Assessment Method for Incentives and their Optimization considering Demand Response of Consumers

T. Holtschneider, *Student Member, IEEE*, and I. Erlich, *Senior Member, IEEE*

Abstract – **In a smart grid, communication technology allows short-term application of incentives in monetary form and thus dynamic pricing to the consumers. Incentives can help to reduce critical situations in grids, but for cost efficient application, they have to be optimized before the most suitable incentive is provided to the consumers. This paper introduces an assessment method for incentives taking into account demand response and the participation of individual consumers. Thereby, a model describing rational decision of individuals to incentives is presented. As the model uses adaptive neuro-fuzzy inference system (ANFIS) it can easily be trained. The assessment method includes heuristic optimization, namely the Mean-Variance Mapping Optimization (MVMO), which provides excellent performance in terms of convergence behavior and accuracy. MVMO can be used within the method to optimize the incentive with respects to the defined objective and given constraints. Structure of the model and procedure of the assessment method are illustrated, and performance of the method is demonstrated based on examples.**

Index Terms – **demand response, demand side management, demand side participation, incentives, dynamic pricing, heuristic optimization, Mean-Variance Mapping Optimization**

I. Introduction

Influence of incentives on the energy demand of consumers underlies certain uncertainties. However, before uncertainties come to bear, first, it should be noted that demand response of consumers to incentives is mostly unknown currently, even if this is the key issue for demand side management programs. Assessment of incentives in relation to efficiency or optimization requires consideration of consumers' price elasticity of demand, the measure of responsiveness of the quantity demanded to changes in its price. Unfortunately, previous approaches [1]-[3] in which price elasticities are considered appear incomplete. As authors arrange price elasticities to matrices considering different scenarios, elasticities are static and cannot be trained, for which reason results of demand response estimation for novel incentives are arguable. Furthermore, those price elasticities are not universally applicable due to the dissimilarity of countries, cultures and so on. For this reason, adaptive model of consumers' demand response to incentives was created and initialized with observed correlations and cognitions of the demand side participation and response [3]. New insights of consumers' demand response can be included easily. On basis of this model, this paper introduces an assessment method, which allows investigating the effect of different incentives considering demand response of consumers. As MVMO allows further optimization of the incentives, the proposed methodology is very useful when efficient incentive has to be identified.

II. Consumer Acceptance of Demand Side Management

Demand side management is a smart grid application. Intention of that management is influence of consumers' energy consumption. On the demand side, consumers' energy consumption varies for the most part due to seasonal and daily factors such as weather conditions. Moreover, most consumers are less interested in the consumption itself as in the consequence what they have to pay for it. For this reason, modification of consumers' demand only can be achieved when consumer needs are considered; they have to be incentivized to save money.

For this purpose, incentives in terms of dynamic pricings are required at which prices should not be increased at peak times, but rather should be decreased at off-peak times; they have to be understood as positive stimulations. If consumers do not feel penalized for erratic behavior in terms of electrical energy but rewarded for ideal behavior with a reduction of their electricity bills, than they accept demand side management and are encouraged to respond to explicit requests with a delay of their load. Delaying loads implies to reduce demand by turning off or shut-down certain appliances or, at times of high energy production and unexpectedly low demand, to increase load by turning on or power-on appliances. If applicable on site generation exists, alternatively generation of electricity can be adjusted, started or stopped. The number of consumers that is influenced can vary and has to be matched separately for particular problems. The success of demand side management will be enhanced, especially on short-term incentives, when proliferation of applications with

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automated control systems for response is more common. However, price elasticity of energy demanded is relatively inelastic.

III. Model of Consumers' Demand Response

As consumers' demand response has to be considered during assessment of incentives, rational decision-making model of residential consumers and their behavior in reference to price responsiveness to incentives was developed [4]. According to this, demand response of individual results from the motivation of consumer and the amount of electrical power that consumer can presumably reduce or increase at corresponding times of day. These parameters are the outcome of a consumer model based on adaptive fuzzy technology. Initial conditions were created with observed correlations and cognitions of the demand side participation and response, further training with data of the German research project „E-DeMa“ [5] [6] is in progress.

Adaptive neuro-fuzzy inference systems (ANFIS) [7] appear most suitable for the description of consumers' behavior. 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.

The model was created and developed in MATLAB® Simulink®; the overall structure is illustrated in Fig. 1.

