

Modeling Demand Response of Consumers to Incentives using Fuzzy Systems

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Abstract -- The requirements of distribution grids are increasing. In a smart grid, critical states and overstress are predictable. If any kind of load shedding is available then grid expansions can be alleviated. Demand response could be used to motivate consumers to load shifting via incentives. Potential of load shifting in households exists, but remains uncertain so far due to the lack of knowledge about responsiveness of consumers to different kinds of incentives even if this is the key issue for demand response programs. This paper introduces a completely new approach for a micro-economic model, which estimates the price responsiveness of consumers to incentives in a rational decision making model based on fuzzy technology. It allows investigating the effect of different kinds of incentives on the demand side participation and response, the impact on residential consumers and the consequences for the low voltage distribution grids.

Index Terms -- demand response, demand side management, demand side participation, fuzzy technology, incentives, influence consumer behavior, load shifting, rational decision making model, Smart Grid, system efficiency

I. INTRODUCTION

The requirements for operating distribution grids are increasing. In the majority of cases, electrical facilities are aged, while consumer demand for electrical energy and penetration of fluctuating distributed generation increase. These problems are well known, but the question is, what can be done. Fact is that some regional distribution grid areas can not always meet peak demand requirements at this stage although in former times they were dimensioned to meet previous estimated high peak load demand with sufficient spare capacity for unanticipated events.

If peak demand limits are often exceeded, then extensions of grid are necessary. However, if such significant off-limits events only occur a few times per year, then the extensions maybe can be postponed up to the original fixed date of reinvestment. For this purpose, any kind of load shedding during high peak times has to be implemented. Thereby, consumer peak demand can be reduced whereby the need for extensions decreases and thus reinvestments have not to be performed earlier.

Although load shedding inconveniences consumers for the

short-term, for long-term there are many benefits. Even if the amount of electricity reduced at significant peak times may be small, lower capital expenditures would be required and existing facilities would work on higher capacity. This would represent a more efficient operation of the grid and would save much money, so the rates consumers pay for electricity could be kept lower overall.

As overstress of electrical facilities does not implicate an imbalance of supply and demand, the frequency cannot be used as a universally available indicator. Consequently, dynamic demand [1] is not an option for load shedding at peak demand. Instead, real time data from consumers, producers and other metering points, which can be quickly provided with the implementation of smart meters and communications in smart grids, give the opportunity for load shedding at peak demand by the use of demand response. If the grid operator determines the need to adjust consumer consumption due to real time data and further predictions, then individuals can be influenced to reduce or increase their energy consumption via load shifting or change in energy supply, when applicable. Influence of the demand side respectively consumers' energy consumption can be performed by incentives in form of dynamic pricing, rebates or other means. Furthermore, incentives can be set to attempt to adapt the electricity demand to fluctuating energy supply conditions. Anyway, influence of consumers' behavior via options of incentives was tested so far only in small field tests and was not approved yet widespread on state level.

For this reason, there is a lack of knowledge about responsiveness of consumers to different kinds of incentives even if this is the key issue for demand response programs. Until now, results of field tests completed were analyzed and characteristics of consumers' behavior were identified in price elasticities of demand, the measure of responsiveness of the quantity of energy demanded to changes in its price [2]. In [3] and [4], authors arrange individual price elasticities to matrices considering different scenarios. This approach appears incomplete, because universal price elasticities cannot be assigned to individuals due to considerable differences of individual behavior at different times of day. In addition, cultural background and individual perceptions may be similar for smaller regions, but vary substantially for different locations. Furthermore, price elasticity matrices are static and cannot be trained, for which reason the resulting elasticities for novel incentives are arguable. Another approach analyzed consumers' price responses with variance methods [5]. As

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changes in consumption were small compared to nominal consumption, approximation by a quadratic form showed an adequate reproduction of the results of field test. The major disadvantage of this approach, however, was that it only worked properly if the dependency between consumption and tariff was of linear nature. Another technique that was used to model the residential use demand is system dynamics theory [6] [7]. This theory is often used for socioeconomic problems, because their influence diagrams are suitable to present those problems clearly. However, disadvantage of system dynamics theory for this problem results from its design as the essence of theory is based on feedback loops. To include further aspects, as well as to enlarge and adapt the model, new feedback loops have to be constructed and simulated. Especially during the development of models regarding smart grid applications and considering consumers, many times new parameters have to be included in the models. For this reason, system dynamic theory is not useful during implementation of complex models in smart grid application. However, a comprehensive model describing consumers' behavior related to incentives or dynamic tariffs does not exist so far.

