Enlightening Customers on Merits of Demand-Side Load Control: A Simple-But-Efficient-Platform

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ABSTRACT The impressive advantages offered by of demand-side participation have accelerated deployment of demand response (DR) programs. However, the first step to attain the benefits of DR programs is to increase awareness level of the customers. This paper proposes a simple-but-efficient platform to enlighten the customers on manifested merits of demand-side load control. The proposed platform is a web-based application which acquires the load profile of the customer, associated flexible appliances, and the customer preferences for using the appliances. In turn, presents the optimal operation schedule for flexible appliances and attained benefits from using the optimal schedule. To calculate the optimal operation schedule, a mixed-integer linear optimization model is devised where the decision variables are settings of flexible appliances, charge/discharge status and amount of storage device, charge/discharge status, and amount of electrical vehicle. The devised optimization engine is linked to a database to acquire required data for optimization which encompasses historical data for customer load, forecasts of renewables, ratings of customers’ flexible appliances, and subjected energy tariff. The attained optimal scheduling for the customer is then returned to the database. On the other hand, the database is linked to the web-based user interface to get the user preferences (write to the database) and represent the recommendation for optimal operation and attained benefits (read from database). To manage the links between web-based user interface, database, and optimization tool, proper linking application programming interfaces (APIs) are devised. The proposed platform is testified using real-world data and its effectiveness is assured by experimental studies.

INDEX TERMS Distribution systems, smart home, community aggregator, renewable energies.

I. INTRODUCTION The manifested merits of demand-side participation have given rise to significant interest on demand response (DR) programs. DR benefits include, but not limited to, improving the economic efficiency of electricity markets, enhancing the reliability of electric power systems, reducing peak demand, and alleviating price volatility [1]. Various DR programs have been upheld by power system operators to promote the active contribution of demand-side entities and harvest associated benefits [2].

Depending on the design and structure of the DR program, DR could be captured from a large customer which meets the demand-side contribution requirements or an independent market player which aggregates small customers’ contribution [3]. Considering large number of small-scale costumers and owing to the proliferation of smart appliances at the household level, the DR aggregation could be acknowledged...
as an efficient solution to increase the disclosure of large volumes of consumers and prosumers to the wholesale electricity markets. A DR aggregator builds a bridge between independent system operator (ISO) and retail customers and takes the responsibility of aggregating and managing customer responses [4]. On the other hand, the aggregators collaborate with load-serving entities to feed the consumers and prosumers with advanced metering data which can be used to monitor and control real-time electricity consumption.

The research on DR at the residential level mainly deals with the modeling of the customer side energy management problem and associated interaction between supplier/aggregator and customers/prosumers. In this regard, several objectives can be identified from different standpoints. The potential profits which can be attained by DR aggregation are quantified in [2]. From the end-user perspective, several objective functions are proposed which offer cost-effective and comfort-aware DR programs [5]–[8]. From aggregator and distribution system operator (DSO) perspective, peak reduction through DR programs might be deemed attractive. A day-ahead market framework for congestion management in smart distribution networks is presented in [9]. Here, the presented scheme provides a platform for collaboration between distribution-level market operator and data traffic operator to alleviate congested feeders.