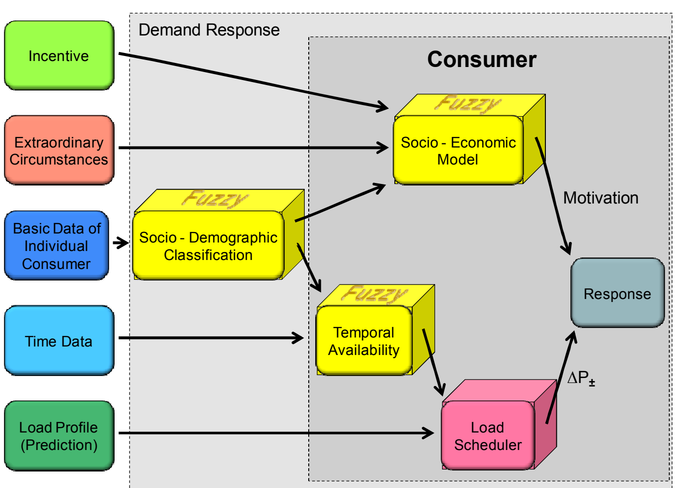

Fig. 1. Structure of rational demand response model

In the model, response of the individual depends on several static and dynamic inputs. *Incentive*, *Load Profile* and *Time Data* are dynamic inputs depending on time, in contrast, *Basic Data* such as the “number of residents in a household” are static. The input *Extraordinary Circumstances* is also depending on time, but usually there is no circumstance; that is why this input also can be seen more or less as static.

At first, *Socio-Demographic Classification* uses basic data of the household to estimate further characteristics of the individual consumer such as the “social class”. If any parameter in basic data of the individual is unknown, then the typical value of the supply area will be taken. Results of classification are needed in the *Socio-Economic Model* and in the model of *Temporal Availability*.

Socio-Economic Model estimates the motivation of consumers to respond to the incentive without taking into account the load profile itself. The level of motivation m(t) 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. When any external circumstance exists, then the motivation is always 0, independent of all the other inputs. Motivation is a time depending function as the incentive varies during the day.

The model of *Temporal Availability* estimates the availability of individual in matters of opportunity to be influenced. 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. The availability is also a time depending function as it depends on the time of day and the day of week, both given by the time data input.

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 corresponding times of day. 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. $\Delta P_-(t)$ 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 cannot be shifted without losses in comfort. For $\Delta P_+(t)$ it is assumed that appliances with higher power over a longer period are only operated when temporal availability is near to 1. For this reason, 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 corresponding times to define $\Delta P_+(t)$.

The *Response* finally indicates the changes in power that can be expected during the day in consequence of an incentive. Response r(t) results from the multiplication of motivation m(t) and the amount of electrical power that consumer can presumably reduce $\Delta P_-(t)$ or increase $\Delta P_+(t)$ at a corresponding time of day.

If there is a motivation to activate loads, response results from (1).

$$r(t) = m(t) \cdot \Delta P_+(t) \quad \text{for} \quad m(t) > 0 \tag{1}$$

In case, that there is the motivation to switch-off loads, response results from (2).

$$r(t) = m(t) \cdot \Delta P_{-}(t) \quad \text{for} \quad m(t) < 0 \tag{2}$$

In case, that there is no motivation to change any load, response is (3).

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

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

For the assessment method, not the demand response and accordingly the price elasticity of an individual to the current incentive is important, but the responsiveness of all consumers located in the considered grid area of supply. In this approach, the aggregated response is realized by an integration of individual responses. Later, the model of individual demand response should be converted to an adaptive model as equivalent for the aggregated demand response. Such a model of aggregated demand response will be computationally less intensive and thus the demand response could be calculated much faster (reduction of computing time by the factor of the total amount of consumers influenced).

IV. Proposed Assessment Method

The overall structure of the proposed approach is illustrated in the flowchart of Fig. 2, the workflow of methodology is explained in the following.