This paper introduces a completely new approach for modeling the price responsiveness of consumers. According to this, temporal responsiveness results from the motivation of consumers and the amount of electrical power that consumers can reduce or increase at corresponding times of day. These parameters are the result of a micro-economic model of residential consumers based on fuzzy technology, which was created and initialized with observed correlations and cognitions of the demand side participation and response. The model of residential consumers will be further trained with data of the German research project „E-DeMa“ [8] [9] to be valid to this date. Afterwards, the micro-economic model should be converted to an aggregated model for the responsiveness at feeders of substations.

II. DEMAND RESPONSE

Demand response is a smart grid application. In smart grids, metered and counted values as well as predictions of situations allow estimation of critical states and fails of peak demand requirements. In this case, grid operators can use communication channels and can try to influence consumers' demand by dynamic pricings or other means to ensure secure operation of the distribution grid. In addition, the energy supplier could try to influence consumers by handing market prices of current supply conditions on them to sensitize them to the costs of production in short term. However, intention of demand response in each case is influence of consumers' energy consumption by incentives so that they are encouraged to respond to explicit requests with delay of their load. Delaying loads implies reduced demand by turning off or shut-down certain appliances or, at times of high energy production and unexpectedly low demand, to increase load demand by turning on or power-on appliances. When applicable on site generation exists, alternatively generation of electricity can be adjusted, started or stopped. The number of

consumers that will be influenced can vary and has to be matched separately for a particular problem.

Demand response is a quite different concept from energy efficiency, which means using less power to perform the same tasks. Nevertheless, demand response is economic, because it serves to reduce inefficient and wasteful use of and the need for capital expenditures in transmission and generation resources and thus keeps rates lower overall.

If costs of technology are justified to the investments that can be avoided depends largely upon the success of demand response. This results from the influence of actual power used and depends again on the level of consumers' participation and with it on a suitable incentive as well as on the handling time, an appropriate underlying technology and their further development for lower prices so that it is feasible for many applications. Up to now, in the majority of cases, consumer response can only be performed manually as existence and proliferation of applications with automated control systems for response to a request according to a preplanned load prioritization scheme during critical times is rare. With a higher proliferation of appliances equipped with automated response mechanisms, the success of demand response will be enhanced, especially on short-dated incentives. Furthermore, appliances with demand response may thereby practice some kind of energy storage if they attempt to reduce variability of electrical use according to the periods of low and high prices during a day.

The grid can benefit by the use of demand response through a higher efficiency and lower costs overall, and the participants can benefit with a reduction of their electricity costs, depending on the amount of energy that they are able to delay forward or afterward the peak demand periods, when pricing should be lower.

However, it is misleading to look only at the cost savings demand response can produce. On the demand side, consumers' energy consumption varies for the most part due to seasonal and daily factors such as weather conditions. In addition, price elasticity of energy demanded is relatively inelastic. Moreover, most consumers are less interested in the consumption itself as in the consequence what they have to pay for that. Therefore, pricings for electricity have to induce a change in demand during short time periods for which reason incentives have to be understood as a positive stimulation. That means that costs should not be increased at peak times, but rather should be decreased at off-peak times. Consumers should not feel penalized for erratic behavior in terms of electrical energy, but rewarded for ideal behavior and willingness with a reduction of their electricity bills. Furthermore, it is to keep in mind that the demand during peak times is higher than in off-peak times whereby the perquisite in off-peak times can be even higher. If all this would be considered within the creation of incentives, then consumers would adapt their energy consumption more and more to the incentives.

III. FUZZY TECHNOLOGY

For solving the problem described in the introduction, adaptive fuzzy technology appears most suitable. The advantage of fuzzy logic over other algorithms in computational intelligence is the usage of non-numeric linguistic values for model description while usually numerical values are taken. Furthermore, in comparison to the familiar sharp-edged Boolean logic, fuzzy logic is able to distinguish between intermediate values (in-between values) just as humans make decisions.

Fuzzy inference systems (FIS) allow modeling qualitative aspects of human knowledge in form of linguistic if-then statements without employing precise quantitative analyses. An example that describes such a statement, called rule, is

“If *input* has *this attribute*, then *output* has *that attribute*” where *input* and *output* are linguistic variables and the *attributes* are linguistic values that are characterized by appropriate membership functions. Typically, membership functions are curves with subjective interpretations and appropriate units that vary smoothly without sharp boundaries between 0 and 1. In the majority of cases, several inputs result in one output. In this case, input variables have to be combined with the logical operations *and*, *or* and *not*. Thereby, *and* represents a minimum function, *or* a maximum function and *not* an additive complement.

As the price responsiveness of consumers is not static, the model has to be adaptive and able to be optimized by further training. For this reason, a sugeno type fuzzy inference system has to be taken. Fig. 1 shows a FIS model structure.