In [10], peak load energy consumption is studied by the optimal scheduling of HVAC devices through a centralized mechanism. In [11], controlling HVAC by the aggregators is investigated to mitigate the intermittency of renewable generation. Scheduling of flexible appliances taking operational safety into the account is discussed in [8] and [12] considered management of household-level electrical vehicles (EV) as flexible appliances. In [13], the flexible load scheduling and energy trading with upstream network problems in presence of home-scale renewable resources are addressed. A regret-based stochastic bi-level framework for optimal decision making of a DR aggregator to purchase energy from short term electricity market and wind generation units is proposed in [14]. Here, the aggregator offers selling prices to the customers, aiming at maximize its expected profit in a competitive market. The impact of network operation indices and DSO’s policies on the aggregator’s performance and associated self-scheduling is presented in [15]. Community level DR aiming at minimization of energy cost is studied in [16]–[20] where the main decision index is considered as the electricity price signal from a retailer/wholesale market. In [16], an agent-based learning strategy is used to adapt storage devices of end-users to the mark market conditions. Minimizing overall energy procurement cost through a cooperative game theory-based approach is proposed [17]. The authors in [18] devised an incentive mechanism to realized DR aggregation based on the penalty and reward scheme which aims at minimization of energy procurement from the upstream network. Besides aggregation of DR, clustered-based power network management is proposed which aims at managing the renewable energy resources at the community level and controls the power transaction of community aggregators with the upstream network. In [21], energy management of a price-responsive demand clusters is studied which controls the energy exchange among the clusters and the upstream network. References [22]–[24] propose a hierarchical cluster network structure which describes community aggregators as fractal clusters and deal with associated control to optimize energy exchange.

The first step to attain the benefits of DR programs is to increase awareness level of the customers. To do so, the advantage gained from altering utilization pattern of controllable loads should be highlighted to the end users. According to the research applicability model proposed by [25], technology, adoption, and market aspects should be considered in a research work so that it can be easily accepted and used by the end-users. Despite merits and impressive innovations offered by the above-reviewed researches, all of them are dealing with technology aspect and DR programs are still in challenge with customers’ awareness and adoption concerns. To cover this gap, this paper deals with a simple-but-efficient platform to enlighten the costumers on manifested merits of demand-side load control.

In this paper, it is aimed to devise a platform which can demonstrate the benefits of DR programs to the end-user particularly those programs which are offered by the community aggregator as the optimal operation plan. The proposed approach acquires the end-user’s profiles pertaining to on-site generation, i.e. renewable-based generation, and consumption, i.e. fixed and flexible load; in turn, the platform represents the cost difference between user-preferred and optimal scheduling pertaining to flexible appliance such as dishwasher, washer & dryer, pump, storage device, and EV. To investigate user-preferred operation condition, daily operation of a community aggregator is simulated where the controllable appliances are set by the end-user considering comfort constraints. On the contrary for offering the optimal operation, an optimization model is devised where the objective is to minimize operation cost of customer considering technical constraints pertaining to permissible operation range of equipment. Here, controllable loads are decision variables where their optimal setting is attained by solving the devised optimization model. An indicator is tailored to show the difference between usual and optimal operation and steer the user towards the optimal operation. Comparing to the commercially available similar solution, the available platforms are only dedicated to a single device, say storage devices and electrical vehicles [25] and [26]. However, the proposed approach considers all flexible appliances, say washing machine, dish washer, pump, etc. In addition, all technical constraints pertaining to the flexible appliances are considered in devising the optimization model which brings about realistic optimal scheduling plan.

The devised platform is encompassed from three main components:

- **User Interface:** A user interface is envisioned to acquire the user data and preferred settings as inputs; and, rep-
resent gained benefits and optimal operation settings to the end-user as the outputs.

- **Optimization Engine:** The optimization engine derives the proposed optimization model and calculates the optimal operation settings.

- **Data Management Algorithm:** The data management algorithm acts as the master unit by transferring and controlling the data flow among user interface, database, and optimization engine.

The salient contribution of the conducted study might be summarized as:

- Designing an efficient platform to enlighten end-users on manifested merits of DR programs;
- Proposing a linear optimization model to calculate optimum settings for controllable appliances;
- Developing a data management algorithm as the master unit controls the data flow and provides proper link among user interface, database, and optimization engine; and,
- Exploiting a user-friendly user interface for acquiring the input data and demonstrating the results.

The devised platform is a web-based service where associated effectiveness and robustness are testified using real-world data of AKEDAS distribution system operator.

## II. THE DEVISED PLATFORM

### A. OVERVIEW

Fig. 1 depicts the outline of the proposed platform. In Fig. 1, the proposed platform is encompassed from three layers, i.e. user interface as front end, optimization engine as the backbone, and the data management engine as the main driver of the platform.

