Prosumer flexibility management in smart grids

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***Abstract*— Diverse electricity consumption and distributed production present serious challenges in future smart grids. Smart grid end users can have a role of a consumer and a producer at the same time. So-called prosumers are considered to play a major role in the future grid operation, management and maintenance. One of main concepts supporting this novel role is prosumer flexibility, namely an ability of the prosumers to adapt their consumption or production according to the smart grid needs. Understanding, managing and utilizing the prosumers flexibility remains a serious research challenge that needs to be evaluated and proved in practice.**

In this paper we will present a synergy of two research projects addressing the area of prosumer flexibility management. First one is a horizon project Flex4Grid, which aims at prosumer flexibility management by using advanced information technology solutions, while the second one is a national Critical Peak Tariff project in Slovenia, that enables distribution system operators to test novel prosumer flexibility management incentives in real life operation. The projects' cooperation allows to utilize modern smart grid infrastructure, boost its usage with advanced IT, and evaluate prosumer flexibility management in practice. We introduce the conceptual model and implementation of our technical solution, as well as some preliminary evaluation results of a large-scale pilot.

Keywords— prosumer; flexibility management; smart grid; large scale pilot; information technologies

I. Introduction

Electricity demand in households is increasing with the expansion of smart electronic devices. Technology for harvesting energy from alternative sources, whether solar, wind, geothermal or biomass, is also becoming more accessible and in demand. Integration of alternatives into the grid is on the rise, which causes some operational issues in the power system [1]. One such problem concerns the overload of energy production from alternatives and also a critical demand for energy consumption at certain time intervals in the day.

Traditional supply-side flexibility (from centralized power plants) is not enough to manage new smart grid overloads, thus additional flexibility is needed from a range of generators, storage, and demand. In this paper we present and overview two projects addressing demand-side flexibility with a prosumer flexibility management scheme [2]. Our solution allows the end users to actively participate in managing consumption overloads, as well as production overloads from alternative sources connected to their local network. Preliminary results from the project pilot show there is an active response from participants in the pilot, which contributes to reducing peak consumption in households.

Flex4Grid (F4G) [3] is a European project with a focus on creation and provision of an open data and service framework, that enables prosumer flexibility management in households. Project F4G aims to provide a holistic data management solution with a secure and private data exchange between the distribution system operators (DSOs) and their customers, which in turn manages flexibility of prosumer demand and generation to the benefit of all stakeholders. Project F4G will be concluded at end of March 2018.

Primary goal of the F4G project is to build a system with an ability to balance the demand by reducing the peak loads (so called peak clipping). Secondary goal is to allow the system to match an excessive supply from alternative sources by shifting the load. Tertiary goal is to understand how the incentives for participation affect the project solution. And lastly, we are interested in the nature of the flexibility achieved by analysing environmental, technology, and human factors affecting the utility of the proposed solution [4].

Testing and validation of F4G management system is conducted via pilots in three real electricity networks with different characteristics. One pilot site is in Slovenia, where there are smart meters already integrated in households. Two sites are placed in Germany and are of smaller scale, due to necessity and complexity of introducing and installing extended kits to pilot users, as there are no smart meters installed. Extended kits consist of a Flex4Grid gateway, five smart plugs, and optional electricity meters to measure household consumption in real-time, [5]. Preliminary results presented here will be from the Slovenian pilot.

Simultaneously, there is a national Pilot Critical Peak Tariff Project (PCPT) [6] in Slovenia, where dynamic pricing is introduced and tested as a form of demand response regulation [7]. Besides a standard fee, which is a bit lower than current fixed fee, it features a special high network fee, which DSOs can charge during the peak load periods. The intent is to provide incentive for the prosumers to dynamically respond and redistribute their consumption in order to avoid network overload, which can occur with additional production from alternative sources or very high consumption demand. This overload is considered as a critical peak. In the PCPT project it is possible to use dynamic tariff on real prosumers for 50 hours per year. While PCPT project provides incentive for users to participate in F4G pilot, the F4G solution offers means to measure and evaluate the demand response for each predicted critical peak.

