COMBINING LEARNING CLASSIFIER SYSTEMS WITH THE DECISION THEORY FOR CREATING A SMART HOME SYSTEM

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ABSTRACT

An adaptive, optimizing device management system for households called ENKOS is described that is basing on learning classifier systems (LCS) as well as methods of the decision theory to solve specific generalization and adoption problems. The two aims of ENKOS are firstly to minimize the electrical energy consumption inside the household by interpreting the user's wishes (controlling the devices), and secondly to enhance the consumer comfort by predicting the wishes of them by learning. This paper shows the feasibility to meet the aims by using learning classifier systems with extensions of the decision making theory, and the influence of several parameters towards the value of the learning rate of the objective function.

Index Terms – Smart Home, Intelligent Home, Assisted Living

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 [1]. 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 the presented system. Today, these devices are not controlled adaptively; 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 [2]. On the other hand 60 % of the German consumers are interested in Smart Home applications to enlarge their living comfort [3], whereas usage is 2… 3 % today.
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 [4]. Another approach is the agent based smart home control system [5] where human behaviour is modeled 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 [6] 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 [7]. 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 in combination with methods of the psychology theory to adopt the human decision making process.

2. SYSTEM 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.

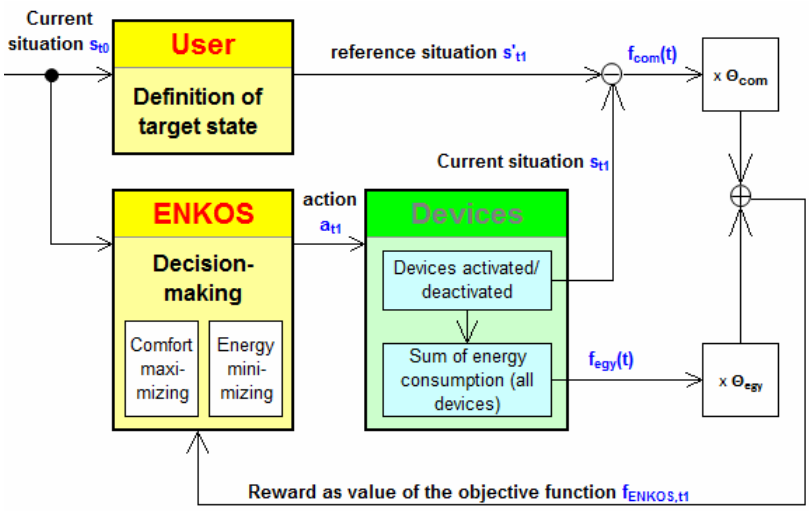

Fig. 1. The general topology of ENKOS with the logical devices for comfort maximizing and energy minimization.

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 (these are 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 (action a_{t1}) and transfers it as a control signal to the controllable devices in the household. Then a new situation vector s_{t1} is measured containing the updated device information and the uncontrollable information at time stamp $t = t_1$ (time index as subscript).
In parallel the user makes a decision basing on the current situation s_{t0} how to control the devices in his mind. 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 parts of it. This gives the difference of zero (if accepting) or greater than zero (if correcting), and is a measure for 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 exist 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 $\mathbf{l_x}$ inside the room then the situation s'_{t1} takes this lamp $\mathbf{l_x}$ = "1" as the reference (desired state of the household's lamp $\mathbf{l_x}$) in the user's mind. If ENKOS also forces switching the lamp $\mathbf{l_x}$ on it transmits this wish by the action a_{t1} where the value $\mathbf{l_x}$ is set to "1". After that the "Devices" block receives this command and switches the lamp $\mathbf{l_x}$ 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 $\mathbf{l_x}$ will be "1" and the difference will be zero, so the user is satisfied regarding lamp l_x.

