Collaborative demand response in smart electric grid with virtual system operator

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Abstract: The authors present a novel concept of virtual system operator (VSO) and its mechanism. This mechanism aims to determine load consumption pattern on day-ahead basis which suits all the involved entities individually in real-time pricing environment. The demand profile is scheduled by every consumer by performing demand response (DR) without having to coordinate with other consumers in the system. In the process flow, the VSO which remains in communication with the system operator and the consumer relays information regarding day-ahead electricity tariff to consumers. Based on which the consumers simultaneously perform DR to optimise their electricity bill and forward the schedule to the VSO. This process repeats iteratively until a balanced price profile as well as load schedule is established in the system. Such schedules are capable of reducing dynamics in the electricity market. The proposed concept is demonstrated through three different types of consumers. These consumers realise DR through different objective functions and up to different extents. Ultimately, the load schedules are obtained for all individual users and corresponding price profile which suits every entity of the system.

1 Introduction

Adoption of real-time pricing (RTP) has encouraged users to optimise their usage of electricity. With the developed communication infrastructure and instruments in electrical systems, users are more aware of their usage and can take more informed decision regarding their usage of electric power. Adjusting personal electricity usage to coincide with times of lower demand can save consumers money by taking advantage of lower prices. On the other hand, RTP also acts as a control parameter dictated by the load serving entity (LSE) to command the usage pattern of the consumers. The schedule of operation opted by consumers in answer to RTP in order to minimise own electricity bill is termed as demand response (DR).

Implementation of DR techniques into smart grid empowers the various role players to operate economically and reliably. DR techniques when reduces the peak demands also known as peak shaving, enable the power providers to meet demands without having to install new generation capacities. It also builds up confidence of grid operators to incorporate intermittent renewable energy sources on large scale. On the other hand, to the consumers the economy of usage happens to be the biggest motivation to adopt DR techniques.

Different types of DR technologies have evolved over time, of which price- and incentive-based mechanisms are most popular. These mechanisms are elaborated in [1]. The incentive-based mechanisms are mostly controlled by utilities and require consumers to willfully enrol for load curtailment programmes. Such programmes enable the utilities to more reliably operate the grid with virtual system operator (VSO) before scheduling the energy transaction. This would speed up the process of attaining equilibrium through an iterative process. The schedule then obtained would avoid dynamics in the electricity market. The proposed concept is demonstrated through three different types of consumers. These consumers realise DR through different objective functions and up to different extents. Ultimately, the load schedules are obtained for all individual users and corresponding price profile which suits every entity of the system.
In this paper, we assumed three different types of consumers to illustrate the proposed concept. First consumer is an industrial facility (IN) which without violating the production constraints wills to minimise the electricity bill through conservation of loads. Second consumer is a charging station (CS), which operates commercially to maximise its profit over a day. The CS cannot shift loads gain optimal profit through providing charging or discharging services to EVs by optimising charging and discharging price to offer to EVs. The IN and CS are commercial units and consume large amount of electricity and hence are very conscious of electricity bill. The third consumer is residential loads treated as a single large load, i.e. aggregated residential load. The residential load does not respond towards DR opportunities to same extent as CS or IN commercial units.

The IN is equipped with schedulable and non-schedulable loads and is expected to meet the production demand throughout the day. The industry also equipped with battery energy storage system (BESS) to stores or dispatches power at strategic instances such that cost is minimised throughout the day with respect to the effective price profile. Instead of scheduling the determined energy requirement with the DSO, the industry first uses the VSO to obtain expected tariff profile and evaluates the economy of operation. It also allows the industry to shift the schedulable loads and reserves more effectively. Accordingly estimate the expected cost of operation enabling to place the most suitable bid for power scheduling with the DSO. Demand response has been established at IN as efficient means to optimise energy usage. According to [13], industries account for nearly 42% of world’s electricity consumption in 2015. At industrial facilities several measures like spinning reserve, on-site generating systems [14] have been employed to perform demand side management. Moreover, load rescheduling and load prioritisation have also been helpful for DR at industrial facilities [15].

On the other hand, CS equipped with renewable generation and BESS tends to maximise net income throughout the day. Since the charging or discharging decision is completely controlled by EV owners, the CS attempts to alter their decision by changing the charging price with respect to the grid offered price. This leads to change in load profile. If the load profile so obtained is communicated with VSO which in turn returns a new expected price profile while also considering effect of loads from other constituent units of the system. Hence, the CS is able to foresee the impact of its DR action in cohesion with other loads in the system. EV CSs have adopted several DR techniques such as [7] has used real-time charging scheme where charging scheduling is formulated as a binary optimisation problem; the authors [16] have proposed a real-time price-based DR strategy, whereas the authors [17] have proposed DR at CS using dynamic pricing as well as energy management. In [18], Yang et al. studied RTP to regulate charging loads by introducing probabilistic charging decision model to study the effect of charging price variation on charging decision of customers.

The role of SO has been eminent in a distribution network. According to [19], the goal of a DSO, through the grid and market functions, is to empower customers’ engagement and maintain reliability and integrity of the grid. In this relation, there have been numerous studies regarding steps taken by DSO to improve system discipline, and reduce contingencies by using dynamic pricing scheme [20]. Therefore, in this paper the main objective of the LSE/DSO is assumed to uniformly distribute the loads to avoid peaks and valleys in load profile, and also be profitable by varying the electricity tariff.

In purview of above plan, this study aims to assess feasibility and improvement in the system health/discipline when the consumers opt to communicate with VSO to optimise their schedules before actually scheduling with the DSO. When DR programme is employed in a system, the change in net load demand causes dynamics in the electricity market. The introduction of VSO in the vertical system structure helps in determining in advance a balanced load schedule for the consumers in the system. The consumers would have no further incentives for deviating from the determined load profile. Such load profile scheduled in electricity market would avoid dynamics and dependence on balancing market. These dynamics arise due to load rescheduling from consumer end.

