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ENKOS – A Smart Home control system basing on learning classifier systems

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Abstract: An adaptive, optimizing device management system for households called ENKOS is developed that is based on learning classifier systems (LCS). Established methods and algorithms are extended, and psychology methods are introduced to solve specific generalization and adoption problems. The two aims of ENKOS are firstly to minimize the electrical energy consumption within the household by interpreting the user's wishes as servable and controlling the devices in that kind, and secondly to maximize the consumer comfort by predicting the wishes of them by learning. This paper shows both the feasibility to meet the aims by using learning classifier systems with extensions as new methods, and the influence of several parameters towards the value of the learning rate of the objective function.

1. INTRODUCTION

The total consumption of electrical and heating energy in Germany per head grew up from 1586 kWh per Person in 1960 to 7215 kWh in 2010 because of the bettering of the standard of living (Bundesministerium, 2013). This is about 25 % of the total energy consumption in Germany.

About 14 % of the energy consumption in households is used for the lightning, 7 % for the information and entertainment electronics and 4 % for the home office. These are the focus areas addressed by our system. Today, these devices are not controlled centrally, consequently, energy could not be saved in a smart way.

On the one hand the goal of the most citizens is to reduce the energy consumption of their households because the price for electrical energy grew from 14 €-ct/kWh in the year 2000 to more than 21 €-ct/kWh in 2011 (BDEW, 2013). On the other hand 60 % of the German consumers are interested in Smart Home applications to enlarge their living comfort (VDI Nachrichten, 2013), whereas usage is today 2 … 3 %.

The existing Smart Home systems, that are controlling devices in the households, have to be programmed by the users. Two of the biggest networks on the German market, Qivicon and SmartHome Deutschland, are developing platforms for devices to communicate with each other (Qivicon, 2013, SmartHome Deutschland, 2013).

Another approach is the agent based smart home control system (Reinisch, 2011) where human behaviour is modelled by BDI agents (Belief-Desire-Intention agents) as a multi-agent system, where the agents learn and represent decisions of users. Besides this the OLA (Observe, Learn, and Adopt) algorithm based system (Qela, 2012) is a rule based approach which controls thermostats in smart homes. Here a static knowledge base is created which contains the rules. The adaptive scenario-based reasoning system (ASBR) in opposite to the introduced attempts detects the environment including the persons by sensors and orders these data into a description file as knowledge base (Cheng, 2010). This is the learning process to make predictions for exaggerating the user comfort.

ENKOS (Energy and comfort management system) is created to manage the consumption of the energy by switching the devices in a smart way to reduce it, and to enlarge the comfort of the daily living by controlling the devices in households. The difference to the systems mentioned is the rule-based approach with the ability to generate, explore and generalize rules besides exploiting them.

2. DEFINITION OF TOPOLOGY AND GOALS

2.1 General topology

The goal of ENKOS is to maximize the user comfort and to minimize the energy consumption by managing the devices centrally. That means the user satisfaction has to be measured as well as the energy consumption. The topology to do both is shown in Fig. 1.

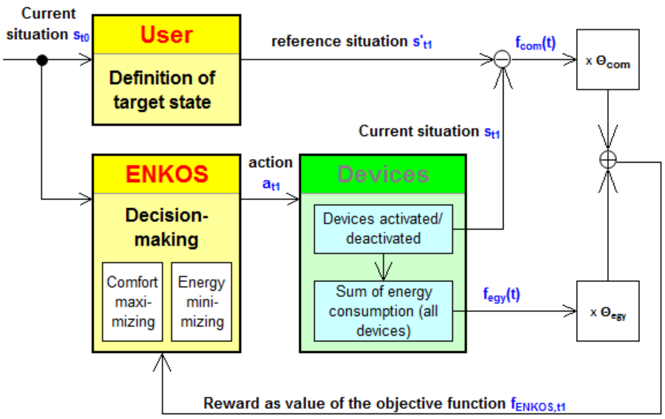


Fig. 1. General topology of ENKOS.

The situation s_{t0} comprises all the measured information of the environment including the brightness and the time stamp $t = t_0$ besides whether each room in the household is empty or not (as not controllable information), and the states of all the electrical devices (as controllable information) to ENKOS and to the user. After that ENKOS makes a decision a_{t1} and transfers it as a control signal to the devices in the household. After that a new situation vector s_{t1} is measured containing the updated device information and the uncontrollable information at time stamp $t = t_1$.

