l_j} \cdot tDoF_j \rceil}{\sum_{i=1}^{n+1} gray^{-1}(b_{j,i}) \ / \ \lceil 2^{l_j} \cdot tDoF_j \rceil}$$

The interpretation of the bit string of an appliance, which can be interrupted once in its operation cycle, is illustrated in Fig. 5: The ratio of the value of a single $b_{j,k}$ to the sum of all $b_{j,k}$ determines the allocation of the $tDoF$ to pause $k \in \{1,2,3\}$. Through this encoding, two different search behaviors with fixed parameters in the EA are possible: If the values of both $b_{j,1}$ and $b_{j,2}$ are small and $b_{j,3}$ remains fixed, minor changes to $b_{j,1}$ or $b_{j,2}$ cause tremendous changes in their respective share of the $tDoF$ and therefore *exploration*. Correspondingly, high values of $b_{j,1}$ and $b_{j,2}$ cause *exploitation*, because changes of their values then cause small changes to their share of $tDoF$.

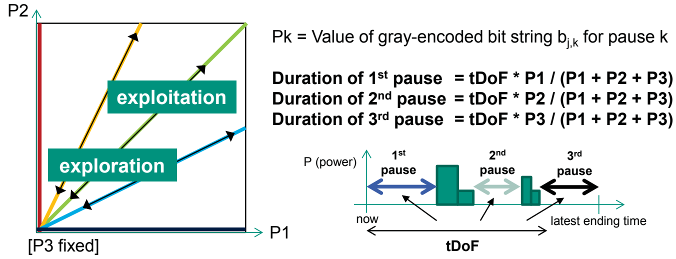


Fig. 5. Interpretation of the encoding scheme of an interruptible load

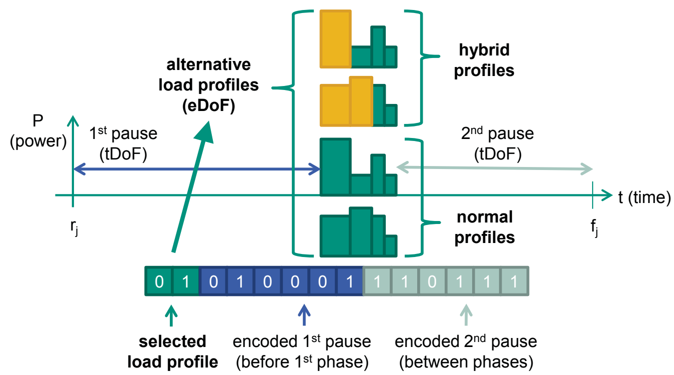


Fig. 6. Interpretation of the encoding scheme of a load with alternative load profiles (e.g., appliances with hybrid profiles using different energy carriers)

C. Encoding of devices with alternative profiles

Some of the devices used in buildings have alternative profiles of their energy consumption. This may either be due to simply different operation cycles for the same program, as e.g, the possibility to reduce peak loads of a heating phase by lengthening this phase, or due to the capability of the devices to use different energy carriers. As mentioned before, devices with the latter capability are often called hybrid or bivalent devices with respect to their energy consumption. The possibility to use different energy carriers for energy-intensive processes offers tremendous opportunities to shift the energy consumption from one energy carrier to another exploiting the $eDoF$.

The alternative profiles using different energy carriers or operation cycles are enumerated, encoded, and then added as additional sub-string to the previously presented encoding (see Fig. 6). In case of $i_{j,max}$ alternative profiles $0, ..., i_{max} - 1$ for device j, the bit string $b_{j,i}$ for profile selection has to be of length l_i:

$$l_i = \lceil \log_2 i_{j,max} \rceil$$

The selected profile i_j is then calculated as follows:

$$i_j = \lfloor |b_{j,i}| * i_{j,max} / 2^{l_i} \rfloor$$

This enables the inclusion of the profile selection into the optimization process. As a matter of fact, this scheme of encoding can be applied to both the encoding delayable devices and interruptible devices.

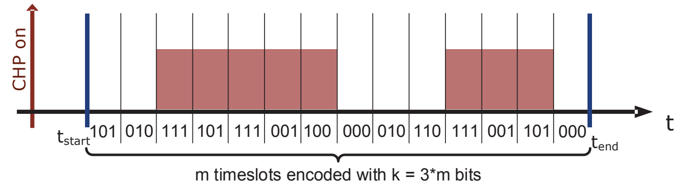


Fig. 7. Interpretation of the encoding of a CHP

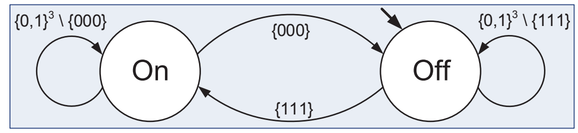


Fig. 8. Automaton of the encoding scheme of a CHP

D. Encoding of a controllable CHP

While most CHPs are managed with respect to thermal demand only (referred to as *non-controllable*), which is meaning that their electricity generation is not coordinated with the load in the household, the *controllable* CHP is able to split up its operating times into sequences, so it can be coordinated with the operating times of other devices. It is therefore encoded differently as depicted in Fig. 7. The finite optimization horizon, which is typically several hours, is segmented into n_p time periods of a defined duration, while every period is encoded with a sequence of 3 bits. This leads to a bit string b_c of a length l_c:

$$l_c = 3 \cdot n_p$$
$$b_c = [0, 1]^{l_c}$$

Every triad of bits in the bit string is then interpreted as the input of an automaton (see Fig. 8). If the bit string is equal to '111' the CHP is switched on, whereas it is switched off if the string is equal to '000'. Other bit strings let the CHP remain in its current state, no matter whether it is on or off.