The first role of the user interface is to acquire data from the user which includes flexible appliances of the user, the date understudy, the subject energy tariff, and user preference for appliances. The other role is acquiring data from the database which encompasses historical fixed demand of the user, optimal setting for appliances, and preferred and optimum operation costs. The second role of the user interface is to visualize illustrative indicators such as load profile, settings of appliances, and operation cost pertaining to preferred and optimal scheduling.

The second layer is the data management engine which is built up from two main units, i.e. database and application programming interface (API). A database is envisioned for the proposed platform for structuring, extracting, and load the data. The devised database includes 9 interconnected units which will be discussed in Section II.C. The data management layer also takes advantage of an embedded web-based API for managing data flow between the user interface and optimization engine. In other words, the devised API acts as a master unit for acquiring the data, executing the optimization layer, refreshing the user interface, etc.

Last but not the least, the proposed platform utilizes an optimization engine in the third layer. Within the envisioned optimization engine, a linear optimization model is embedded which minimizes the operation cost of the user subject to a suite of constraints. Here, the end-user operation cost is modeled through the subject tariff and amount of power transaction with the community aggregator. The considered constraints are permissible operation range of flexible appliances, power balance, the permissible range of renewable-based generation, storage device, and EV charging and discharging ranges. For the proposed optimization model, the amount of power traded with the community aggregator, and operation time of the flexible appliances are considered as the main decision variables. Based on the selected date and preferences offered by the user, the devised API extract the corresponding data from the database, load the data to the optimization model, execute the optimization engine, and finally, write the results to the database. Once the optimization results are attained and loaded to the database, the devised API sends the required data to the user interface and executes the user interface engine to represent the illustrative

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**FIGURE 1. Outline of the proposed approach.**
indicators to the user. The devised platform is accessible via smart-mla-app.stimasoft.com.

Detailed design and formulation of the layers are presented in the following.

**B. LAYER 1: USER INTERFACE**

Fig. 2 depicts schematic the authorization and login page of the devised platform. The user can be the aggregator who is controlling the customers or the consumer for whom the user and password is provided by the associated aggregator. The authentication is performed using the database security built-in mechanisms that store the usernames and passwords in columns encrypted with TDE (Transparent Data Encryption) column encryption [27]. TDE allows encryption of sensitive data that is stored in columns without an encryption key. Also, the TDE advantage is that the procedures to decrypt data are not required, as it is decrypted as the user passes the access check.

**C. LAYER 2: DATA MANAGEMENT ENGINE**

The data management engine presents a critical role in the proposed platform which includes a database and a web-based API unit. The database devised for the proposed platform is depicted in Fig. 6. Data is stored based on a relational schema design depicted in Fig. 6 and composed of tables that represent the entities with their attributes and relationships. Each table contains multiple attributes (including a unique identifier) for shaping and storing the data required by the optimization model and the user interface. Therefore, consumers’ information such as name, address, phone, and type are stored into T_CONSUMERS table. Consumers may have multiple consumption places, e.g. two or more houses. For each consumption place, several details are stored in T_CONSUMER_PLACES table such as maximum consumption, generation capacity, type of generation sources (PVs, wind turbines), storage, and number of occupants. The relationship between
FIGURE 6. Devised data base structure and associated links.