3. CREATING THE MODEL

As the first step on the way creating a model six criteria are discussed in respect to the usage for ENKOS. The first criterion is the correctness. That means that both, the linear describable electrical devices and the very nonlinear behaviors of human beings have to be modeled with the correct physical dimensions of the input and the output parameters [8]. Due to the nonlinear behaviour of humans in respect to the switching to electrical devices a machine learning algorithm has to be implemented to obtain the information from experiences [9]. There are three general possibilities for teaching machine learning systems, the supervised learning, the unsupervised learning and the reinforcement learning system [10]. Because of the nature of the system's environment ENKOS will be created as a reinforcement system. As such a system it senses the status of the devices, and the environmental status (as brightness or current time) in every sampling time step. 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 itself. In our case the reinforcement learning is the basis for ENKOS because it can model the environmental structure the best, works rule based as humans do and can handle with incomplete data sets. And it starts working dynamically once the rule base is consistent enough. Besides this genetic algorithms allow a continuing progress of the data base and there are methods for creating rules (e. g. changing of habits). The reinforcement approach flows into Learning Classifier Systems (LCS) to create the basis of ENKOS.
As the next criterion the complexity of a model should be as small as possible to reflect the important aspects of the environment but not the unimportant ones. Here the method of the decreasing complexity is used to find the right complexity of the model [11]. Here all possible environment parameters are integrated in the first shot of the model and are left out step by step if the prediction of the system is not deteriorated. The complexity of ENKOS is defined by the adoption of the human decision making process because the energy saving methods are of a low complexity compared to the psychological ones.
The next criterion to create a model is the efficiency for the modeling itself. Here the obtained information must fit into a certain time frame. But the usage of modern sensors and

microcontrollers make it possible to read all the needed inputs and outputs that are necessary in a very short time range.
Criterion number four is the comparability of the model. That is the possibility to firstly integrate the model into the environment itself and secondly to have a clear statement which change of the parameters leads to which effect(s).
And the models should be interpretable, so that the internal information could be evaluated by an expert. The stored information in a neural network, for instance, is interpretable very badly compared to an expert system that stores its information in a readable text format.
As the last criterion a systematic structure should be recognizable inside the model. That means for ENKOS both the energy flow and the human behaviour making decisions are transparent by themselves and not mixed with each other. For the human behaviour 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.
Besides this generalization methods will force rules to become 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. THE IMPLEMENTATION OF ENKOS

These criteria are used to create the model. The method to maximize the user comfort by ENKOS with the ability of learning and modeling the users' behaviour is the usage of learning classifier systems (LCS). And the methods to adopt human decisions inside the rooms are derived from the decision theory. These techniques are the basic model structure shown in Fig. 2.

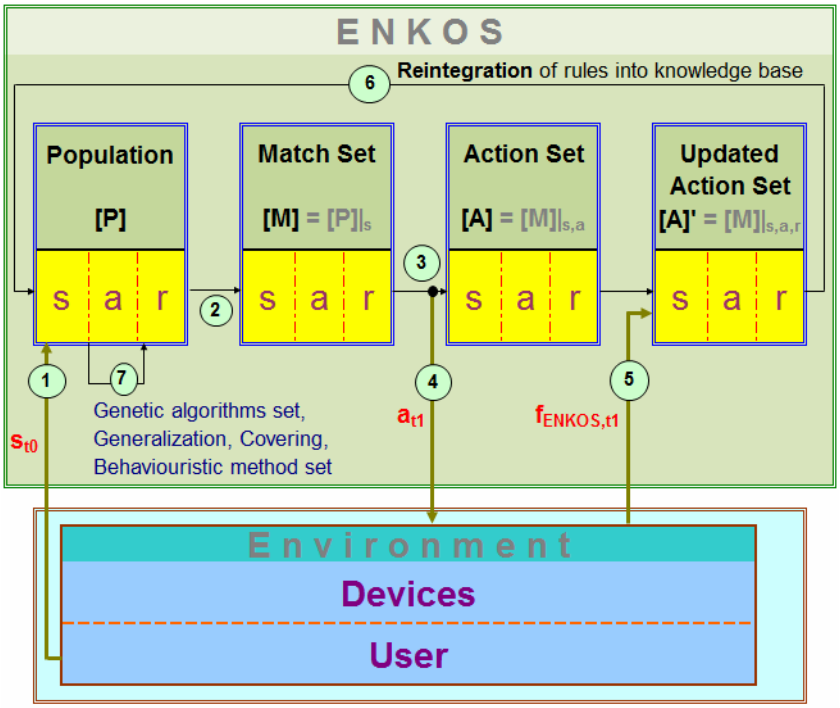

Fig. 2. Internal general topology of ENKOS using LCS.