This encoding automatically favors longer continuous operating times, which are typically less wear for CHPs. This effect may be strengthened by increasing the number of bits per time slot and therefore the weighting of the transition remaining in the current state. Regardless of the number of bits per time slot, whether it is, e.g., three or five, the CHP can still be optimized in time slots of, e.g., five minutes, and a horizon of three hours, without causing more than a few hundred bits.

V. Experimental Setups and Results

The capabilities of the encodings have been tested in extensive simulations, with some of the results presented in the following. The simulations used a time-variable electricity price and a fixed load-limitation signal, which causes a doubling of the electricity price during the phases it is violated (see Tab. II). The following results have been obtained as average results of the month January with different setups of the devices in Tab. III and the setup of *jMetal-gGA* as shown in Tab. I. The overall optimization objective was the reduction of average electricity costs that originate from electricity consumption and natural gas usage for electricity generation in the CHP.

TABLE I
SETUP OF EA IN JMETAL

Parameter	Value
Population Size	20
Number of Generations	50
Crossover Operator	SinglePointCrossover
Crossover Probability	0.7
Mutation Operator	BitFlipMutation
Mutation Probability	0.1

TABLE II
ELECTRICITY AND LOAD-LIMITATION SIGNAL

Maximum Price	39.24 Cent/kWh
Average Price	24.47 Cent/kWh
Minimum Price	3.56 Cent/kWh
Standard Deviation	5.91 Cent/kWh
Accuracy	1 hour
Load limitation	3000 Watt

TABLE III
DEVICES USED IN SIMULATIONS

Name	Device	Type
D1N	Hob	Non-delayable
D2N	Dishwasher	Non-delayable
D2D	Dishwasher	Delayable
D3N	Oven	Non-delayable
D4N	Dryer	Non-delayable
D4D	Dryer	Delayable
D4I	Dryer	Interruptible
D5N	Washing machine	Non-delayable
D5D	Washing machine	Delayable
D5H	Washing machine	Hybrid, non-delayable
CHP0	CHP	Non-controllable
CHP1	CHP	Controllable

TABLE IV
CONFIGURATIONS OF HOUSEHOLDS IN SIMULATIONS

Configuration	Devices
H0	D1N, D2N, D3N, D4N, D5N, CHP0
H1	D1N, D2N, D3N, D4N, D5N, CHP1
H2	D1N, D2D, D3N, D4D, D5D, CHP1
H3	D1N, D2D, D3N, D4I, D5D, CHP1
H4	D1N, D2D, D3N, D4D, D5H

TABLE V
RESULTS OF SIMULATION *A* WITH DIFFERENT HOUSEHOLD CONFIGURATIONS

Configuration	Average Electricity Costs	Compared to H1	Average Self-consumption Rate
H1	28.63 ct/kWh	–	17.1 %
H2	26.78 ct/kWh	-6.5 %	20.4 %
H3	26.49 ct/kWh	-7.5 %	21.1 %

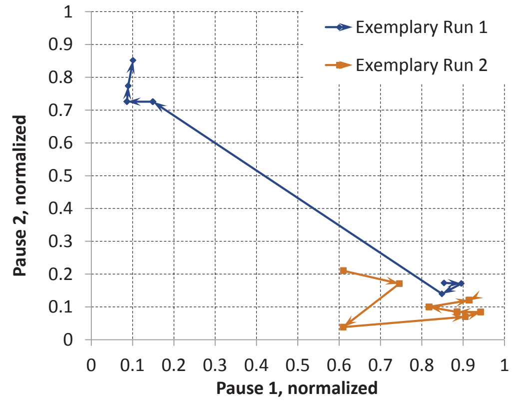


Fig. 9. Exemplary evolution of best individuals in two runs

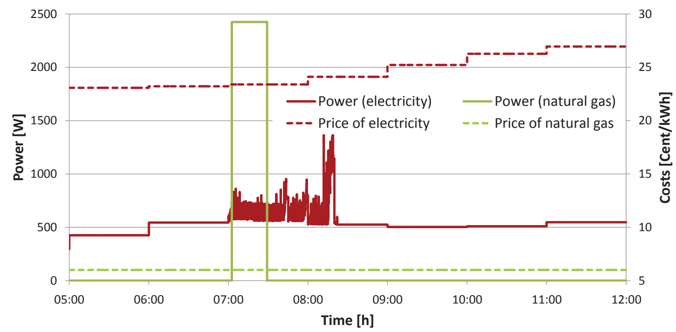


Fig. 10. Exemplary results using a hybrid appliance (washing machine)