A consumer and its consumption places is modelled in T_CONSUMER_CONTRACTS table and the available tariffs are stored in T_TARIFFS table. Since the tariffs are designed in hourly resolution, T_TARIFFS_RECORDS table stores daily records for the consumption and generation prices at each hour. Consumption and generation data are recorded by smart meters installed at consumption places and then, stored at T_METERS and T_METER_READINGS tables. Here, the fixed load and generation at consumption place can be estimated for the next day of operation through a simple regression forecast algorithm. The forecasted profiles are passed as input to the optimization model. Table T_CONSUMER_APPLIANCES stores the data related to electrical appliances characteristics. The corresponding characteristics are description, type (dishwasher, dryer, pump, EV, storage), maximum/minimum power for consumption or charging, efficiency, maximum/minimum power for discharging, maximum/minimum state of charge, required operational time (in minutes), time needed between consecutive operations (in minutes), number of operations per day, flexibility source, i.e. flexible load, generation, storage. Through the user interface, the consumer sends the preferred hours for operating the flexible appliances for the next day. The inputs acquired from the user are then stored in T_APPLIANCE_OPTIMAL_OPER table. In addition, the solution of optimization problem is also stored this table. Based on preferred and optimal start hours, the daily total cost associated with preferred and optimized costs can be calculated and compared. Note that the database schema represents in the conducted study is a classical modelling technique for relational databases which is the most common practice. Regarding the private data (address, email, phone, etc.), these fields are visible only to the authenticated electricity consumer through username and encrypted password in the web-application. Here, the aggregator that manages the data according to the confidentiality provisions of their agreements (consumer-aggregator). Usually, the encrypted passwords and the security protocols of the database access are sufficient as we are dealing with a central database and no distributed nodes are involved.

Once the data base is designed, an API is required to realize data management role which includes loading data to the data base, reading the data from data base, load the optimization engine, calling back the results of optimization engine, and sending data to the user interface. To do so, a web-based API is devised in the conducted study. The flowchart of devised API is depicted in Fig. 7. The API shown in Fig. 7 embeds the optimization algorithm and its auxiliary services. It provides a proper communication protocol for the user interface that calls the optimization algorithm through a web address or URL (Uniform Resource Locator). The web API is implemented in Python using Flask that runs as a web service.

The API is connected to the database for retrieving the data from the tables using SQL queries. Since the database runs on an Oracle Database 18c instance, cx_Oracle database connector is used for communication between Python and Oracle [27]. The data related to tariffs (consumption and generation hourly prices), consumer’s preferred hours and characteristics of the appliances are loaded into Pandas Data Frames as follows:

- df_prices – Data Frame containing tariffs records;
- df_flex_app – Data Frame containing the characteristics of the appliances and user-preferred start hours;
FIGURE 7. Flow chart of proposed API for web-based data management.

- `df_generation_dev` – Data Frame containing the capacity and characteristics of the generation devices; and,
- `df_load` – Data Frame containing the fixed load forecast and generation for the next day.

In addition, the hourly generation and fixed loads for the next day are determined using a regression algorithm based on historical data and weather conditions. The forecasted values are loaded into a Pandas Data Frame. All Data Frames are passed as input parameters to the optimization algorithm that runs on a MATLAB engine. The output of the optimization algorithm is sent back to the database and saved in table `T_APPLIANCE_OPTIMAL_OPER` as optimal operating hours for appliances.

**D. LAYER 3: OPTIMIZATION ENGINE**

This section describes the embedded optimization engine within the proposed platform. Fig. 8 depicts schematic of a community (smart home) which includes a connection to the community aggregator, renewable generations (wind and solar), fixed loads, controllable loads (washer & dryer, dishwasher, and pump), storage device, and plug-in electric vehicle.

For optimal operation, the objective is minimum cost while satisfying technical constraints pertaining to nodal power balance, power transactions with upstream network, permissible operation range of elements. The objective function can be formulated as:

\[
\text{Minimize } OF = \sum_{t \in I_T} \left( \lambda_t^{Buy} P_t^{Buy} - \lambda_t^{Sell} P_t^{Sell} \right)
\]  

where,
- \( t, I_T \) Index and set of time
- \( Buy, Sell \) Superscript for buying from and selling to market
- \( P \) Active power
- \( \lambda \) Price per kilowatt