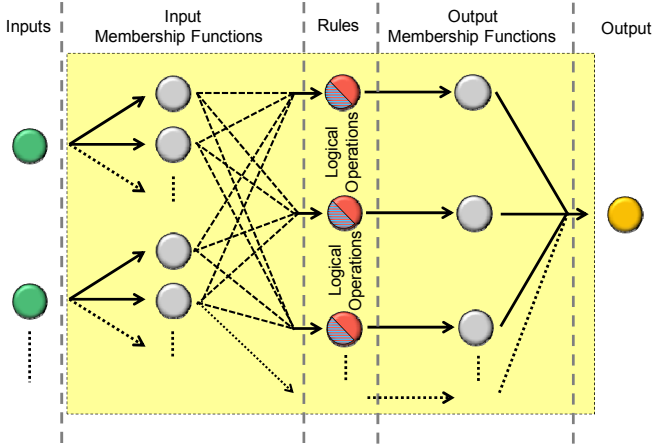


Fig. 1. FIS model structure

The general process of fuzzy logic in sugeno style can be described as the following: Input values are fuzzified, which means, that they are mapped to the associated input membership functions, and degrees of membership are assigned. Then statements of the rule base assign these partial memberships to the associated output membership functions in consideration of the logic operations of inputs. Thereafter, outputs are weighted depending on the strength of each rule. Final output of the system is the weighted average or sum of all rule outputs, depending on the respective defuzzification method applied.

Enhancement to fuzzy inference systems are adaptive neuro-fuzzy inference systems (ANFIS), which are functionally equivalent to fuzzy inference systems, but belong to the class of adaptive networks. As ANFIS works similarly to the learning method of neural networks; it provides an algorithm for the fuzzy modeling procedure to learn information about data sets [10]. Thereby, the FIS model is required to provide initial conditions; posterior ANFIS can either purpose a validation of this model or train it by modifying the membership function parameters according to a chosen error criterion.

IV. MODEL DESCRIPTION

Models of consumers and their behavior in reference to responsiveness to incentives do not exist so far. For this reason, it was decided to implement such a model. Firstly, the important criteria for the process and the result were identified. Then, a structure for a rational decision making model considering all influencing parameters was created and developed in MATLAB[®] using Simulink[®] and additional Fuzzy Logic Toolbox[™]. With the help of this structure shown in Fig. 2 the model will be illustrated and explained in the following in more detail.

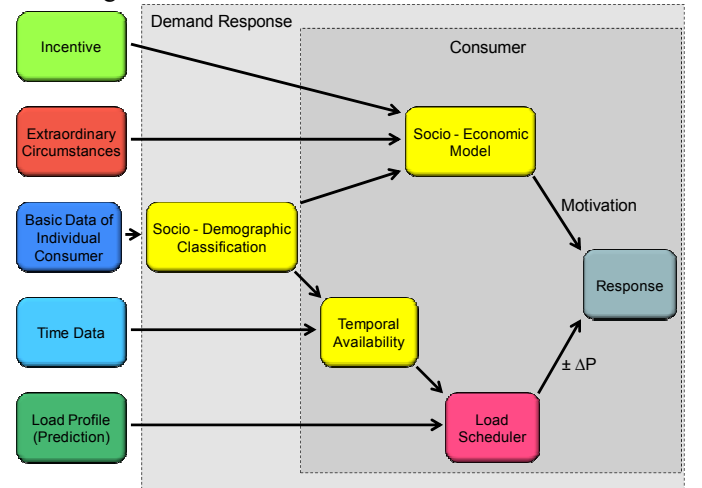


Fig. 2. Structure of rational demand response model

Inputs for this model are the load profile and the incentive dependent on time (both green colored), basic data of individual consumer respectively household and time data (both blue colored) as well as extraordinary circumstances (red colored). At first, socio-demographic classification is applied using basic data of households to classify individual consumers. Basic data are the number of residents in a household (Single, 2 Persons, ≥ 3 Persons), type of household (house, apartment), social level of urban district (rich, mixed, poor) and energy consumption per year (high, medium, low in relation to average value), which should be available for the grid operator. If one parameter is missing, then the average value of the supply area can be taken. By the use of FIS, the socio-demographic classification model estimates static values for existence of children in the household, existence of occupation and social level as well as the general amount of

time, capital and technical interest. These values are needed in the socio-economic model for estimation of the motivation as function over time and in the model of temporal availability. Before going into detail about fuzzy logic and FIS structures respectively, which are yellow colored in Fig. 2, the constraints of the Fuzzy Logic Toolbox™ by the use of ANFIS have to be specified [11]. ANFIS only supports first- or zero-order sugeno type systems with single output obtained using weighted average defuzzification. In addition, all output membership functions must be of the same type and be either linear or constant. Furthermore, ANFIS does not allow rule sharing or different weight for a rule. Moreover, ANFIS does not accept own membership functions or defuzzification functions. These limitations in degree of freedom do not matter, as initially modeling in general should be kept simple. For modeling of demand response only simple types of input membership functions were selected (z-, s-, pi- and trapezoidal shaped) as expansive membership functions are not necessary for good fuzzy inference systems [12]. Furthermore, constant type of membership functions and weighted average of all rules were taken for output.