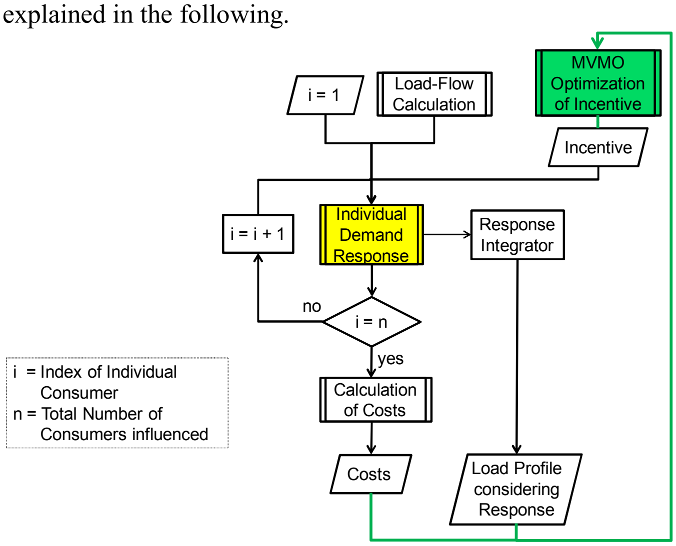

Fig. 2. Framework of the proposed approach

At first, a *Load-Flow Calculation* is performed, which uses metered load profiles and corresponding predictions of consumers' individual energy demand. Next, the results of the load-flow calculation and the given *Incentive* are taken to estimates the *Individual Demand Response* that can be expected. This routine is called in a loop for every individual consumer that is influenced. Responses of individuals are integrated to achieve aggregated demand response of all consumers. When the stop criterion is fulfilled, then any expenses are calculated. Advantage of the aggregated response over the individual response is the partial compensation of individual differences between estimation and reality. The method can stop here, and the results of the aggregated demand response and their costs can be compared to the results of other incentives with regard to influence and modification of load profile and the costs that are incurred.

In addition, the method has also the capability to improve the incentives. For this purpose, the method has an optional outer loop, which is green colored in Fig. 2. This loop allows the optimization of the incentive in consideration of the demand response of consumers and the conditions that are required for maintaining consumer acceptance. The heuristic optimization routine is repeated until a stop criterion is fulfilled (e.g. completion of a pre-specified number of function evaluations, or no improvement of the best fitness).

This optimization problem can be solved by several optimization methods. In this paper, a new heuristic optimization algorithm called Mean-Variance Mapping Optimization (MVMO) is used to solve the problem. The theoretical background of MVMO has been published in [8]. Based on the application experiences, the algorithm of MVMO has been further improved [9]. MVMO algorithm is particularly suited for solving this optimization problem, because it shows excellent convergence behavior in comparison to other heuristic methods. Especially at the beginning of the iteration, it outperforms all other methods. This quality is very useful because the computational speed of the model of individual demand response is relatively slow, so the time that is required to find a satisfied solution is minimal. Fig. 3 shows the convergence behavior of a unified solution [10].

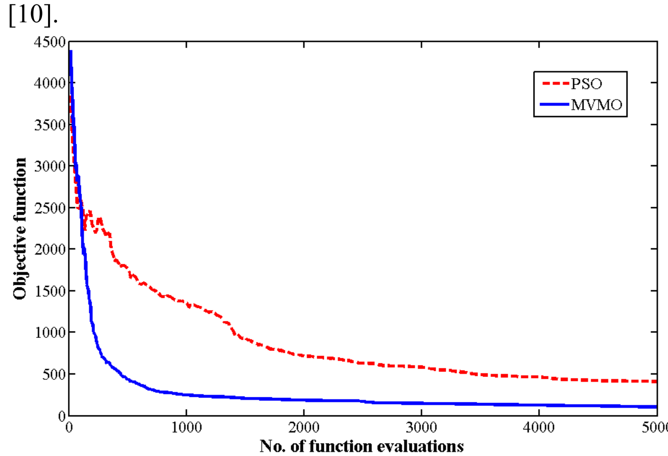

Fig. 3. Performance of MVMO in comparison to standard PSO. Task: [10]

V. Test Results

In the following, the possibilities of the assessment method are demonstrated in example cases. As the model of individual demand response within the assessment method 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.

A. *Comparison of two different Time-of-Use Pricings*

To begin with, two different time-of-use incentives are compared to each other. In this example, the number of consumers that are influenced is 27. Consumers are supplied along a low voltage line, depicted in Fig 4, on which neither any decentralized energy supply nor any special load such as night storage heater nor heat pump exist.