The main constraint is to maintain nodal power balance which is formulated as:

\[
p_t^{Gen} - p_t^{Load} = 0 \quad \forall t \in I_T
\]  

\[
p_t^{Gen} = p_t^{Buy} + p_t^{PV} + p_t^{Wind} + p_t^{Bat} - p_t^{EV} - p_t^{Fix} - p_t^{W&D} - p_t^{DW} - p_t^{Pup} + p_t^{Bat} + p_t^{EV} \quad \forall t \in I_T
\]  

\[
p_t^{Load} = p_t^{Sell} + p_t^{Fix} + p_t^{W&D} + p_t^{DW} + p_t^{Pup} + p_t^{Bat} + p_t^{EV} \quad \forall t \in I_T
\]

where, \( PV, Wind, Bat, EV, Fix, W&D, DW, \) and \( Pup \) are superscripts for solar generation, wind generation, plug-in electrical vehicle, fixed load at home, washer and dryer, dishwasher and pump load for pool, respectively. Here, + and - superscripts show the charging / discharging stage of battery storage and plug-in electrical vehicle, respectively.

The suite of technical constraints for community aggregator (smart home) operation are represented by (5)-(36). The power transacted between the community and upstream network should be within a pre-defined range which is modeled by (5) and (6).

\[
0 \leq p_t^{Buy} \leq \alpha_t^M p_t^{Buy, Max}
\]  

\[
0 \leq p_t^{Sell} \leq (1 - \alpha_t^M) p_t^{Sell, Max}
\]

where, \( M \) is the symbol for market-related quantities, \( Min \) and \( Max \) are symbols for lower and upper limits, respectively. In (5) and (6), the binary variable \( \alpha_t^M \) is used to avoid enabling both selling and buying options at the same time. The upper and lower limits of renewable generation are modeled by (7) and (8).

\[
p_t^{Wind, Min} \leq p_t^{Wind} \leq p_t^{Wind, Max}
\]  

\[
p_t^{PV, Min} \leq p_t^{PV} \leq p_t^{PV, Max}
\]
The state-of-charge (SOC) of the storage device at each time period is calculated by (9). Constraints (10)-(12) are limitations on SOC, and charge/discharge power (11)-(12) associated with storages.

\[
SoC_{i}^{Bat} = SoC_{i-1}^{Bat} + \frac{\eta^{Bat} \Delta t}{E_{Bat, Max}} \times \left( P_{Bat,+}^{i} - \left( \eta^{Bat} \right)^{-2} P_{Bat,-}^{i} \right) - \alpha^{i} \quad (9)
\]

where, \( \eta \) is conversion efficiency coefficient, \( \alpha \) is binary decision variable, \( E \) is energy capacity for storage unit. The EV charge/discharge constraints are modeled by (13)-(14) associated with storages. In (15), the SOC of parking lots in various time intervals is computed. Constraints on the target SOC of parking lots are stated by (16)-(18), respectively.

\[
0 \leq P_{EV,+}^{i} \leq \alpha^{i} P_{EV,+,Max} \quad (13)
\]

\[
0 \leq P_{EV,-}^{i} \leq \eta^{EV} \left( 1 - \alpha^{i} \right) P_{EV,-,Max} \quad (14)
\]

\[
SoC_{i}^{EV} = SoC_{i-1}^{EV} + \frac{\eta^{EV} \Delta t}{E_{EV, Max}} \times \left( P_{EV,+}^{i} - \left( \eta^{EV} \right)^{-2} P_{EV,-}^{i} \right) - \alpha^{i} \quad (15)
\]

where, \( \eta^{EV} \) is conversion efficiency coefficient, \( \alpha^{i} \) is binary decision variable, \( E_{EV} \) is energy capacity for storage unit. The EV charge/discharge constraints are modeled by (13)-(14) associated with storages. In (15), the SOC of parking lots in various time intervals is computed. Constraints on the target SOC of parking lots are stated by (16)-(18), respectively.

\[
0 \leq P_{EV,+}^{i} \leq \alpha^{i} P_{EV,+,Max} \quad (13)
\]

\[
0 \leq P_{EV,-}^{i} \leq \eta^{EV} \left( 1 - \alpha^{i} \right) P_{EV,-,Max} \quad (14)
\]

\[
SoC_{i}^{EV} = SoC_{i-1}^{EV} + \frac{\eta^{EV} \Delta t}{E_{EV, Max}} \times \left( P_{EV,+}^{i} - \left( \eta^{EV} \right)^{-2} P_{EV,-}^{i} \right) - \alpha^{i} \quad (15)
\]