In parallel the user makes a decision basing on the current situation s_{t0} how to control the devices in his mind (Betsch, 2001). Together with the uncontrollable information at $t = t_1$ the vector s'_{t1} is a reference in the user's mind.

After perceiving the new state s_{t1} forced by ENKOS the user is either accepting the state of all the devices or is correcting it. This gives the difference of zero (if accepting) or greater than zero (if correcting), and describes the satisfaction of the user.

Besides this each device is in a certain state with a certain energy consumption at $t = t_1$. The sum of all the consumed energy is also measured to evaluate the decision concerning the second goal of ENKOS.

Every situation vector s_{t0}, s_{t1} and s'_{t1} of ENKOS is describing one possible operating range of the complete household. Every device in this household is represented in the situation vector as "1" if the device is switched on, as "0" if the device is switched off. In the vector s_{t0} another state, the "#" (joker), is possible to indicate that the device is either switched on or off. While s_{t0} is representing the current situation read before the decision of ENKOS, s_{t1} is showing the observable situation after making the decision and implementing is to all the devices. The situation s'_{t1} is the reference situation of the user and shows, what situation would have been if the user would have made the decision.

The action vector a_{t1} is containing the wish to influence the environment. Hence, all the electrical switchable devices of the focussed area of the household are contained here. If the "User" in Fig. 1 would switch on any lamp l_x inside the room then the situation s'_{t1} takes this lamp l_x = "1" as the reference (desired state of the household's lamp l_x) in the user's mind. If ENKOS also forces switching the lamp l_x on it transmits this wish by the action a_{t1} where the value l_x is set to "1". After that the "Devices" block receives this command and switches the lamp lx on. Then the vector s_{t1} (real state of all devices in the household) is read at time stamp $t = t_1$. The entry for lamp lx will be "1" and the difference will be zero, so the user is satisfied regarding lamp l_x.

The user comfort is calculated in Eq. (1) while the energy consumption $f_{\text{egy}}(t)$ of all the devices in the households is measured directly.

$$f_{\text{com}}(t) = \left\| s_{t1} - s'_{t1} \right\| \tag{1}$$

2.2 Objective function

After measuring the energy consumption and the user satisfaction both are weighted to bring them in a balance. That is necessary that ENKOS is not considering only one of the goals during the learning phase.

The objective function containing all the information is defined as shown in Eq. (2).

$$f_{\text{ENKOS}} = \int_{1\,\text{year}} \left[\theta_{\text{com}} \cdot f_{\text{com}}(t)\right] + \left[\theta_{\text{egy}} \cdot f_{\text{egy}}(t)\right] dt \tag{2}$$

In this equation θ_{com} and θ_{egy} are the weighting factors for the user comfort and the energy saving, respectively.

3. DEFINING THE LEARNING ALGORITHM OF ENKOS

ENKOS should be a machine learning system because it has to construct a model that automatically is learning from experiences as the basis of the system (Mitchell, 1997). There are three general possibilities (Reichel, 2008) for teaching machine learning systems:

- ➔ As s*upervised learning system* ENKOS would be taught by vectors of input and output data (e. g. Switching of all lights and presence of all persons besides all environment conditions). Many thousands of data sets are necessary to finish teaching. Besides of this thousands of independent data are necessary to validate the result of the teaching. One assumption is that the influence of cultural effects and habits are negligible because the inclusions of these as features are nearly impossible. Both the huge number of data sets and the big influence of the changing of habits are making the usage of supervised learning systems impossible. Besides these actions have to be provided by ENKOS as soon as possible what is not possible with supervised learning systems as well.
- ➔ As *unsupervised learning system* ENKOS would also receive thousands of input data of the presence of persons, the status of the devices (switched on or off) and the environment. The difference to the supervised one is that the system choses its own strategy (by switching the devices) and the consumer is giving a feedback as the teacher of the system. In this line the number of learning cases has to be very big as well and the person has to evaluate all the cases. So ENKOS cannot use an unsupervised learning system as its basis because the online teaching by a person as teacher in a direct and quantitative sufficient is unsuitable.
- ➔ As classic *reinforcement system* ENKOS would create its own strategy and rule basis while using this from the first moment on. That means in every moment the system senses the status of the devices, and the environmental status. After that it tries to find an internal rule out of the rule basis that maps the current situation the best. This rule will define the strategy how to control all the devices to ensure the goals of ENKOS and earning feedback to evaluate its internal model of the household (rule