Here 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 will be 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} (with the greatest expected reward r) 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's action a is admitted to the environment a a_{t1} by actors (step 4) and the environment's reaction to the chosen action 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) [12]. Then all the rules with the updated reward are written from [A]' back into [P] (step 6) and the algorithms of generalization [13] are exploiting the whole knowledge base to find general correlations (step 7).
In all the rule sets "Population", "Match Set", "Action Set" and "Updated Action Set" (see Fig. 2) the same structure of rules is used. 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. (1) under the integral). It is calculated of both, the satisfaction of the user faced with the chosen action a_{t1}, and the total energy consumption of the devices.
If a situation occurs that cannot been identified by the current Population [P] a new rule is created by covering [13]. Here an existing situation is copied and modified to map the incoming one.

5. INTEGRATION OF THE DECISION THEORY INTO THE OBJECTIVE FUNCTION

5.1 The main structure of the objective function

After measuring the energy consumption and the user satisfaction both are weighted to bring them to a balanced relationship. That is necessary that ENKOS is not considering only one of the goals during the learning phase. The objective function is defined as shown in Eq. (1) in a general structure. The goal of ENKOS is to maximize $f_{ENKOS,kont}$.

$$f_{ENKOS,kont} = \int_{Jahr} (f_{ENKOS,comfort}(t) + f_{ENKOS,energy}(t))dt \tag{1}$$

In this equation $f_{ENKOS,comfort}(\bullet)$ and $f_{ENKOS,energy}(\bullet)$ are the two terms to be optimized, the first one to enhance user comfort and the second one to save energy. The integral marks to consider one year for an evaluation of the current system (with its parameters).

5.2 To define the comfort evaluation term

The main task for the model is to predict human behaviour in respect to the switching of electrical devices in a household. The introduced model basing on LCS serves an adaptive structure in general while the psychology of decision making is providing general rules for the human beings modelled by the LCS. So the integration of the psychological rules to the LCS shown in Fig. 2 is described. The first step of making a decision is the collecting of possible solutions for a given situation before calculating all the utility values for each of these

potential decisions (evaluation). After that the subjective expected utility value is calculated for every possible action using the fact, that the higher the objective value becomes the smaller the increasing gradient of the subjective utility value is. This phenomenon is called dimishing sensitivity. Another rule of human thinking is the loss aversion what means that the loss of a certain value (e. g. money) has a stronger influence on human behaviour than the win of the same value. After calculating the value of the subjective utility the best decision (the greatest value) is chosen to be executed.
The subjective utility value corresponds to the expected reward value r that is stored in every rule of the LCS. In step 2 (Fig. 2) all (known) potential decisions are put into [A] as potential candidates for the action a_{t1}, and in step 3 the best value is chosen to be executed. So the value of r_{t1} is interpret as the subjective utility value earned from the environment.
This fact is taken into account by replacing $f_{ENKOS,comfort}(t)$ in the objective function (Eq. (1)) by Eq. (2) and Eq. (3), where h' marks half-hourly sampling intervals of the environment (to avoid an infinite number of read values).

$$f_{ENKOS,comfort}(t) = k_{Norm}(10e^{3.9318 s_{korr}} - 10) \tag{2}$$

$$k_{Norm} = \frac{1}{576}\frac{a}{h'} \tag{3}$$

Here all the mentioned facts of human decision making theory are included in the general form of the e-function and the parameters are determined by comprising the marginal conditions.

5.3 Integration of the energy minimizing part

The second term in the objective function in Eq. (1) is to be maximized by using the methods to save as much electrical energy as possible without the loss of living comfort. As the first point the conflicting of electrical devices (such as two radios providing acustic signals to the same user) all except one have to be switched off. Besides this media that cannot be consumed (in case of an empty room) should be deactivated. As the third method devices should be substituted if there is another one to provide the same services. For example a switched on light is consuming 45 W and could, regarding to the physical structure of the household, be replaced by another (switched off) light using 35 W, the second one should be used instead of the first one to save electrical power (of 10 W).

$$f_{ENKOS,energy}(E(t)) = 500 \quad k_{Norm}(1 - \frac{E(t)}{E_{\max}}) \tag{4}$$

To make these methods run a physical model of the household is learnt successively by measuring the usage of devices according to the presence of persons in certain rooms. The minimum possible energy consumption regarding to the model is interpret as the potential of storing electrical power (see Eq. (4)).