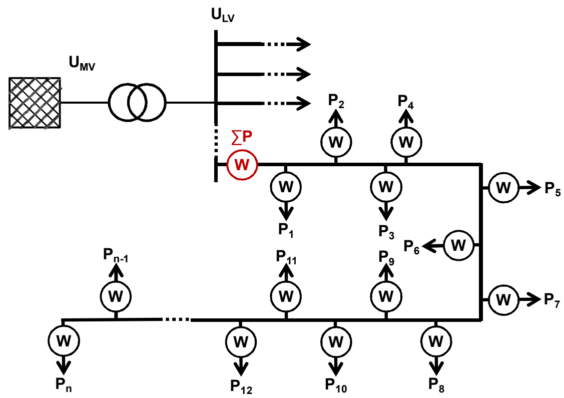

Fig. 4. Test grid for simulation

The Incentives are specified as multipliers to a fixed price for the kilowatt-hour.

- *Incentive 1*: high-rate period from 7:30 o'clock a.m. to 20:29 o'clock p.m.: 1 × uniform tariff; at all other times low-rate period: 0,75 × uniform tariff
- *Incentive 2*: high-rate period from 7:00 o'clock a.m. to 20:59 o'clock p.m.: 1 × uniform tariff, at all other times low-rate period: 0,6 × uniform tariff

Prices in high-rate periods are the same. In low-rate periods, *Incentive 2* is cheaper, but duration of low-rate period at *Incentive 2* is also shorter. Assessment method is used to answer the question which tariff is better. Here, the tariff that achieves maximum cost effective peak demand reduction will be preferred.

Prediction of the uninfluenced load profile at feeder (mean values for every quarter of an hour, location is red colored in Fig. 4) is shown in Fig. 5.

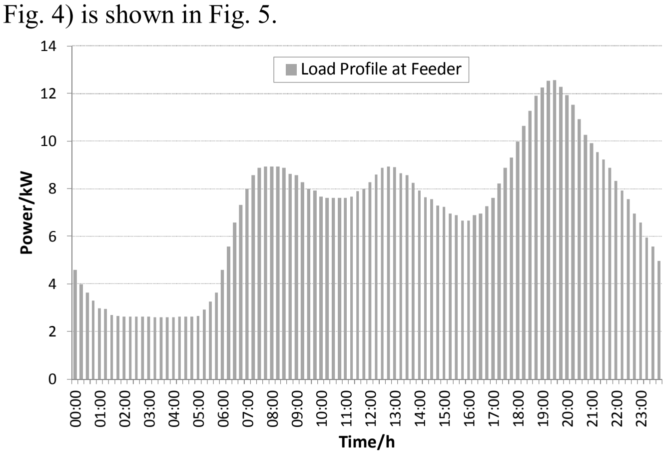

Fig. 5. Uninfluenced load profile at feeder

Next, the results for the estimated demand responses of all consumers aggregated for the feeder are shown in Fig. 6.

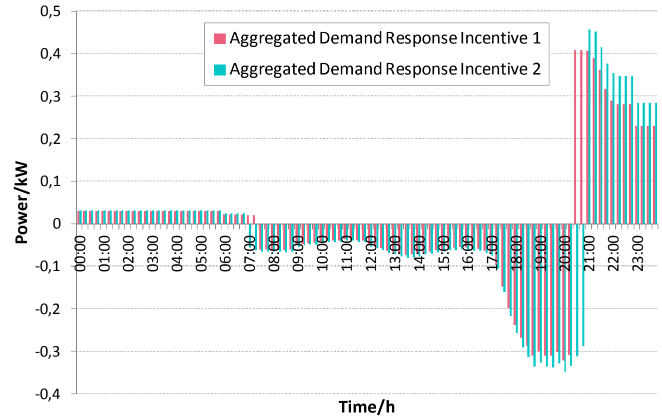

Fig. 6. Estimation of aggregated demand responses

It can be seen, that changes in demand are higher when incentive is higher (and accordingly prices are lower). Finally, Fig. 7 shows the load profile at feeder in consideration of the aggregated demand responses.

