The role of user interaction and acceptance in a cloud-based demand response model

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***Abstract*—Demand response management is one of the key applications of future energy systems. Most of the corresponding models and algorithms require a certain amount of user interaction to define appliances and rules for these processes. In this paper we implemented a cloud-based demand response approach to evaluate its efficiency depending on users input data. For simulation we used results of an online survey, mainly focusing on selection of devices and temporal flexibility concerning possible switch-off times. Contrary to our expectations the costs per load reduction (incentive prices to be paid by the utility) does not decrease when users have more than the day/night option to define switch-off timeslots. A high effect on cost cutting can be identified in the amount of participating users which underlines the relevance of user acceptance concerning demand response solutions.**

I. Introduction

Intelligent energy networks worldwide are about to evolve rapidly. The term "smart grid" is used to describe the next-generation energy systems. Smart grids employ state-of-the-art information and communication technology to control generation, distribution and consumption of energy. With smart grids the power network organization moves from a hierarchical to a decentralized structure and communication flow moves from largely uni-directional to bi-directional.

Spreading Smart Grid technologies will be inherently difficult without addressing user concerns. Privacy, security, and user control in the smart grid user domain are critical for establishing end-user trust and enabling end-user participation.

A typical application requiring a certain amount of user acceptance and interaction to work efficiently is demand response management (DRM). Demand response in this context refers to "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [1, p. viii].

Considering the research activities in DRM a high potential of user control is given in this application. Several algorithms and models like, e.g., Integer Linear Programming [2], Game Theory [3], [4], Markov chains [5], [6], and cloud-based approaches [7] are used in order to optimize DRM systems mainly considering the aspect of increasing grid efficiency and network stability.

The aim of this paper is to complement these efficiency considerations by taking into account the aspects of user interaction and acceptance for a cloud-based demand response (CDR) architecture as proposed in [7]. With the underlying publisher-subscriber approach this model realizes a decentralized data-centric information infrastructure [8]. Assuming a secure communication network this concept provides several benefits concerning privacy and hence an increased user acceptance which was one of the main reasons for choosing this specific approach.

Our implementation allows modeling of different demand response input parameters like power deficit, number of involved users and appliances, incentives prices, possible switch-off times and grade of user-interaction to analyze energy efficiency of the CDR model. For simulation beside values from literature and random assumptions we used results of an additional online survey which was conducted in this context. This allows the estimation of energy efficiency depending on realistic input data. Thus the aspect of user acceptance was directly integrated into the model.

The rest of this paper is structured as follows: in Section II we give an overview of related work in the field of demand response systems especially the cloud-based approach will be described in more detail. Our system model including the implementation, design of the survey and assumptions for simulation are presented in Section III. Results from both simulation and survey will be shown and discussed in Section IV; we conclude in Section V with a summary and an outlook on future work.

II. Related work

A. Demand response models

In [7] the following requirements for demand response architecture are listed:

- Security: assuring secure message exchange and end users' privacy
- Reliability: avoiding any single point of failure
- Scalability: with respect to the large number of customers
- Speed: fast matching of supply and demand as an essential service for the power grid

- Effectiveness: achieving the objectives of all participants of the Smart Grid

Concerning the integration of users/customers in DRM the proposed optimization methods can be categorized as follows [2]:

- Single-user scenario: optimization models to schedule the energy consumption/production of a single user
- Multi-user scenario: optimization models to schedule the energy consumption/production of a group of users

The topic of user-controlled energy management is often discussed using an incentive-based approach to energy scheduling, as in [9], [10]. In the work of Pedrasa [11], [12] the users can actively choose between pre-calculated schedules.

In [2] Integer Linear Programming is used to model an optimal scheduling of house appliance activities for both scenarios with the goal to minimize the energy costs. In [13] the same group developed a forecast model based on appliance meter data collected by a Wireless Power meter Sensor Network (WPSN) and processed every 24 hours. The prediction includes: which devices will be used, at what time and for how long. This information represents important input parameters for DRM systems and avoids complex manual settings by the user.

In order to further optimize decision processes in DRM systems, [14] identifies a high potential of mobile devices and services for additional user interaction to support, e.g., user-assisted prediction and user integration concerning on/off decisions.

In contrast, the authors of [6] argue that only few customers will be willing to continuously make such decisions and inputs. To make management of home energy usage acceptable to consumer they consider fully-automated energy management systems (EMS) necessary for residential DRM. In the proposed algorithm the consumer only decides what devices need to be run. The automated scheduling process then models both the consumer energy reservation and energy prices to finally allocate energy on the residential level to appliances (single-user scenario).