5.4 The resulting objective function

The resulting objective function is presented in Eq. (5). While the first part of the term is representing the comfort maximizing part the second one is coding the energy minimizing.

$$f_{ENKOS}(t) = k_{Norm}(10 \bullet e^{3.9318 s_{korr}} - 10 + 500(1 - \frac{E(t)}{E_{\max}})) \tag{5}$$

The term $f_{ENKOS}(t)$ is equal to the answer of the environment (= r_{t1}) stressed with the current action a_{t1}. That results in the learning algorithm where the expected reward r of the rule sending a_{t1} is updated using the the real system reaction $f_{ENKOS}(t)$ at a certain time step. The objective function for one year is calculated by the integral for all time steps t regarding to Eq. (5) for t = (0, 0.01, ... 1) year.

6. THE VERIFICATION OF THE SYSTEM "ENKOS"

6.1 Simulation environment

To simulate the current situation firstly all the controllable (all electrical switchable devices) and uncontrollable (e. g. brightness) environment parameters are admitted to ENKOS for each sampled time step of the year. These information are presented as the situation s_{t0} (see Fig. 2, step 1). The data are derived from the statistical data of energy consumption of Germany. Secondly the generation of an answer a_{t1} to the admitted situation is done by ENKOS. This one is transmitted back to the simulation of the environment. The answer of the environment as the evaluation of both the consumer satisfaction and the energy concumption is calculated with the help of Eq. (5).
The simulation of one year is done for every half-hourly time step presented 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 shown. 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.

	Electrical device	Electrical power consumption [W]	ENKOS Monthly consumption [kWh]	SIMULATION Monthly consumption [kWh]
	Number of persons in workroom			
	Number of persons in bath room			
Lights	Light outside	50	3.65	0.83
	Bath room	55	4.81	1.10
	Light bath room	25	0.78	0.50
	Light Mirror 1	45	2.30	2.34
	Light Mirror 2	25	0.91	0.50
	Light Shower	30	0.93	0.90
	Light Child room 1	45	1.40	0.90
	Light Child room 2	45	1.15	1.15
	Light sleeping	30	0.47	0.77
	Light workroom	50	2.33	0.50

Calculation of the Objective function value									
	Real Energy consumption	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Minimal Energy consumption	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Reward Energy consumption $f_{egy}(t)$ [0 % _ 100 %]	97	94	95	93	88	92	87	90
	Reward prediction (comfort) $f_{com}(t)$ [0 % _ 100 %]	89	89	50	57	57	61	71	64
	$f_{ENKOS}(t)$	881	866	600	627	602	646	687	655

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.

6.2 The main parameters of the system

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.

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

Table 1. Main parameters

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)					
		Lightness		Timestamp	
#P_Bath	#P_Work	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.

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 greater 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.

6.3 The learning rate as one parameter of the ENKOS system

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).

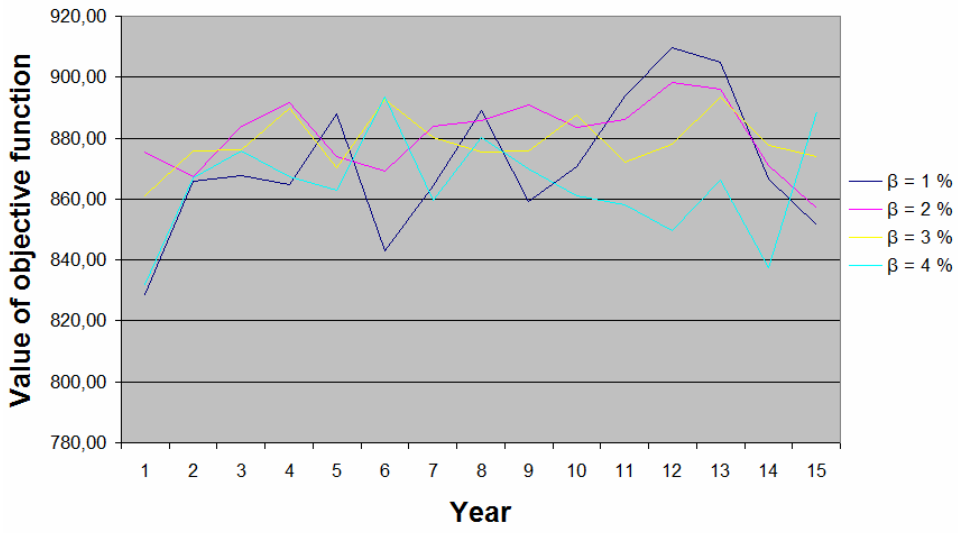

Fig. 5. The evaluation of the first rule of the Population over the first time stamps for different learning rates

7. CONCLUSIONS 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 and the integration of methods of the decision making theory is implemented successfully. 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.
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.

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