A. Fuzzy Inference System for Socio-Economic Model

The socio-economic model estimates the motivation of consumers to respond to the incentive without taking into account the load profile itself. In this approach, motivation depends on the given incentive, the general amount of time, capital and technical interest as well as on external circumstances. Accordingly, these five criteria are the inputs for the fuzzy inference system. Fig. 3 shows corresponding membership functions for these inputs.

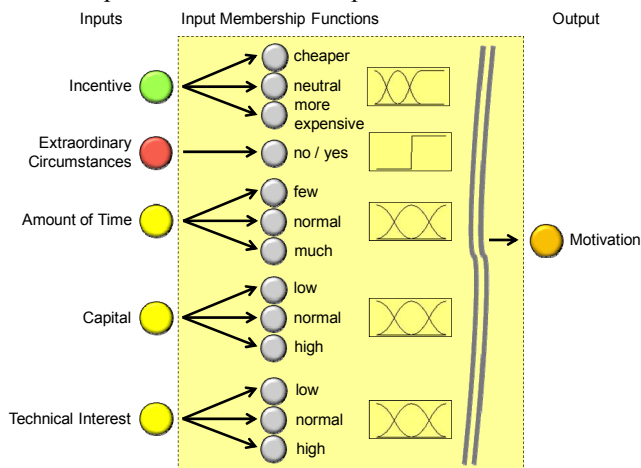


Fig. 3. Fuzzy Inference System for socio-economic model

About 80 rules were created for the decision process of this fuzzy model based on observed correlations and cognitions of the demand side participation and response. Due to the lack of knowledge for this special topic, maybe partial rules have to be reinitialized afterwards if required. It is purposed to validate the model with data of field test mentioned in the introduction.

The level of motivation can range from -1 to +1 at which +1 stands for maximum motivation for activate loads and -1

for maximum motivation to switch-off load. A motivation of 0 represents the case that there is not any motivation for a change in load generally. Amount of time, capital and technical interest are output values from the socio-demographic classification model and are static for the individual consumer. However, motivation is a time depending function as the incentive varies during the day. In addition, external circumstances such as a party at home or other events strongly influence the motivation.

As an example, Fig. 4 shows a plot of the motivation depending on the incentive and the technical interest. While the technical interest is static for an individual, the motivation varies depending on the given incentive.

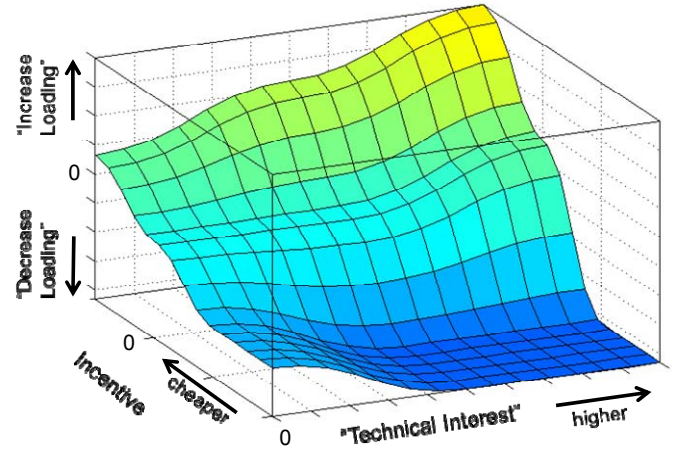


Fig. 4. Motivation depending on the incentive and the technical interest

B. Fuzzy Inference System for Temporal Availability

This model estimates the temporal availability of consumers during the day. The inputs for the fuzzy inference system are the four criteria of

- temporal availability depending on existence of occupation,
- number of residents in the household,
- existence of children in the household as well as
- the time of day.

Fig. 5 shows corresponding membership functions for these inputs.