base intrinsic). In our case the Reinforcement learning is the basis for ENKOS because it can model the people the best, works rule based as people do and can handle with incomplete data sets, and starts working dynamically once the rule base is consistent enough. Besides these genetic algorithms allow a continuing progress of the data base and there are methods for creating new rules (e. g. changing of habits). The reinforcement approach flows into *Learning Classifier Systems* (LCS) to create the basis of ENKOS

A genetic algorithms set is containing mutation and recombination methods and is taking care for the rules to develop themselves by exploring the household's working space. That is by trying out different combinations of switching devices which are not stored in the rule base at this certain timestamp. In the ENKOS system, as an example, a combination of switched on lights could be the best one (in respect to the main function) that was never, or for very long time not, tried out before, or was cleared out by mutation. By trying to find such an action to choose as the best one the randomly change of existing rules is implemented. Furthermore a model of the household's devices is created and validated inside the Population over time automatically.

Besides this generalization methods will force making rules more general. In the ENKOS system it could happen that the switching of light, for example, is not depending to certain conditions such as whether the TV is switched on. So the aim of the generalization is to maximize the covering range of each rule in the knowledge base without losing the main information. In that way the exploitation of the knowledge base is realized.

4. IMPLEMENTATION OF ENKOS

4.1 Maximizing user comfort by Learning Classifier Systems

The method to maximize the user comfort by ENKOS by learning and modelling the users' behaviour is the usage of learning classifier systems (LCS). The resulting internal structure is presented in Fig. 2.

In ENKOS the current situation is read out of the environment (Fig. 2, step 1) and is compared to all the existing rules in the population **[P]** (= knowledge base). Every rule consists of the situation **s** (representing a whole set of environmental states), the recommended action *a*, and the expected reward *r* if this action is chosen. All rules representing the read situation are transferred to the Match Set **[M]** (step 2) as a subset of the population. Out of **[M]** one action a_{t1} is chosen as the best one and all rules containing this action are copied to the action set **[A]** (step 3). After that this rule is admitted to the environment itself (step 4) and the environment's reaction to the chosen action a_{t1} is assessed by the reward r_{t1} got for updating all rules inside the Action Set by creating the updated action set **[A]'** (step 5) (Bacardit, 2008, Kaminski, 1997). Then all the rules with the updated reward are written from **[A]**' back into **[P]** (step 6) and the algorithms of generalization (Bull, 2005) are exploiting the whole knowledge base to find general correlations (step 7).

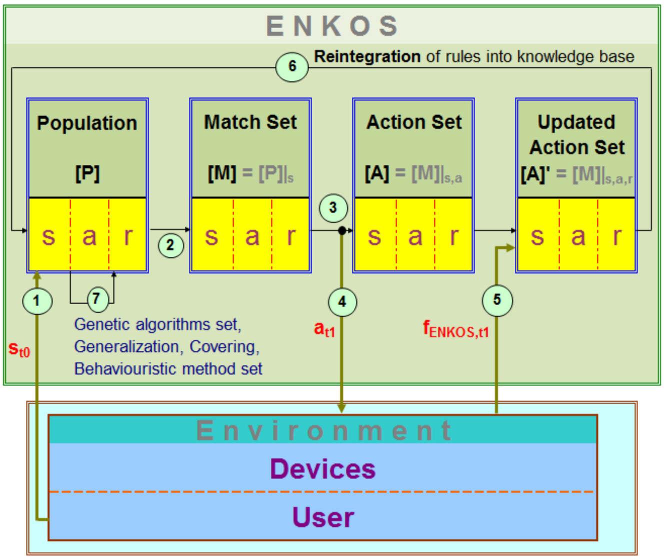


Fig. 2. Internal topology of ENKOS using LCS.

In all the rule sets "Population", "Match Set", "Action Set" and "Updated Action Set" (see Fig. 2) the same structure of rules is used. Every rule is consisting of the situation *s*, the action *a*, and the expected reward *r* in the table. The maximum number of rules in the Population **[P]** is set to 20 in this paper to enable comparability of the different learning rates.