In the following section we introduce the main elements of the F4G solution and its implementation to a real power system environment. The data and testing events are presented in the third section. In the fourth section we present the preliminary results gathered from four events. Corresponding challenges discovered during evaluation are discussed in the fifth section. We end the paper with main conclusions.

Related work

Operational flexibility in power systems is a known and researched subject since the integration of alternative sources in bulk, see [8] and [9]. Demand response programs with multi-hour peak loads have been effectively implemented in past years, but were used as a limited resource. Due to advances in communications and controls in smart grids, the demand response is now being used as an ancillary service to the power system [10]. There are several approaches to regulate demand response, such as time-of-use rates, real-time pricing, and critical peak pricing [11], which were tested on small-scaled grids with different success rates, see [12] and [13].

Demand response refers to a procedure of motivating users to change their power consumption habits as a response to the electricity price. Five large-scale cases studies [14] in USA researched pricing incentives for peak reduction and response sustainability. All employed some form of dynamic pricing and found peak reduction substantially greater with the use of enabling technologies. However, the real-world impact is still limited by the lack of an IP-based network architecture that is reliable, safe, and efficient in managing the complexity of a smart grid communication infrastructure [15].

Another analysis of consumer engagement in Europe [16] revealed that money incentive alone may not be strong enough to get a noticeable consumer response. It is also necessary to have a reliable solution of communicating and informing the costumers, as well as developing social marketing strategies to help increase active response and help change the perception of electricity as a commodity.

Here we present prosumer flexibility management as a service and the effect of dynamic pricing on customer response in a real large-scale pilot. Promising results of the later, will help propose and implement necessary regulatory changes, which are needed in the smart power systems, while the former provides a marketable technical solution to manage the demand response in case of such regulatory changes. Complementary nature of F4G and PCTP projects allows for large-scale pilot testing in a real smart power system environment.

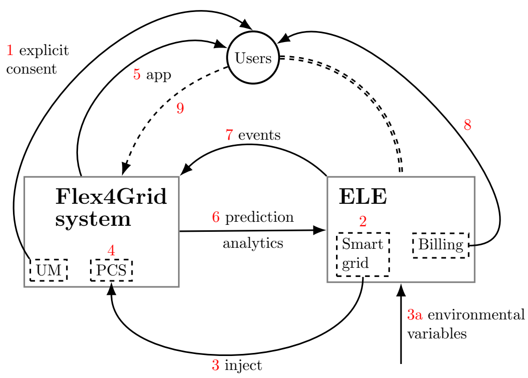

Fig 1. Conceptual model of F4G system implementation.

II. IMPLEMENTATION

The implementation of F4G solution and information flows are presented in Fig 1. The F4G solution uses an existing smart grid metering system. A billing system at Elektro Celje d.d. (ELE) has been adapted to support PCPT billing at one-hour granularity. Users connected to the smart grid interact with F4G system through a mobile application, with which they can monitor their consumption and receive notifications about the test events.

Implementation process flow between F4G system and ELEs smart grid with end users (presented with double dashed line) is as follows:

1. Explicit consent for the use of consumption data, gained during participation in the project, is obtained for each user via user management (UM) module.
2. At ELE, smart grid consumption data from each end user is aggregated at substation level. Household consumption is read at 15-minute interval from smart meters.
3. The aggregated data and corresponding environmental data (3a) are then injected into F4G system. Hourly predicted values of environmental variables (3a) for 3-days in advance are added to the historical data and sent to the F4G system.
4. At Prosumer Cloud Service (PCS) module the data is then pre-processed and inputted into the prediction model.
5. F4G provides a mobile application for a 2-way communication with the user.
6. Prediction for the time and the magnitude of the peak is sent back to ELE.
7. Based on the prediction, an event is organised and notifications are sent to the participants via mobile application.
8. Taking all of the events into account and using the PCTP pilot tariff scheme, corresponding billing is made and sent to the participants.
9. User feedback is sent to F4G system via user satisfaction questionnaires.