A similar approach is introduced in [15] but in the context of a multi-user scenario: Modeling the energy need of the appliances as non-stationary arrival processes a Community Energy Management System between Home Energy Management Systems and utility is responsible for scheduling the loads.

In [16] an energy on demand concept is proposed where an electric power management system intelligently manages power flows among decentralized energy generation/storage devices and appliances in single- and multi-user scenarios [16]. A dynamic priority model is used to control these flows in real time.

Considering strategies especially developed for building DR optimization the proposed models can be easily adapted to single and multi-user scenarios. For instance in [5] a policy-based framework is developed that takes into account local energy storage and load shiftability. The corresponding algorithm operates on real-time data with respect to the stochastic nature of the inputs (renewable energy source and load).

[4] proposes a day-ahead bidding process complemented by a real-time penalty system to limit short term load fluctuations. The used algorithms allow computing optimal strategies of the users with minimal information exchange between the utility and the customer.

B. *Cloud-based demand response*

In contrast to demand response approaches that follow the master/slave paradigm, cloud-based demand response architectures as proposed in [7] outsource the demand response optimization problem completely to a cloud. In this multi-user scenario the utility does not directly interact with the customers but sends a request to the cloud with the following parameters: the power deficit D and the maximum incentive price λ_0. The cloud appears as a black box information system which solves the demand response optimization problem and returns the solution to the utility.

This is possible by following the publisher-subscriber paradigm and topic-based group communication. The cloud publishes a message for load reduction to a specific incentive price. All subscribed customers have the ability to answer with an offer or not. An iteration process between cloud and customers will lead to a minimal possible price to reach the necessary load reduction. This optimization result will be offered to the utility and in case of acceptance the customers reduce their power consumption.

Among others [8] lists the following typical properties of publisher-subscriber models:

- Decoupling of information in terms of space and time
- Peer-to-peer characteristic, enabling multicasting by nature
- Scalability
- No single point of failure or bottleneck

With regard to user acceptance related to privacy concerns especially the decoupling of information should be considered as an important advantage: in the proposed CDR model customer-specific information, such as load profiles, will neither be delivered to the utility nor to the cloud. The utility has even no knowledge about which users are involved in a specific load reduction scenario; the functionality of billing the incentive prices is located in the cloud.

III. System model

A. *Implementation*

Based on the ideas in [7] a cloud based demand response model was implemented.

1) Sequence of cloud-based demand response process: As seen in Fig. 1 the cloud-based demand response algorithm is separated into three steps: A) the feasibility check, B) the bargaining iteration and C) the decision making. In step A the utility injects only the maximum or initial incentive price λ_0 and the deficit D into the cloud. All subscribed clients make an offer for load reduction x_i to λ_0. If $\sum_i x_i(\lambda_0) \leq D$ the cloud notifies the infeasibility to the utility and the process terminates. Otherwise it continues with step B. The update