The reward of the environment in Fig. 2 is the objective function value $f_{ENKOS,t1}$ at one certain time stamp t_1 (see Eq. (2) under the integral). It is calculated of both, the satisfaction of the user facing the current situation, and the total energy consumption of the devices.

If a situation occurs that cannot been identified by the current Population **[P]** a new role is created by *covering* (Bull, 2005). Here an existing situation is copied and modified to map the incoming one.

4.2 Energy minimizing methods

To save energy in the household the following assumptions are the basis for the exploitation of the rules. Every rule is permanently checked whether it is contrary to any of these assumptions. If yes, the rule is modified to solve the conflict in the existing rule.

→ Conflicts of different information or energy sources have to be avoided. E. g. if two auditive sources (radios) are working in the same room at the same time there might be a conflict of sound. Then ENKOS would modify its rules in a way that in maximum one audio source is switched on at the same time.

→ If there is information or energy sources which is not required by the consumer at the moment the ENKOS has to switch off these sources (negative noticeability). If, for example, the music is playing, but cannot been heard by anybody, this music has to be switched off until someone can hear it. All the rules would be checked whether empty rooms with playing music exist and be modified in this case.

5. THE VERIFICATION OF ENKOS BY THE SIMULATION OF ONE YEAR

5.1 The simulation structure

The simulation of the environment consists of two steps during the simulation.

1. The first step is to simulate the current situation of the *controllable (all electrical switchable devices)* and *uncontrollable (e. g. brightness)* environment. This step is to admit ENKOS with every situation measured over one year. The situation s_{t0} is presented to the ENKOS system (see Fig. 2, step 1). These data are a tuning of the self-experiment to the statistical consumption data of Germany. That means the points of switching an electrical device on or off were measured in the own household on a normal (statistical representative) working day but the scaling of the energy consumption was done to reach a statistical German standard household as the absolute reference (Bundesministerium, 2013).

2. After the generation of the action a_{t1} by ENKOS this action is transmitted back to the simulation of the environment.

   The evaluation of the consumer satisfaction ($f_{\mathrm{com}}(t)$ in Eq. (2)) is done by a comparison of the action as the prediction of the consumers wishes to the real wishes of him. This difference multiplied with the weighting is the first part of the reward and hence the objective function.

The next step is the evaluation of the energy consumption ($f_{\mathrm{egy}}(t)$ in Eq. (2)) in the household. Here, the minimal possible consumption over all the devices is taken as the reference value. Therefore, the basic idea to gain this reference value is not to take the devices in mind at all, but therefore the services they provide to the consumer. For example, if there is a “light 1” switched on that spends P_{light1} = 45 W and another “light 2” with P_{light2} = 35 W and switched off could provide the same service (lightning the room) to the person the saving potential is to save $P_{potential} = P_{light1} - P_{light2}$ = 10 W. In this case the usage of “light 1” would be rewarded proportional less than the usage of “light 2” (maximum point).

5.2 The simulation of one year

The simulation of one year is divided into time slots for every 30 minutes over the whole year as shown in Fig. 3. For each time slot the status is sent to the ENKOS system which evaluates the knowledge base. The simulation of 8 time slots (18:00 to 22:00) is represented. On the left side of the figure there are the controllable devices named, in the shown case 10 different lights inside the household. The nominal electrical power input of each of them is listed in the third column before the monthly energy consumption using the ENKOS system as central control unit. In the next column the monthly energy consumption of the current simulation is shown for comparison. Then the simulation and ENKOS matrix field is following to the right. Here for every time slot (“Time area *t*”) the measured outside lightness and the number of present persons is listed in the top of the table (yellow colour is more than one person, while uncoloured would be zero). In the big field below the light yellow fields stand for the status of the devices in the simulation while the dark fields represent the ENKOS ones out of the current knowledge base.