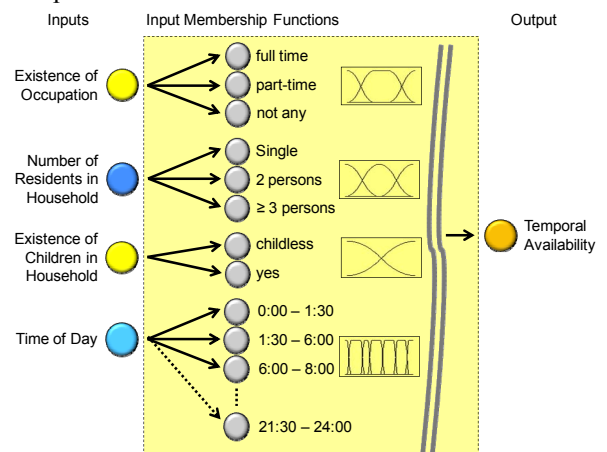


Fig. 5. Fuzzy Inference System for temporal availability

Over 100 rules were created for the decision process of this fuzzy model. The level of temporal availability can range from 0 to 1 at which 1 stands for maximum availability to act and 0 for no availability. Existences of occupation and of children are output values from the socio-demographic classification model and the number of residents in a household is one of the basic data. These are static for an individual consumer, but also the temporal availability is a time depending function as it depends on the time of day and the day of week, both given by the time data input.

C. Load Scheduler

The load scheduler estimates the amount of electrical power that an individual can increase $+\Delta P(t)$ or reduce $-\Delta P(t)$ compared to the actual power at a corresponding times of day. Inputs of this scheduler are the a) load profile, b) energy consumption, c) day of week and d) the season as well as e) the temporal availability and f) the number of residents in household. In the first instance, the four inputs a) load profile, b) energy consumption, c) day of week and d) season are used to calculate the average power for every quarter of an hour exclusive of the base load. These are multiplied with e) the temporal availability to obtain a time depending load profile of the individual consumer in consideration of temporal availability as provisional result. With the actual load profile prediction, also weather conditions are regarded in addition to the consideration of season and day of week.

Within the model, there is a large database of household appliances categorized by suitability with their characteristics such as typical runtime, power and energy consumption and peak load, which was developed by analysis of statistical data. The f) number of residents in a household is used to read out the probability of existence of different household appliances from a lookup table. Theoretically, $-\Delta P(t)$ matches the time depending load profile of an individual in consideration of temporal availability, but not in reality. Therefore, $-\Delta P(t)$ is defined by the power value taken from the individual load profile considering the temporal availability at the corresponding time minus the base load minus the power of household appliances assumed to be operated at this point of time, which can not be shifted without losses in comfort.

For $+\Delta P(t)$ it is assumed that appliances with higher power over a longer time period such as dishwashers, washing machines or clothes dryers are only operated when temporal availability is near to 1. For this reason, the e) temporal availability is analyzed accordingly. This result is used together with the probability of existence and the power consumption of appliances assumed to be operated at the corresponding times to define $+\Delta P(t)$. The process also considers reasonable assumptions such as that the clothes dryer will not be started before the run of washing machine is over.

D. Consumer Response

Consumer response indicates the changes in power that can be expected during the day in consequence of an incentive. In this approach, the response depends on the motivation of an individual and the amount of electrical power that a consumer can presumably reduce or increase at a corresponding time of day. The amount of power is a time depending function of $+\Delta P(t)$ and $-\Delta P(t)$ in watts, which is outcome of the load scheduler. The time dependent motivation $m(t)$ is the outcome of the socio-economic model and can vary within the range of -1 to +1. Response $r(t)$ can be calculated from the multiplication of these two values.

In case that $m(t)$ is positive – which stands for the motivation to activate loads – it is (1).

$$\frac{r(t)}{W} = m(t) \cdot \frac{+\Delta P(t)}{W} \quad \text{for } m(t) > 0 \quad (1)$$

In case, that $m(t)$ is negative – which stands for the motivation to switch-off loads – (2) have to be used.

$$\frac{r(t)}{W} = m(t) \cdot \frac{-\Delta P(t)}{W} \quad \text{for } m(t) < 0 \quad (2)$$

In case, that $m(t)$ is zero – which stands for no motivation to change any load – it is (3).

$$\frac{r(t)}{W} = 0 \quad \text{for } m(t) = 0 \quad (3)$$

Therefore, the response varies during the day according to all the inputs, especially in subject to the given incentive.

V. SIMULATION

For demonstrating the simulation model, an example case is considered and the results will be discussed in the following. As the model is not yet validated, the exact results are less interesting than the functionality of this approach. For this reason, the inputs are selected in such a way, that comprehension, analysis and interpretation of results can be done easily.

To begin with, Table I shows the inputs that are static for an individual consumer.

TABLE I
STATIC INPUTS OF INDIVIDUAL HOUSEHOLD

Basic Data of Individual Household:	
Number of Residents in Household	3 Persons
Type of Household	Single Family House
Urban District	New Estate, Single Family Houses, Rich
Energy Consumption per Year	Medium

From this, the socio-demographic classification model estimates the results that are shown in Table II.