TABLE I. DESCRIPTIVE STATISTICS FOR ALL ENVIRONMENTAL VARIABLES AND TOTAL CONSUMPTION ACROSS ALL YEARS (2013 – 2017) AND EACH INDIVIDUAL YEAR

	Temperature [°C]				Radiation [W/m^2]				Precipitation [mm]				Consumption (total) [kW]			
	mean	std	min	max	mean	std	min	max	Mean	Std	min	max	mean	std	min	max
All	11.22	9.08	-20	39	148.15	239.79	0	1068	11.88	74.50	0	3014	**10267.26**	3275.19	141.96	**23303.93**
2013	10.66	9.19	-14	39	141.03	235.99	0	1052	12.06	68.31	0	2503	**8409.55**	2867.39	2886.73	**18353.84**
2014	11.81	7.77	-20	34	135.54	226.20	0	1068	14.92	83.54	0	1773	**9490.51**	2794.56	4483.64	**20062.62**
2015	11.04	9.16	-15	36	147.49	238.46	0	1020	10.47	67.50	0	2029	**10298.71**	2992.97	4760.01	**19972.50**
2016	10.70	8.96	-14	33	142.61	233.74	0	1050	11.77	73.00	0	2636	**10731.79**	3171.64	4998.16	**21969.40**
2017	12.17	10.53	-19	38	186.01	269.68	0	1034	9.44	80.58	0	3014	**12405.74**	4191.45	141.96	**23303.93**

III. EVALUATION

Slovenian pilot is conducted at ELE in the municipality of Celje. Since households in Slovenia are equipped with smart meters, the users do not need the kits to participate in the pilot. The number of participants is thus larger (748 in preliminary phase gathered from 10956 invitations). All participants are consumers who are connected to one of 209 different local transformer substations (TP).

Eligible candidates for the pilot are the household consumers with two-tariff billing, who are connected to the distribution network of ELE. They must have an electricity meter, which can remotely read the load profile in 15-minute intervals, and reliable communication between the electrical meter and the data centre. Participation is formalized with the explicit consent for participation, which was signed by each participant [5].

Candidates were invited to the project with an invitation letter, which contained basic project information and a registration code. Incentives for the participants are: 1) dynamic pricing as defined in the PCTP project, 2) a lottery with material prizes (electrical scooters and bicycles) conducted by ELE, and 3) detailed insight into their electricity consumption via Flex4Grid mobile application.

Flex4Grid system provides a way for the consumer to actively adjust their consumption, when prompted by their DSO. In the case of Slovenian pilot, the prompt is a scheduled event with a 24-hour advance notice. Event represents one hour in a day, for which dynamic pricing applies. Main goal during each event is for users to actively reduce their consumption. For each event a prediction of overall consumption and peak load of that day was made using a prediction model.

For experimental testing the population of consumers was divided into a pilot and a control group. The pilot group represents the pilot participants, who receive event notifications, while the control group is the rest of the population considered by the project.

A. Data

All smart meter measurements are aggregated at substation level. Analysis and prediction are then done on the sum of consumption values across substations. In addition, environmental variables such as temperature, radiation, and precipitation are recorded at every hour and attached to the measurement data by corresponding timestamps.

Historical data from January 2013 until November 2017 is available for all four variables. Descriptive statistics for these variables is presented in Table I. The yearly mean consumption is increasing at a minimum 4% rate. Similar trend can be noticed for yearly maximum consumption.