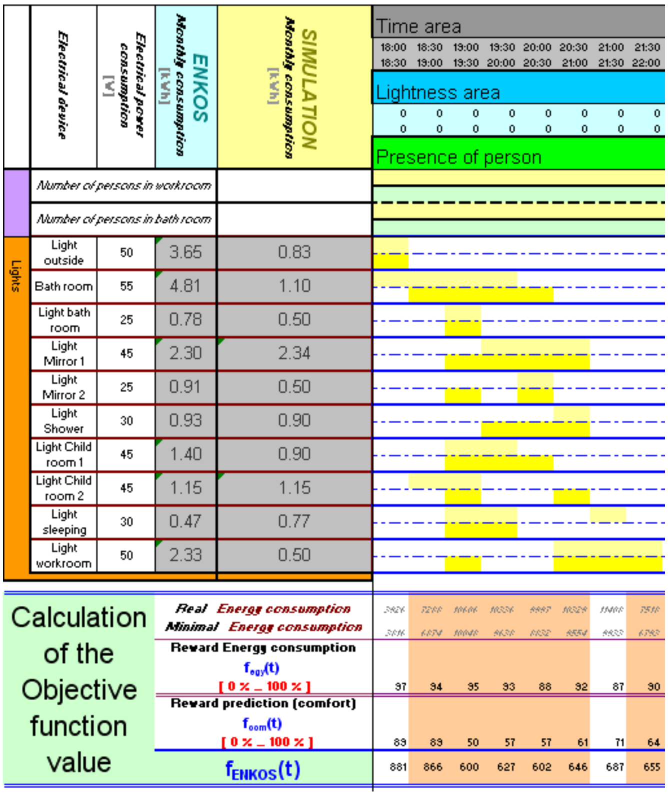


Fig. 3. The simulation of 8 time slots.

The light inside the shower, for example, is turned off in the simulation (real measurement) during the whole business day except the time slot between 20:30 and 21:00. However ENKOS would turn it on from 19:30 to 21:00 using the current knowledge base. That means that ENKOS would not satisfy the consumer in the household in a very good way. Because of this evaluation in the second line from bottom up the values are very low (57 to 61 % in the investigated time slots in a possible range from 0 to 100 %). The energy saving potential on the other hand is in the range of 88 ... 92 % so the switched on devices do not have a big potential to be substituted to save energy by keeping the service “light inside the shower”.

The fields shaded orange are covered ones. At these time slots the situations are not matching to any of the existing rules inside the knowledge base so that rules have to be created basing on the read situation. Then the Match Set is containing exactly one rule – the covered one before the Genetic Algorithm makes some exploring.

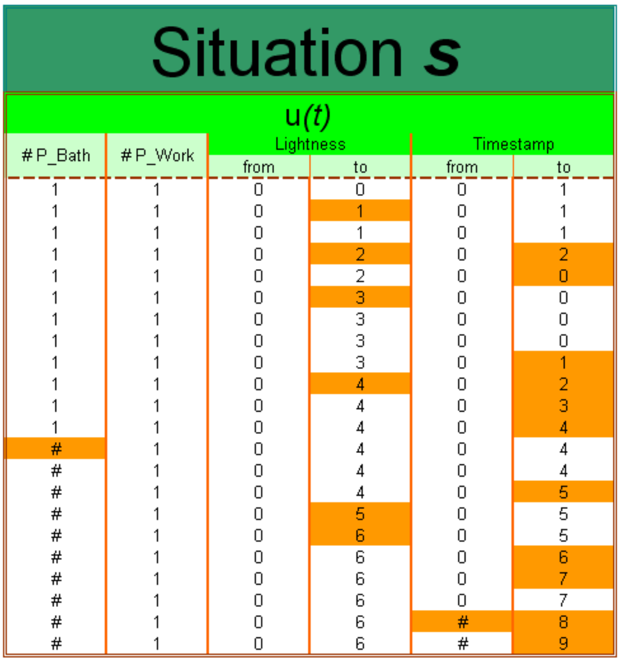
5.3 The main parameters of ENKOS

In the simulation two different way of representation of the knowledge base are shown. The first one is the whole knowledge base at every certain timestamp and the second one is the evolution of every single rule during the whole simulation phase of one year. The other parameters of the LCS system are used as shown in Table 1.