TABLE II
STATIC VALUES ESTIMATION OF SOCIO-DEMOGRAPHIC CLASSIFICATION MODEL

Socio-Demographic Classification:	
Existence of Children in Household	Tendency to Yes
Existence of Occupation	Tendency to Full Time
Social Level	Tendency to Upper Middle Class
General Amount of Time	Tendency to Normal
Capital	Tendency to High
Technical Interest	Tendency to High

In the example, a weekend day in springtime is considered and it is assumed, that there are no extraordinary circumstances. Fig. 6 shows the prediction of the uninfluenced load profile of the individual consumer and, additionally, the load profile at the feeder divided by the number of households supplied by that feeder.

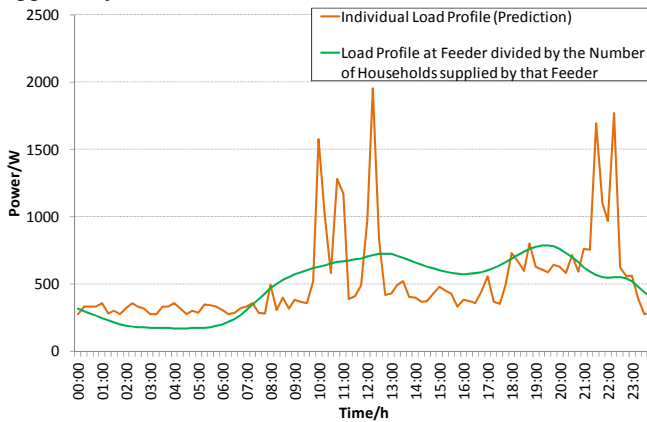


Fig. 6. Uninfluenced Load Profile of Individual Consumer

In order to influence the consumer's energy demand, a day-ahead incentive is assumed, which is specified as a multiplier to the fixed price for the kilowatt-hour. This incentive, shown in Fig. 7, has a multiplier of 0,5 at times when the ratio of load value at the corresponding time is $< 0,7$ to the predicted maximum load, otherwise the multiplier is 1.

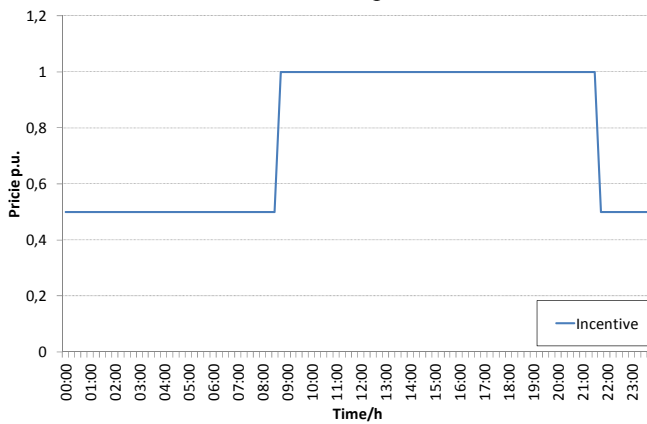


Fig. 7. Day-Ahead Incentive

Then the socio-economic model estimates the motivation of consumers to respond to the incentive taking into account the static values of the socio-demographic classification model and the variable incentive. As there are no external

circumstances, changes in motivation only depend on the incentive. Fig. 8 shows the time dependent motivation of the individual household to changes in price.

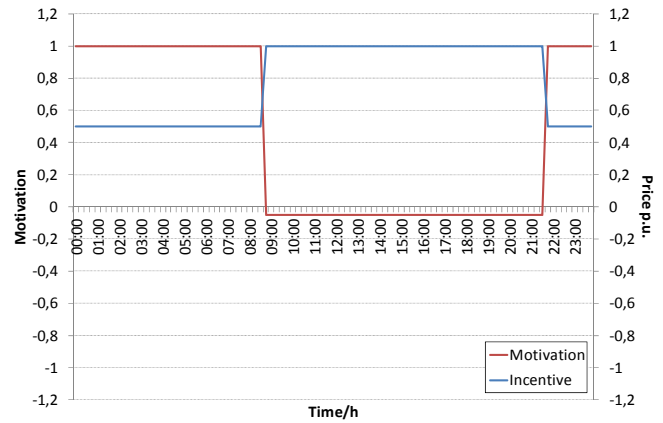


Fig. 8. Time Depending Motivation to the Given Incentive

Next to the socio-economic model, the load scheduler estimates the amount of power that can be reduced and increased at corresponding times of day. Fig. 9 shows the power that can be reduced and a provisional result of that power before the subtraction of the power of household appliances assumed to be operated at corresponding times.