Since we are also involved in the PCPT project, where defining yearly critical peaks is the primary goal, we explored the daily peak distributions in different seasons, as shown in Fig 2. Daily peak is the highest consumption value of the day. All four distributions are bimodal, with one extreme in the morning to midday and the other in the evening. There is a noticeable shift of an hour between evening peaks in cooler months of shorter days (autumn and winter) and warmer months with longer days (spring and summer). On weekdays the highest peaks occur in the evening, while on weekends and holidays they occur at midday.

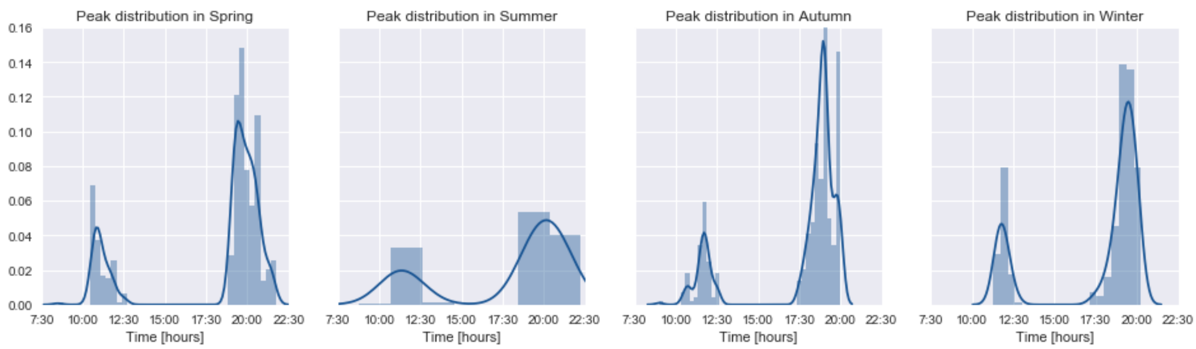

Fig 2. Daily peak distributions (in percentages [%]) for all four seasons.

B. Prediction model

In order to predict the highest daily peak, a prediction model was build using artificial neural networks (ANN), specifically Long Short-Term Memory (LSTM) networks. Using ANN as a tool for energy consumption prediction showed promising results in previous studies [17]. A machine learning approach was made possible due to a large amount of historical data. Because there are several periodical patterns in the consumption data (yearly, weekly, and daily), we wanted to use this information when making the predictions. The LSTM networks were shown to successfully model long term and short-term intervals of a time series and were therefore considered for the prediction model [18]. We build a network with two hidden layers with 200 hidden neutrons per layer.

The input vector contains the consumption values (of one week previous the prediction day), values of three environmental variables, and time depended variables, such as season, day of the week (weekend or weekday), and time of the day (separated into eight three-hour intervals) corresponding to each consumption measurement. The output variable is the consumption. Optimization of the weights on edges between layers was done through supervised learning with an Adamax optimizer [19].

IV. RESULTS

Preliminary results of the project presented here were collected from four events. For each event, the critical peak interval was predicted 48 hours in advance. After the event, consumption distributions were analysed and visualised for the pilot group and the control group. We also evaluated the percentage of pilot users, who actively participated in the event. Event summary is presented with Table II.

A. Consumption profiles

Two examples of an event day are shown in figures Fig 4 and Fig 3. The distributions of mean consumption for the pilot and the control group are coloured blue and green, respectively. The event interval is shaded with dark grey. In October the event interval was from 7:15 pm until 8:15 pm with real peak occurring at 8 pm. In December the event started at 7 pm and the peak occurred at 8 pm. In both cases, the distribution of the mean consumption was, on average, higher in the pilot group than the control group throughout the day.