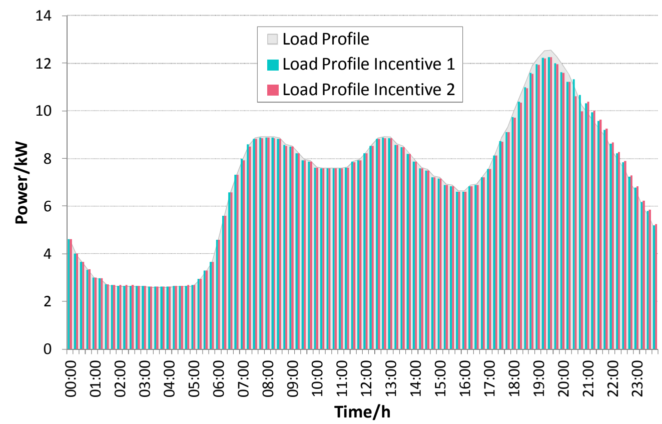

Fig. 7. Load profile at feeder considering aggregated demand responses

Peak demand can be reduced with both incentives; both lead to a more efficient operation of the grid. Table I shows the results of peak demand reduction and their costs.

TABLE I
RESULTS OF SIMULATION I

	Incentive 1	Incentive 2
Peak Demand Reduction*	- 2,6 %	- 2,9 %
Costs for Incentive*	+ 6,1 %	+ 8,6 %
* Compared to Uninfluenced Load Profile with Uniform Tariff		

As peak load reduction of both incentives is similarly, incentive 1 is to be preferred due to the lower costs.

B. *Optimization of an Incentive*

If the operator wants to modify the energy demand in the grid by the use of incentives, then he has to pay for the plan. Of course, operator wants to reach the intended goal while having lowest costs. With the help of the assessment method, it is possible to optimize incentives in consideration of the conditions that are required for maintaining consumer acceptance. In this example, the same group of consumers is influenced as in the previous example. The plan of the operator here is to reduce the peak load P_{0_max} to the max while having lowest costs for the incentive. According to this, the ideas that are required to formulate the minimization problem are:

- If the *incentive* is lower priced than 1 p.u., then 1-*incentive* is a positive number (that means costs).
- If the *incentive* is 1 p.u., then 1-*incentive* is zero (neither costs nor profit).
- If the *incentive* is higher priced than 1, then 1-*incentive* is a negative number (that means profit).

Thus, the optimization problem is structured as follows:
Minimize

$$C = \sum_{t=1}^{96} W(t) \cdot \left(1 - incentive(t)\right) \tag{4}$$

subject to

$$P_{0\_\max} \geq P_{\max} \tag{5}$$

where $W(t)$ is the aggregated electrical energy of all consumers for a quarter of an hour and P_{max} is the peak load while using the incentive.

The incentive that is optimized in the following uses the framework of Fig. 8.

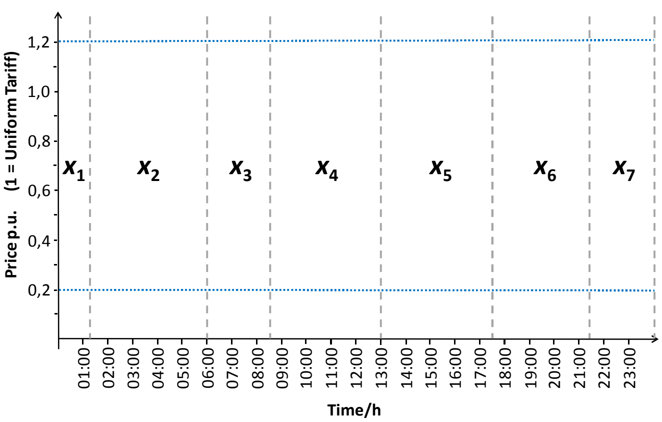

Fig. 8. Framework of the incentive

This incentive has fixed periods where the pricing should be unchanged, so there are seven continuous variables x_1–x_7 with a lower limit of 0,2 p.u. and an upper limit of 1,2 p.u.. The optimization is used to find optimal values for the variables considering demand response of consumers. Starting with random parameters for the values x_1–x_7, MVMO shows excellent convergence behavior. After 50 function evaluations, solution is found that fulfill the constraint. After 110 evaluations, convergence is reached. Fig. 9 shows the result of the optimized values x_1–x_7.