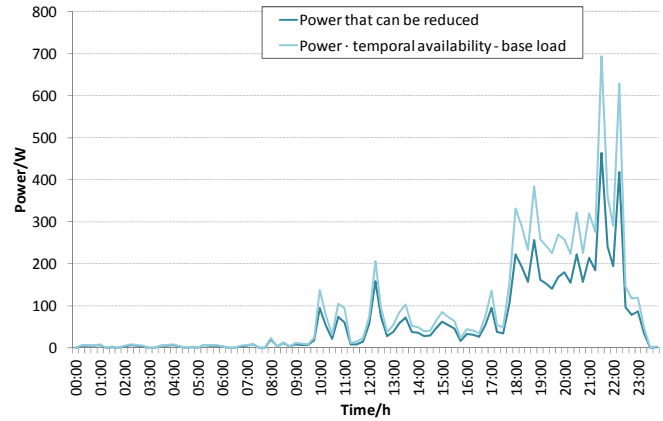


Fig. 9. Time Depending Power that can be reduced $-\Delta P(t)$

Fig. 10 shows the power which can be increased at every point of time.

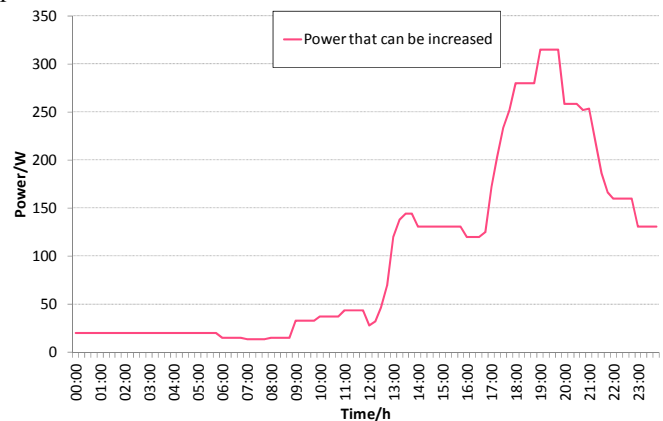


Fig. 10. Time Depending Power that can be Increased $+\Delta P(t)$

Now, the response can be calculated with eq. (1)-(3). Fig. 11 shows the time dependent demand response of the individual consumer to the given incentive.

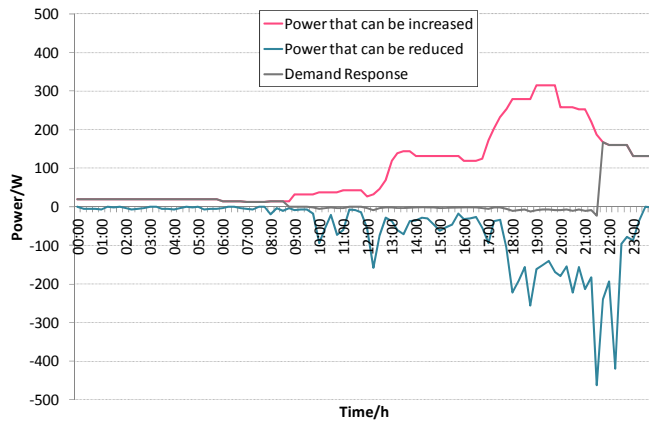


Fig. 11. Time Depending Demand Response of Individual

Demand response of the consumer during nighttime is low; indeed, the consumer is motivated, but the individual temporal availability is low and that is why response is low. With a higher proliferation of applications with automated response systems, the response during nighttime would be much higher. During the daytime, the motivation of the consumer to this incentive is low regarding the tendency to reduce load. As the motivation is low, the response is also low. At the end of day, shortly before the price falls, the power can be reduced a bit more because there are some loads that can be time-shifted up to some hours. In the evening, this consumer is highly motivated and has some loads that can be switched on. Thus, the response of the consumer matches the total power $+\Delta P(t)$ that can be increased.

The time depending response also allows the estimation of energy consumption and costs for the individual customer. According to this, the individual energy consumption would be probably higher – about 0,43kWh more than the predicted consumption of 12,54kWh (+3,4%) – but costs for this energy would be lower. The consumer would have to pay 10,514 times the fixed price for the kilowatt-hour compared to 12,54 times the price (-16,1%). The grid operator has to accept these losses in income, but in favor, the peak load demand would be lower. Fig. 12 shows the individual load profile of the regarded consumer considering consumers' demand response.