Equations (19)-(24) model washer and dryer within the community as a controllable load.

\[
P_{W&D}^{W&D} = \alpha^{i} P_{W&D,Dep} \quad (19)
\]

\[
\sum_{t=1}^{T} \alpha^{i} P_{W&D}^{W&D} = T_{W&D} \quad (20)
\]

\[
\alpha^{i} P_{W&D}^{W&D} - \alpha^{i-1} P_{W&D}^{W&D} = \beta^{i} P_{W&D}^{W&D} - \xi^{i} P_{W&D}^{W&D} \forall t \in [2, 24] \quad (21)
\]

\[
\sum_{t=1}^{T} \beta^{i} P_{W&D}^{W&D} \leq \alpha^{i} P_{W&D}^{W&D} \forall t \in [T_{W&D} + 1, 24] \quad (22)
\]

\[
\sum_{t=1}^{T} \xi^{i} P_{W&D}^{W&D} \leq 1 - \alpha^{i} P_{W&D}^{W&D} \forall t \in [DT_{W&D} + 1, 24] \quad (23)
\]

\[
DT_{W&D} = 24 - T_{W&D} \quad (24)
\]

where, \textit{Dep} is superscript for deployment, \( T \) is the time required for complete operation of the equipment, and \( \beta, \xi \) are auxiliary binary variables. Equation (19) expresses that the power consumed by the washer and dryer at time \( t \), i.e. \( P_{W&D}^{W&D} \), is equal to its nominal power consumption while deployment if it is in operation, i.e. \( \alpha^{i} P_{W&D} = 1 \); otherwise, \( P_{W&D}^{W&D} \) is 0. In addition, the operation time of washer and dryer should be equal to the required time for its complete operation which is modeled by (20). Here, continues operation of washer and dryer should be also considered. In other words, when washer and dryer machine is committed, it should be continuously in operation until the time required for its complete operation (interruption is not allowed). To this end, suit of constraints represented by (21)-(24) is added. For the rest of the appliances, the similar constraints are considered for dishwasher (25)-(29), and pump (30)-(35).

\[
\sum_{t=1}^{T} \alpha^{i} P_{Pup}^{Pup} = T_{Pup} \quad (25)
\]

\[
\alpha^{i} P_{Pup}^{Pup} - \alpha^{i-1} P_{Pup}^{Pup} = \beta^{i} P_{Pup}^{Pup} - \xi^{i} P_{Pup}^{Pup} \forall t \in [2, 24] \quad (26)
\]

\[
\sum_{t=1}^{T} \beta^{i} P_{Pup}^{Pup} \leq \alpha^{i} P_{Pup}^{Pup} \forall t \in [T_{Pup} + 1, 24] \quad (27)
\]

\[
\sum_{t=1}^{T} \xi^{i} P_{Pup}^{Pup} \leq 1 - \alpha^{i} P_{Pup}^{Pup} \forall t \in [DT_{Pup} + 1, 24] \quad (28)
\]

\[
DT_{Pup} = 24 - T_{Pup} \quad (29)
\]

Once the model is completed, the objective function represented by (1) is solved subject to (2)-(35). The output of optimization engine are:

- Optimal amount of renewable-based generation to be consumed at each hour;
- Optimal amount of power to be traded with the upstream network;
- Optimal charging \ discharging pattern for battery storage and EV;
- Optimal commitment of controllable loads, i.e. washer and dryer, dishwashing machine, pump for pool;
- Hourly cost of community operation.