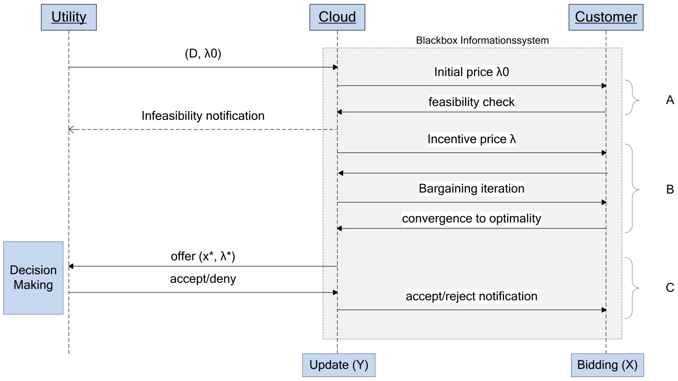

Fig. 1. Cloud-based demand response bidding diagram

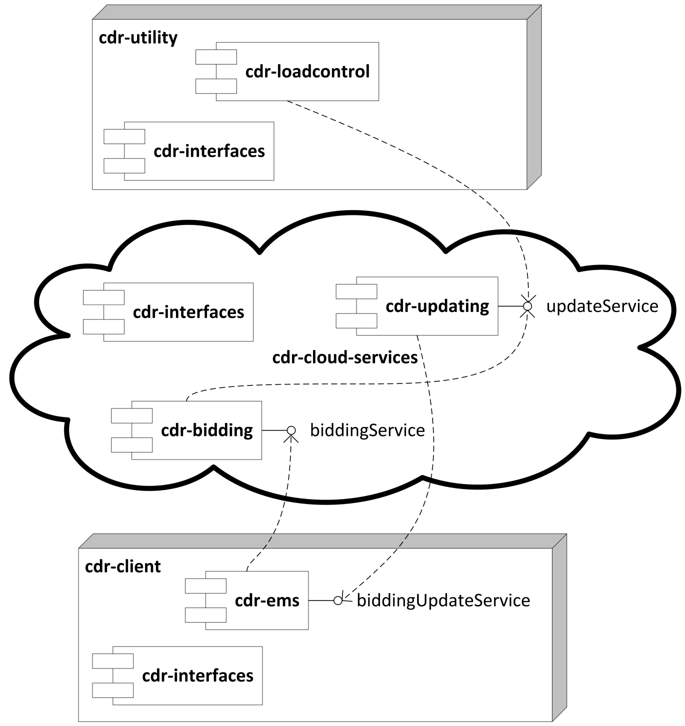

Fig. 2. Software components of CDR architecture

function Y uses the bisection method to calculate the next incentive price λ_k. This is described more detailed in section III-A3. At the end the optimum incentive price λ^* and a load reduction x^* is found an returned to the utility. The utility now has two options: accept this offer or start another DRM process.

2) Software components: The cloud-based demand response algorithm is implemented in a distributed components architecture within three layers: i) utility, ii) cloud and iii) client (see Fig.2). This is implemented with Java and Distributed OSGi[1]. The components communicate via asynchronous publish/subscriber technology as described in [7]. The service provider operates as a subscriber and the service consumer as a publisher. Each component is implemented in a separate OSGi bundle. The interfaces are shared in a separate bundle. All services are available as a WSDL XML-file on a discovery service which runs on a cloud server so that the application is like running in one container and the services are linked dynamically with service trackers.

After utility and clients are deployed and connected, a demand response process starts at the *cdr-loadcontrol* component. This request is sent to the cloud (*cdr-updating*) and forwarded to N subscribed customers. Each client (*cdr-ems*) calculates an offer by using the bidding function X and returns it to the cloud (*cdr-bidding*). There the update function Y is waiting for all offers (load reduction x_k for incentive price λ_k) and calculates the next incentive price λ_{k+1}. This is forwarded via the *cdr-updating* component to all customers and done until convergence.

3) Price update function Y: The price update function calculates the actual incentive price λ_k within an iteration k by using the following bisection method:

$$\lambda_k = \frac{\lambda_{max} + \lambda_{min}}{2} \tag{1}$$

This is done until λ_k converges to the optimum incentive price λ^*. The first incentive price is calculated with $\lambda_{max} = \lambda_0$ and $\lambda_{min} = 0$. This is injected into the cloud and all subscribed clients calculate their x_i with bidding function X. If $\sum\limits_{i \epsilon N} x_i^k > D$ the load reduction is more than what is needed so λ_k is higher than λ^*. The incentive price will be reduced with $\lambda_{max} = \lambda_k$. Otherwise the incentive price should be increased. This is done by $\lambda_{min} = \lambda_k$ [7]. The iteration steps and results are hidden to customer and utility. They only get λ^*.

[1]http://cxf.apache.org/distributed-osgi.html

4) Bidding function X: A customer i participating in the CDR scenario has the ability to add appliances to the customer energy management system (EMS). Per appliance a incentive prices $\lambda_{i,a}$ and timeslots TS in which short-term shut-down is allowed can be defined (see Table I). These detailed information are only visible to the customer and not to the cloud and utility.

TABLE I. APPLIANCES WITHIN CUSTOMER EMS

id	name	$x_{i,a}$	$\lambda_{i,a}$	time slots
1	washing machine	2,50 kW	0,1 €/kW	00:00 - 24:00
2	dryer	3,90 kW	0,1 €/kW	00:00 - 24:00
3	air condition	5,00 kW	0,2 €/kW	21:00 - 0:00, 0:00 - 6:00
4	computer	0,36 kW	0,4 €/kW	12:00 - 15:00, 15:00 - 18:00
5	television	0,30 kW	0,3 €/kW	06:00 - 09:00, 12:00 - 15:00