Table 1. Main parameters

Para-meter	Description	Unit	Range
β	Learning rate	%	0 ... 100
η_{Mut}	Mutation rate	%	0 ... 100
η_{Gen}	Generalization rate	%	0 ... 100

In the classic LCS the generalization rate is the probability to change an existing value to the joker (don't care) in the situation **s** in the rule base. In the ENKOS system a second (additional) generalization method is implemented by extending the range of both the lightness and the timestamp area with the generalization rates, respectively. This method is created to allow a "soft generalization" besides the hard, classic one and can be seen at lines 3 to 4 in Fig. 4 (extension from lightness range 0 … 3 to lightness range 0 … 4).



Situation *s*					
		u(*t*)			
#P_Bath	#P_Work	Lightness		Timestamp	
		from	to	from	to
1	1	0	0	0	1
1	1	0	1	0	1
1	1	0	1	0	1
1	1	0	2	0	2
1	1	0	2	0	0
1	1	0	3	0	0
1	1	0	3	0	0
1	1	0	3	0	0
1	1	0	3	0	1
1	1	0	4	0	2
1	1	0	4	0	3
1	1	0	4	0	4
#	1	0	4	0	4
#	1	0	4	0	4
#	1	0	4	0	5
#	1	0	5	0	5
#	1	0	6	0	5
#	1	0	6	0	6
#	1	0	6	0	7
#	1	0	6	0	7
#	1	0	6	#	8
#	1	0	6	#	9

Fig. 4. The evaluation of the first rule of the Population over the first time stamps.

The learning for learning classifier systems is done for all the selected actions in **[A]'** after receiving the reward from the environment and is shown in (3). Here **r** is the calculated reward to be written to the knowledge base after the receiving of the environmental reward while $\mathbf{r}_{read}$ is the currently read reward in **[A]**. The exact receivement from the environment is r_{t1}.

$$r = r_{\text{read}} + \beta\left(r_{read} - r_{t1}\right) \tag{3}$$

In Fig. 4 one single rule of the population is shown at the end of the first month of simulation (with reference parameters used as in Table 1). The number of jokers is low and is becoming higher over the time. Because no rules of the set are being cut out from a certain point on all the rules consist of jokers only.

6. THE INFLUENCE OF THE LEARNING RATE

Basing on the parameters of the reference system (see Table 1) the learning rate was changed stepwise from β = 1 % to β = 4 %. By increasing the learning rate the dynamic of the system compared by the years of simulation becomes less (Fig. 5). During the first year a lively change of the objective function value (Δf_{ENKOS} = 67.35) can be detected using a very low learning rate (β = 1) while the change of the objective function is decreasing for a high learning rate (Δf_{ENKOS} = 13.11 for β = 4)

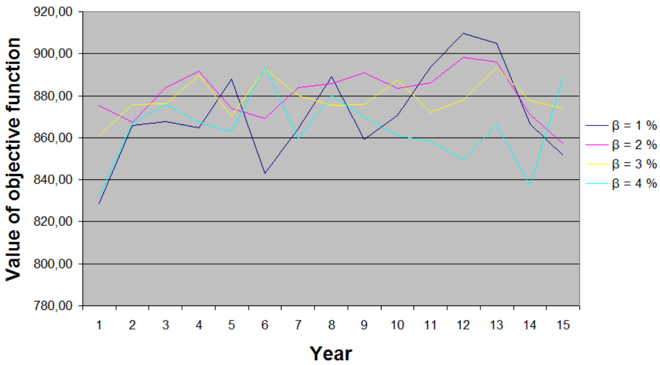


Fig. 5. The evaluation of the first rule of the Population over the first time stamps for different learning rates

7. CONCLUSION AND PROSPECTS

In this paper the possibility to minimize the energy consumption inside a household by maximizing the user's comfort is shown. As the advantage of this approach the learning classifier systems learn the behaviour of the users in a household. Besides this the energy consumption is reduced by modifying the rules of the LCS with general assumptions.

As further steps bad rules have to be identified and removed or modified. The Behaviouristic method set (see Fig. 2) has also to be developed according to psychological laws to model the consumer's behaviour better. Here several approaches have to be tried out.

Afterwards the influence of other parameters, the size of the population, the mutation rate, the generalization rate, the generalization rate lightness, and the generalization rate timestamp to the value of the objective function have to be optimized.

Then other Generic algorithms methods have to be tested and a set of the best parameters has to be created. The scanning of all the parameters can either happen manually or by an evolutionary algorithm, or by an optimization algorithm. All the real influences have to be figured out by a summary.

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