The required inputs for the proposed model are:

- Hourly energy price forecast for the community ($/kWh);
- Hourly load forecast for the community (kW);
- Hourly generation forecast for the renewable energies (kW);
- Installed capacity for renewable generation, battery storage, and EV;
- Permissible operating range of devices.
By this data in place, the devised model offers the optimal operation for the community. In case of usual operation, the flexible loads are committed manually which might not be optimal. Here, indicators are envisioned to show the difference between the optimal and usual operation of the community. Needless for further emphasis that these indicators are for community awareness and direct load control is not envisioned here.

### III. SIMULATION STUDIES

The effectiveness of the proposed approach is testified through simulation studies. For the system depicted earlier in Fig. 8, Table 1 represents the flexible appliances which are considered in the simulation studies. A solar photovoltaic (PV)-based on-site generation with 3kW capacity is envisioned that associated generation profile is depicted in Fig. 9. For the consumption profile, real-world load data provided by AKEDAS DSO is utilized which is depicted in Fig. 10. In addition, it is assumed that the community is subjected to real-time market price in hourly resolution. The price signal received by the community is depicted in Fig. 11. As can be seen, the minimum price happens at night (around 3:00) and the community is faced with the maximum price during the evening, i.e. 18:00). In Fig. 11, the maximum price is roughly 5 times of the minimum price which brings about unprecedented opportunities to take advantage of load flexibilities for cost reduction. The user preference for operating flexible appliances are reported in Table 2.

Given the data presented by Figs. 9-11 and Tables I and II, the simulation results are provided in Fig. 12. As can be seen, the operation cost associated with user-preferred settings deviates 1.99 $ from the optimal operation plan. In other words, the user can save 25% of daily electricity expenses. Fig. 13 illustrates the difference between optimal and user-preferred settings. As can be seen from Fig. 13, a considerable difference between optimal and user-preferred
settings is observable which results in considerable cost difference between the user preferred and optimal operation plans. To offer more details, the load profile associated with user preferred operation and optimal operation cases in breakdown of fixed load, flexible load, storage and on-site PV generation are depicted in Figs. 14 and 15. Referring to Fig. 14, the flexible loads are distributed from 10:00 to 20:00 which is preferred by the user. As can be seen from Fig. 11, the maximum price for electricity is during 18:00 to 22:00 which coincides with user preferred operation time. However, in Fig. 15, the flexible load is concentrated between 3:00 to 6:00 using the proposed optimal operation plan. Here, the maximum amount of consumption coincides with the minimum price time (see Fig. 11). In addition, storage charging and discharging are performed during 3:00 to 6:00 and 18:00 to 21:00, respectively. Doing so, the energy stored during cheap electricity time is used at expensive electricity time which reduces the total load at expensive electricity time and consequently, reduces the total operation cost of consumer/prosumer. This observation implies the effectiveness of the flexible appliances in alleviating the operation cost.

Fig. 16 depicts the operation costs for user preferred and optimal operation cases under different solar PV and storage capacities. As can be seen, the operation cost at both user-preferred and optimal operation cases decreases as we increase solar PV and storage capacities. In addition, the optimal operation cost is always lower than that of user preference represented earlier in Table 2. This observation reveals the effectiveness of on-site generation and storage technologies on cost reduction.

IV. DISCUSSION AND CONCLUSION

This report dealt with a simple-but-efficient platform to enlighten the customers on manifested merits of demand-side load control. The proposed platform is a web-based application encompassing three layers, i.e. user interface, data management engine, and optimization engine. The effectiveness of the proposed approach was testified using real-world data for electricity communities. The studies concluded that:

1) considerable difference between the minimum and maximum daily price of electricity brings about unprecedented opportunities for cost reduction;
2) Considerable rooms for minimum cost operation are available at end-user level;
3) The proposed approach can steer the consumer/prosumer towards a least-cost operation plan;
4) Flexible appliances play significant role in alleviating the operation cost;
5) On-site generation and storage technologies proliferation can further contribute to cost reduction.

 Needless for further emphasis that the proposed approach is devised for intensifying awareness of communities on end-user level opportunities and load control through aggregators are excluded. The load control mechanisms and associated decision-making approaches will be addressed our future studies.

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