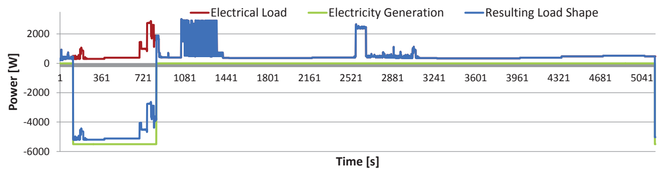
A. Non-delayable, delayable and interruptible devices

There are three different setups of households, H1 – H3, which have been used to simulate and compare the encodings of delayable and interruptible devices and show their potential in optimizing a household environment (see Tab. IV). The optimization potentials rise with the capabilities of the devices to be coordinated with the electricity generation of the CHP, resulting in lower average electricity costs as shown in Tab. V.

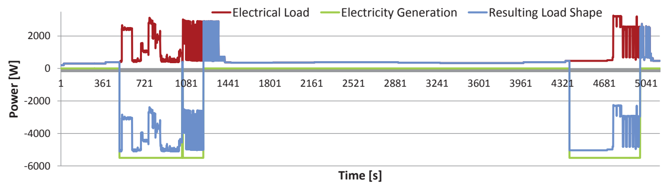
As described in Section IV-B, the encoding of the interruptible devices should allow for both exploitative and explorative search behavior. With a fixed value of the third pause, two exemplary optimization processes with the same parameter settings in the EA show both behaviors for the best individuals. Their evolution paths are depicted in Fig. 9.

B. Hybrid device with alternative load profiles

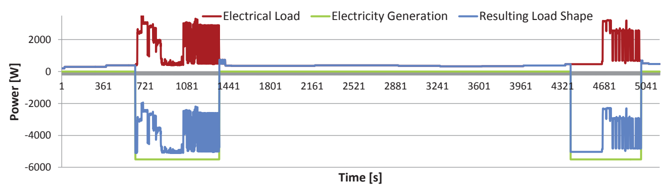
For testing purposes of encodings for devices with alternative load profiles, a hybrid washing machine with natural gas based heating capability was integrated into the OSH. The validity of the encoding scheme suggested in the paper at hand is qualitatively shown in Fig. 10. There, the optimization process takes advantage of a relatively low natural gas price and is thus minimizing the costs for the respective period by limiting the electricity consumption of the washing machine. In periods with lower electricity prices, for example in times of generation surplus in the grid, the electrical heating is preferred.



(a) H0, unoptimized



(b) H2, optimized with default parameters



(c) H2, optimized with calibrated parameters

Fig. 11. Simulation results of configuration H0 without optimization and of configuration H2 with different parameter settings

TABLE VI
RESULTS OF SIMULATION *C* WITH DIFFERENT HOUSEHOLD CONFIGURATIONS

Configuration	Average Electricity Costs	Compared to H0	Average Self-consumption Rate
H0	29.99 ct/kWh	–	14.6 %
H1	28.63 ct/kWh	-4.5 %	17.1 %

C. Non-controllable and controllable CHP

The coordination potentials of a controllable CHP, integrated into the OSH through the proposed encoding, are shown by the qualitative depictions in Fig. 11 of one exemplary day in the results of configuration H2. In Fig. 11(a), the non-controllable CHP just satisfies the hot water demand, producing electricity only as a by-product. It happens only by accident that some of the devices' operating times are concurrent. The integration of a controllable CHP into the optimization process leads to coordinated electricity consumption and generation as shown in Fig. 11(b). An even better coordination can be achieved by calibrating the parameters of the EA. This can be seen in Fig. 11(c), where the same number of evaluations in the EA leads to superior results.

Quantitative results of the integration of a controllable CHP as the only delayable component in a smart building are shown in Tab. VI, also referring to the increase in the self-consumption rate of the building. This self-consumption is beneficial to the local grid, because less feed-in to the grid results in less voltage and congestion problems.

VI. CONCLUSION AND OUTLOOK

This paper presented encodings for delayable respectively interruptible devices, such as household appliances, and controllable CHPs with attached thermal storage. These encodings are used in the EA of the OSH, an EMS for smart buildings which optimizes the energy consumption with respect to variable tariffs, load limit signals, and the user's behavior.

The encodings have been validated in simulations with different scenarios. It has been shown that energy management in households and small business environments that uses the presented encodings may contribute successfully to the future smart grid by providing optimized, flexible electricity consumption and generation, as well as increased self-consumption of the locally generated electricity.

Further encodings for devices considered in this paper and other devices, such as PV systems with battery storage, electrical cars, adsorption chillers, and water heaters, will be published soon. Some have already been integrated into the OSH and are in evaluation using simulations and real-world environments: the *Energy Smart Home Lab* at the Karlsruhe Institute of Technology (KIT) and the *FZI House of Living Labs* at the FZI Research Center for Information Technology . This will enable further verifications of the simulation results presented in this paper by real-world data, which is obtained in trial phases and practical energy management in buildings.

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