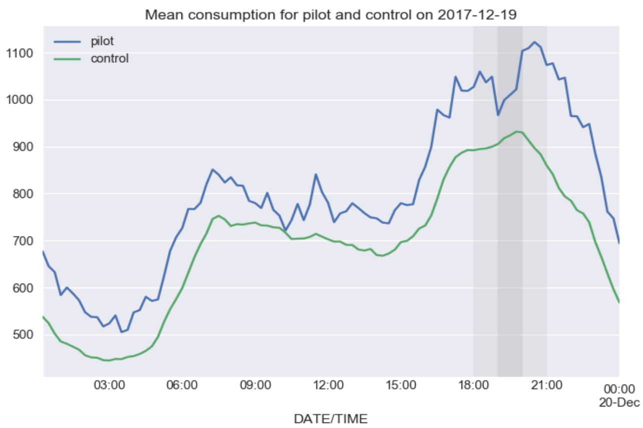

Fig 4. Mean consumption (in watts [W]) for pilot and control groups (December event).

At each timestamp, the consumption distribution is approximately normal for both groups, because the sample sizes are large enough. However, the difference between the interval means of distributions for pilot and control groups is statistically significant at α=0.05 for a paired *t*-test. The discrepancy is more noticeable at the 1-hour interval before and 1-hour interval after the event, as can be seen in Fig 3. There was also a noticeable reduction of consumption in the pilot group, as the pilot mean consumption drops at the start of the event. In the case of the October event, the drop in mean consumption is below the control group mean consumption during the event.

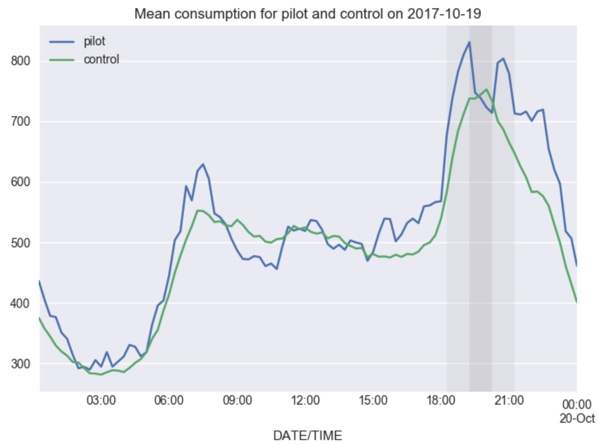

Fig 3. Mean consumption (in watts [W]) for pilot and control groups (October event).

B. User activity

Besides the difference in consumption levels for the time of the event, we are further interested in the percentage of active users. The classifier was built on the comparison between overall energy demand (all consumption per time interval) of the user and the mean consumption of the control. Three 1-hour intervals were considered: before the event, event hour, and after event. When a user has lower energy demand than the demand of the control means during the event interval, then the user is classified as good. If their overall demand is higher for all three intervals, then the user is classified as high. Otherwise, the user was considered bad in terms of the demand response. We consider that the user was active, if their demand was lower during the event compared to their demand of one hour before; regardless of their label. A good user with a higher demand during the event than before the event was regarded as a neutral participant (not responding, but not contributing to the peak).

Otherwise we consider the user inactive. Percentages and summary of the events are available in Table II.

Any dispersion in control and pilot sizes is due to either errors in measurement (missing data), or errors in collection. Maximum percentage of active users was 28 % in December, while minimum percentage of inactive users (35 %) was in November.

V. DISCUSSION

At weekdays the highest peaks mostly happen between 5:30 pm and 10 pm, with the mode shifting from 7 pm, in autumn-winter seasons, to 8 pm, in spring and summer. However, all four of our events had their peak around 8 pm. This could be due to a small sample number of events or some external circumstances. This discrepancy will be evaluated further, when more events are considered.

Our prediction model gives acceptable results, as the predicted daily peak was realized in the chosen event time interval in three events presented. The average error rate for peak time predictions is 30 minutes. Difference between predicted and real peak values is on average 24% of the real peak value. The prediction error for consumption does not yet include the prediction error of environment variables, as these predictions are outsourced.