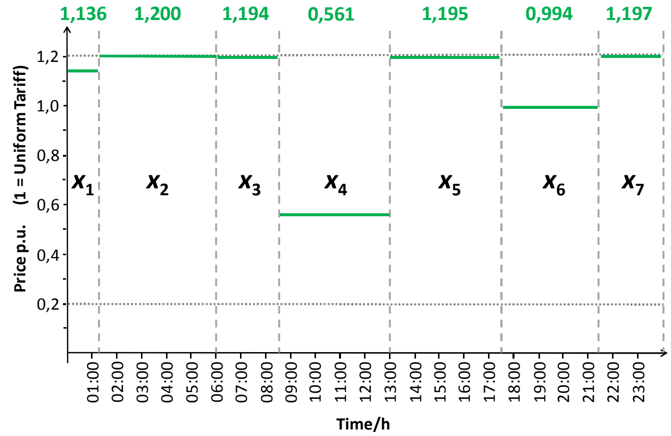

Fig. 9. Optimal pricing

Furthermore, Table II shows the results of peak load reduction using this pricing.

TABLE II
RESULTS OF SIMULATION II

	Uniform Tariff	Optimized Pricing
Peak Load	12,53 kW	12,15 kW
Change in Peak Load	- 3 %	
Energy Demand	168,95 kWh/d	167,45 kWh/d
Change in Energy Demand	-0,89 %	

The values x_1–x_7 of the optimized pricing can be further adjusted: As the results of x_2 and x_3 are nearly the same, the periods could be putted together. Furthermore, all real prices should be rounded after multiplication with the fixed price for the kilowatt-hour so that prices for x_2, x_3, x_5 and x_7 are the same. Results allow an easy interpretation: If operator would give this pricing to the consumers, then peak load could be reduced about 3% at the same profit (minimization of costs to zero). As the energy demand of all consumers is nearly the same, on average consumers have also the same costs with optimized pricing compared to the uniform tariff. Finally, Fig. 10 shows the changes in the power demand while using the optimized pricing.

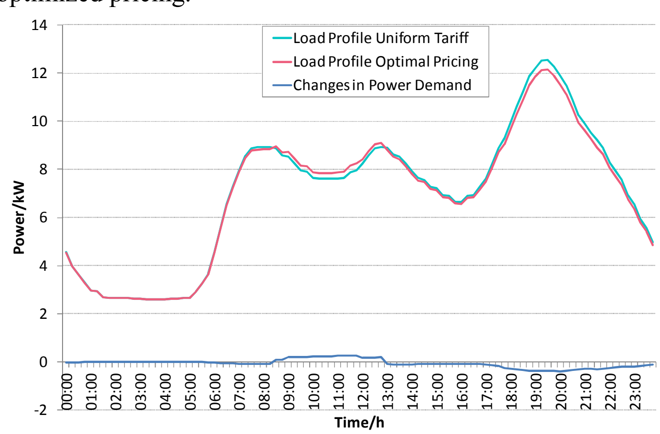

Fig. 10. Changes in power demand with optimized pricing

VI. Conclusion and Future Work

This paper introduces an assessment method for incentives. The method based on an adaptive rational decision-making model of residential consumers, which estimates the demand response of a crowd of individuals to incentives. The assessment method allows the comparison of different incentives in terms of costs incurred and their influence on load demand considering price elasticities of consumers. Furthermore, the method contains a new heuristic optimization algorithm called Mean-Variance Mapping Optimization (MVMO) that is used to optimize the incentives in consideration of the constraints and the conditions that are required for maintaining consumer acceptance.

Structure of consumers' demand response model and framework of the proposed assessment method are illustrated. Furthermore, functionality and suitability of the proposed approach are demonstrated in several simulations. Thereby, MVMO provides excellent performance in terms of convergence behavior.

When validation of the assessment method or rather of the model of residential consumers is done, then it is planed to proof the method practically in field test of a German research project. In the process, assessment method should be used to determine efficient pricing before the incentivizing tariff is finally sent to the consumers.

The results of the simulation show that the grid can benefit by the use of demand side management programs through a higher efficiency and lower costs overall, but also the participants can benefit. As described below, residential consumers should not feel penalized when they do not participate in incentives. However, if incentives help to give consumers an understanding of energy handling then their stewardship of energy will be higher. They will participate in incentives and will try to delay their demand forward or afterward the peak demand periods, when pricing should be lower. Depending on the amount of energy that they are able to delay, they will be rewarded with a reduction of their electricity costs.

Future research work is being directed towards further optimization of pricings in terms of consumer acceptance as they are the persons who contribute to the success of incentives and finance the energy turnaround.

VII. References

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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 management. He is student member of IEEE.

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 assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen/Germany. His major scientific interest is focused on power system stability and control, modeling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and senior member of IEEE.