The bidding function sums up the possible load reduction for all appliances $x_{i,a}$ whose incentive price $\lambda_{i,a}$ is less or equal than λ_k. This could be described as follows:

$$X_i(\lambda_k) = \sum_{a=1}^{A} x_{i,a} \quad \forall x_{i,a} \quad with \quad \lambda_{i,a} \leq \lambda_k \tag{2}$$

B. Survey on user interaction

To provide realistic user input data to the customer EMS (see Table I) we conducted a survey with people working or studying in an IT-related field using an online questionnaire. Via mailing lists 900 persons were invited to participate. The aim of the survey was to obtain information about the selection of appliances for short-term shut down depending on the time of the day and the given temporal flexibility. A list of 16 typical appliances was offered to the participants. For each appliance, time slots could be selected by a mouse click in which the customer would allow shutting down that device. Concerning temporal flexibility three scenarios were addressed:

- 1 timeslot: 0–24h
- 2 timeslots: 8–20, 20–8h
- 7 timeslots: 0–6, 6–9, 9–12,12–15, 15–18, 18–21, 21–0h

Incentive prices were not considered in the survey. The participants were advised that a pre-defined user- and appliance-specific price will be paid in case of shut down.

Four additional questions dealt with the general opinion about temporal flexibility, number of appliances integrated in such scenarios, incentive prices and acceptance of required user interactions.

C. Assumptions for simulation

To simulate a typical demand response scenario we consider a low voltage distribution grid with a maximum of 10,000 customers participating in the above described CDR system. Concerning the simulation parameters we assume the following:

- Energy deficit $D = 1 \ldots 10$MW, steps of 1MW
- Initial incentive price : $\lambda_0 = 1$€/kW
- User and appliance specific incentive price: $\lambda_{i,a} = 0.1 \ldots 1$€/kW, random
- Probability of selecting an appliance in a specific timeslot: $p_{a,TS}$ (results of survey, see Section IV-B)
- Electric power per appliance: $x_{i,a}$, randomly selected from sensible interval (taken from European Commission data[2])

IV. Results

A. Simulation results

To demonstrate the influence of temporal flexibility on incentive prices for different load reduction values, ten simulations with 10,000 customers were performed for each of the three scenarios (1, 2 and 7 timeslots). Corresponding mean values shown in Figure 3 indicate the expected higher price to be paid in case of higher power deficit for all scenarios. Concerning temporal flexibility the lowest cost per load reduction were achieved with two timeslots, but differences between the scenarios are minimal (less than 0.011€/kW).

In order to analyze the effects of the number of participating customers additional simulations were done for a typical 1 MW load reduction (Figure 4). For each scenario the price decreases with an increasing number of users (mean value of ten simulations).

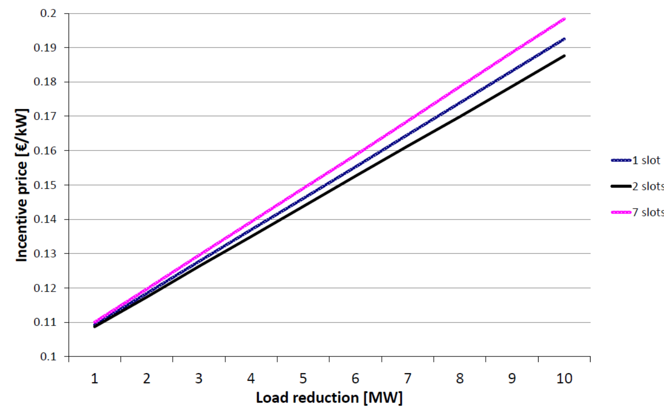

Fig. 3. Incentive price λ^* with different temporal flexibility

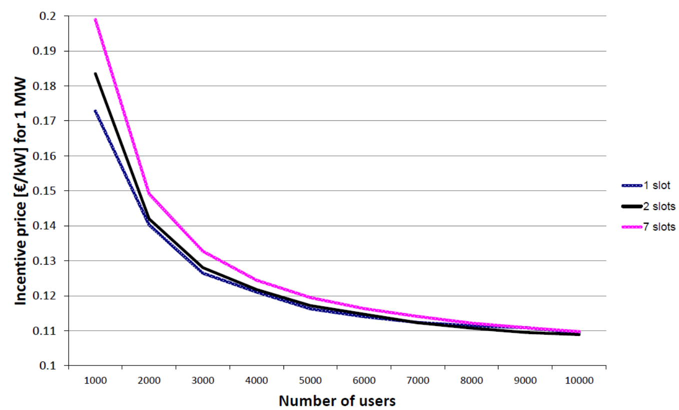

Fig. 4. Influence of number of users on incentive price λ^* ($D = 1$MW)