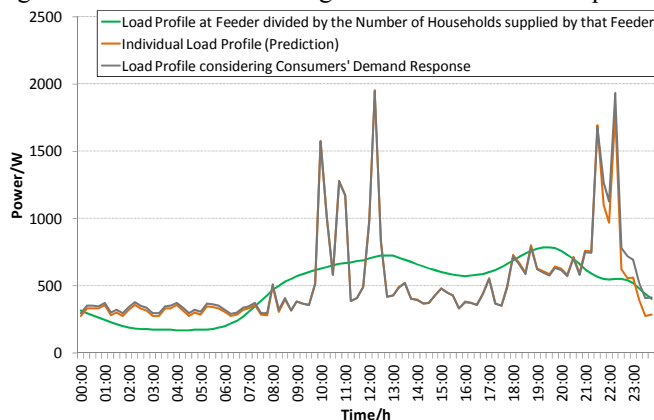


Fig. 12. Load Profile considering Demand Response

VI. CONCLUSIONS AND OUTLOOK

This paper presents a completely new approach for modeling consumer's demand response to incentives in a rational decision making model. According to this, the responsiveness of individual consumers results from the motivation of the individual consumer and the amount of electrical power that the consumer can reduce or increase at corresponding times of day. These parameters are the result of a micro-economic model of residential consumers based on fuzzy technology.

The paper describes how the model was created and implemented in MATLAB[®], and in an example, basic suitability and functionality were demonstrated. The structure of the fuzzy models was specified and the fuzzy inference systems were initialized for posterior validation and further training using ANFIS.

Afterwards, the micro-economic models of individuals should be super-imposed so that an aggregated demand response of the individuals supplied by a feeder of a substation is available. The final model will allow the assimilation of available information in an overstress situation, bring all the relevant learning and past experiences to bear and will allow to quickly and easily decide if short dated incentives can be helpful to solve the problem.

VII. REFERENCES

- [1] J. A. Short, D. G. Infeld, and L. L. Freris, "Stabilization of grid frequency through dynamic demand control", in *Power Systems, IEEE Transactions on*, vol. 22, no. 3, Atlanta, GA, Aug. 2007, pp. 1284-1293
- [2] K. Dietrich, J. M. Latorre, L. Olmos, and A. Ramos, "Demand Response and Its Sensitivity to Participation Rates and Elasticities", in *International Conference on the European Energy Market (EEM)*, Zagreb, Croatia, May 2011
- [3] J. Wang, S. Kennedy, and J. Kirtley, "A new wholesale bidding mechanism for enhanced demand response in smart grids", *Innovative Smart Grid Technologies (ISGT)*, Jan 2010, pp. 1-8
- [4] N. Venkatesan, J. Solanki, and S. K. Solanki, "Demand response Model and its Effects on Voltage Profile of a Distribution System", in *IEEE, Power and Energy Society General Meeting*, July 2011
- [5] M. Räsänen, J. Ruusunen, and R. P. Härmäläinen, "Identification of consumers' price responses in the dynamic pricing of electricity", *Systems, Man and Cybernetics, IEEE International Conference on*, vol. 2, Oct. 1995, pp. 1182-1187
- [6] Y. Cheng, and L. Zhang, "Dynamic Response Model Between Power Demand and Power Tariff", in *Power System Technology, PowerCon, International Conference on*, vol. 2, Nov. 2004, pp. 1416-1421
- [7] I. Dyrer, R. A. Smith, and G. E. Peña, "System Dynamics Modelling for Residential Energy Efficiency Analysis and Management", in *The Journal of the Operational Research Society*, vol. 46, no. 10, Oct. 1995, pp. 1163-1173
- [8] <http://www.e-dema.de/en/>
- [9] G. Krost, T. Holschneider, et al., "Transparency in the Distribution System", *IFAC, World Congress of the International Federation of Automatic Control, 2011*
- [10] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system", in *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 23, Issue 3, May/Jun. 1993, pp. 665-685
- [11] MathWorks[®] Fuzzy Logic Toolbox™ Documentation, [Online] available: <http://www.mathworks.de/help/toolbox/fuzzy/fp715dup12.html>
- [12] MathWorks[®] Fuzzy Logic Toolbox™ Documentation, [Online] available: http://www.mathworks.de/help/toolbox/fuzzy/bp7816_-1.html

VIII. BIOGRAPHIES



Thomas Holtschneider (1983) received his Dipl.-Ing. degree in electrical engineering from the University of Duisburg-Essen/Germany in 2009. Since May 2009, he is doing his PhD studies in the Department of Electrical Power Systems at the same University. His major research interest is focused on Smart Grids and smart substations, improvements in power system efficiency and performance, demand response, demand side management, power economy and energy management as well as asset

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István Erlich (1953) received his Dipl.-Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching

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