Our pilot group has on average higher consumption during the day than the control group. The difference between the interval means of distributions for pilot and control is statistically significant at $\alpha = 0.05$ for a paired t-test. Therefore, consumption profiles and user profiles are needed to explain this discrepancy between the pilot and control groups' mean consumption distributions.

For the pilot group, there can be a noticeable rise in consumption after the event, as shown in Fig 4. In the October event there was also a rise in consumption before the event, see Fig 3. These steep rises in consumption imply that a percentage of users are active and are shifting their consumption, which we further confirmed by classifying the users into active, neutral, and inactive, and calculating their frequencies. Although user activity gives promising results, it exposes the problem of peak shifting, or even increasing consumption after or before the event. How to regulate such responses needs further study and trials, in order to avoid undesired shift in consumption with a peak higher than predicted.

Future work and challenges

Prediction model can be improved in terms of peak value prediction. In addition, the width of the peak should be considered separately, since the consumption can shift as we saw from preliminary results, which in turn affects the duration of critical peak time. One of the steps towards improving the prediction model, is to optimize the data flow in terms of detecting missing data and pre-processing the data set for prediction.

Since the pilot group has a different consumption profile than the control group, a classification method is needed in order to help generalize the expected consumption profile with a flexibility management tool on the whole network (and not just certain substations).

Prosumer flexibility fluctuates during the day and it is influenced by season. There may be also external unknown variables with influence on the degree of prosumer flexibility. One of such influences are the user socio-demographic profiles, as well as their usage of electronic household devices. Those will be additionally explored through a survey.

As the concept of flexibility management of demand response in power systems is quite novel in terms of integration, there is no standard definition of prosumer flexibility yet available. Flexibility measures in these cases also vary, as there are case specific. A flexibility measure has to be properly defined, in order to measure the change (increase/decrease) of flexibility in the pilot group and compare test result of different flexibility management schemes.

Beside comparing pilot mean consumption to the control group mean during the event, we are also interested in the

TABLE II. EVENT SUMMARY AND USER ACTIVITY PERCENTAGES.

Event summary	**2017-09-20, Wednesday**	**2017-10-19, Thursday**	**2017-11-23, Thursday**	**2017-12-19, Tuesday**
Control size	14737	14533	14341	13990
Pilot size	748	731	737	721
Event time	19:00:00 - 20:00:00	19:15:00 - 20:15:00	18:30:00 - 19:30:00	19:00:00 – 20:00:00
Peak time (real)	**20:00:00**	**20:00:00**	**19:45:00**	**20:00:00**
Active (%)	**25**	**23**	**27**	**28**
Neutral (%)	36	33	38	36
Inactive (%)	39	44	35	36
t-test (*p*-value) [a]	**< 0.05**	**< 0.05**	**< 0.05**	**< 0.05**

[a] paired *t*-test at α=0.05

alternative; i.e. what would be the pilot mean consumption if no event was considered. Possible consumption will be simulated with an adaptation of our prediction model, which was developed for peak prediction.

Finally, we will run a simulation based on the distribution of active users, where we explore peak shifts to an interval before or after the event, as we increase the number of active users. Specifically, we will explore the direction and magnitude of the shifted peak in comparison with the event real peak value.

VI. CONCLUSSION

Flex4Grid project offers a technical tool to help DSOs manage demand response in their local smart grids. Since flexibility as a service is a novel approach, there are still challenges of defining a measure for prosumer flexibility and knowing, which incentives are effectively managing the demand response. Depending on the situation, we want to achieve either peak clipping (reduction of peak consumption) or peak shifting (to match the peak production from alternative sources). One such incentive in the form of dynamic pricing is considered in the PTCP project, which makes the evaluation of the F4G solution possible in a real large-scale environment.

Preliminary results show some promise in gaining additional flexibility in the smart grid from responsive consumers. On the other hand, additional challenges, like peak shifting before or after the event, possible peak increase, as well as differences in consumer profiles at different environmental and seasonal conditions, need to be addressed in further research.

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