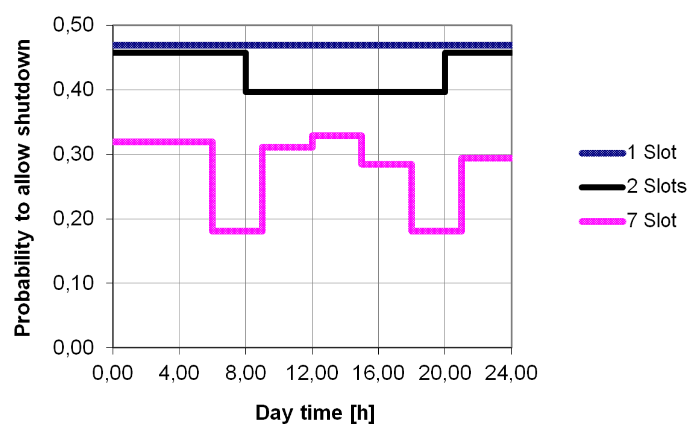

Fig. 5. Probability $p_{a,\mathrm{TS}}$ for a heat pump

B. Survey results

The results of the survey are based on 117 completed online questionnaires (response rate: 13%). The answers were processed as follows:

$$p_{a,\mathrm{TS}} = N_{a,\mathrm{TS}}/N_{\mathrm{all}} \tag{3}$$

where $N_{a,\mathrm{TS}}$ stands for the aggregated number of clicks in a specific timeslot for a certain appliance and N_{all} for the number

[2]http://ec.europa.eu/clima/sites/campaign/pdf/table_appliances_en.pdf

of users who answered this question.

As a typical example Figure 5 shows these probabilities of selecting a heat pump for shutting down at certain day times. The higher temporal flexibility in the 7-slot scenario decreases the probability of selecting this appliance actually for all times of the day.

Table II shows the average answers on the additional four questions about temporal flexibility, number of appliances, incentive prices and acceptance of required user interactions. Participants could click the number 1 to 7, where 1 stands for "I completely agree" and 7 for "I completely disagree".

TABLE II. SURVEY RESULTS

No.	Question (short form)	Average
1	I select more appliances in case of more temporal flexibility.	3.10
2	I accept lower incentive prices in case of more temporal flexibility.	3.77
3	I acccept to spend time for required user-interaction.	3.42
4	The option to prevent a shut down is of high importance.	2.04

C. Discussion

From Figure 4 we notice that a high temporal flexibility for defining possible shut-down timeslots does not lead to a higher efficiency of that CDR model. The average answers of question 1 and 2 (see Table II) also support these results. The "switchable" electric power per user and per appliance on a day seems not to increase with more available timeslots. The following reasons can be considered:

- With higher temporal flexibility users tend not to select certain timeslots (exemplarily see Figure 5).
- Users do not accept the configuration effort for selecting many timeslots (see also answer 3, Table II).

The importance of the number of customers, accepting and participating in this specific CDR system can be seen in Figure 3. The more users are involved in the bidding process, the more "cheap" appliances can be switched off, and thus the resulting incentive price is lower.

Additionally the influence of available slot numbers decreases with higher amount of users. It seems that the selection of fewer slots per appliance can be balanced by more available users and thus appliances.

V. CONCLUSION

Based on the results of our implementation and survey for a specific cloud-based demand response model we can state the following:

- A high customers temporal flexibility does not bring an additional benefit concerning resulting costs for the utility.
- The general acceptance of the DR system is of high importance since the number of participating users has a strong effect on cost cutting for a certain load reduction.
- The user acceptance does not increase with higher temporal flexibility and more configuration possibilities.
- For purposes of acceptance the users option to prevent a shutdown shall be integrated in the DR system.

Since our simulation is based on time-averaged values over the day especially for the seven slot scenario a more detailed view on CDR efficiency at different times of the day would be interesting. From further processing of data acquired in the survey we expect more information concerning users time-dependent choice of specific appliances and the corresponding effect on the DR model. Also mapping of these results on other DR systems and algorithms will be a topic of future work.

ACKNOWLEDGEMENTS

The financial support of the Josef Ressel Center by the Austrian Federal Ministry of Economy, Family and Youth and the Austrian National Foundation for Research, Technology and Development is gratefully acknowledged.

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