In this relation, the major contribution of this study can be highlighted as

i. For the first time, collaborative DR among various types of consumers, i.e. industrial, commercial and residential load in a distribution system is analysed using a novel concept of VSO.

ii. The VSO would allow the considered entities for better DR and motivate to fix optimal schedules that would fulfil every entity's objectives with necessary trade-off by improvising the price profile.

iii. Attractiveness of the proposed concept is illustrated for different consumers, namely oxygen generating industry, CS with 100 slots and aggregated residential loads. Their payoffs obtained through DR are compared with and without support of VSO.

The organisation of the paper is as follows: the concept of VSO is explained along with figures in Section 2. The system considered for this study is described thoroughly in Section 3. The results obtained are analysed and validated in Section 4. Finally, conclusion is presented in Section 5.

2 Virtual SO

The proposed mechanism of VSO is discussed in this section. VSO adopts an iterative process to obtain the demand as well as the price profile which suits all the users along with the SO.
In response, the consumers perform DR to optimally schedule their controllable loads in order to satisfy their objectives. The schedule during the iteration count \( \text{iter} \).

The above procedure, i.e. (2)–(6), is repeated until the maximum price change \( \epsilon \) during any hour is under some tolerable limit \( \hat{\epsilon} \). It is calculated as

\[
\epsilon = \max \left[ \frac{\Delta \lambda_{\text{iter}}}{\lambda_{h \text{iter}}} \right] \quad (7)
\]

The iterative process is stopped when \( \epsilon \leq \hat{\epsilon} \) is achieved. At such a point, the load schedule is determined and is communicated with the SO to schedule for the study period. Process flow for the same is presented in Fig. 2.

### 3 System model description

This section describes the system which comprises of two proactive load centres, namely IN and CS along with aggregated residential load. Whenever the DSO offers a new electricity tariff, the industry and CS actively attempt to schedule their respective loads. Such that power import from grid during peak hours is compromised for any other value of demand elasticity. The price profile is then updated by the VSO as shown in (5). Here, \( \lambda_{\text{iter}}^{-1} \) represents the electricity price for the previous iteration at hour \( h \)

\[
\lambda_{h \text{iter}} = \lambda_{h \text{iter} - 1} + \Delta \lambda_{h \text{iter}} \times \lambda_{h \text{iter} - 1} \quad \forall h = 1, 2, \ldots, 24 \quad (5)
\]

Such that

\[
\lambda_{h \text{iter}} = \left[ \lambda_{h \text{iter}}^{1} \lambda_{h \text{iter}}^{2} \ldots \lambda_{h \text{iter}}^{N} \right] \quad \forall h = 1, 2, \ldots, 24 \quad (6)
\]

The above procedure, i.e. (2)–(6), is repeated until the maximum price change \( \epsilon \) during any hour is under some tolerable limit \( \hat{\epsilon} \). It is calculated as

\[
\epsilon = \max \left[ \frac{\Delta \lambda_{\text{iter}}}{\lambda_{h \text{iter}}} \right] \quad (7)
\]

The iterative process is stopped when \( \epsilon \leq \hat{\epsilon} \) is achieved. At such a point, the load schedule is determined and is communicated with the SO to schedule for the study period. Process flow for the same is presented in Fig. 2.

### 3.1 Industrial load

The considered industrial load in this paper is of an oxygen generating facility [21]. The industry is equipped with overall four generating systems (OGSs) which may or may not operate at any given hour.

\[
\lambda_{h \text{iter}} = \left[ \lambda_{h \text{iter}}^{1} \lambda_{h \text{iter}}^{2} \ldots \lambda_{h \text{iter}}^{N} \right] \quad \forall h = 1, 2, \ldots, 24 \quad (2)
\]

Here, \( \lambda_{h \text{iter}} \) represents the load schedule by consumer \( c \) at hour \( h \) during the iteration count \( \text{iter} \). \( N \) represents total number of consumer entities in the system. The information obtained from (2) is then aggregated for each hour, which is then compared with the previously expected load consumption pattern for the study period of 24 h. The deviation from the expected load profile is calculated corresponding to every hour. It is done as shown in (3). Here, \( \lambda_{h \text{iter} - 1} \) represents the load scheduled by consumer \( c \) at hour \( h \) during the previous iteration count

\[
\Delta \lambda_{h \text{iter}} = \lambda_{h \text{iter} - 1} - \lambda_{h \text{iter}} \quad \forall h = 1, 2, \ldots, 24 \quad (3)
\]

Corresponding to the change in load demand at a particular hour \( h \) the change in electricity price for the said iteration count \( \text{iter} \) is determined as

\[
\lambda_{h \text{iter}} = \lambda_{h \text{iter} - 1} + \frac{\Delta \lambda_{h \text{iter}}}{\epsilon} \quad \forall h = 1, 2, \ldots, 24 \quad (4)
\]

where \( \epsilon \) refers to the inverse of demand elasticity of consumer. Demand elasticity is defined as the ratio of per unit change in demand (\( \Delta P \)) to the per unit change in price (\( \Delta \epsilon \)). It is for convenience considered as 1 w.r.t. all consumers in this paper. Notably, the merit of the proposed methodology would not be compromised for any other value of demand elasticity. The price profile is then updated by the VSO as shown in (5). Here, \( \lambda_{h \text{iter} - 1} \) represents the electricity price for the previous iteration at hour \( h \)
To facilitate the various OGSs with the required amount of cooling water, the water cooling system (WCS) can also operate at three different operating points which have different cold water yield and electricity demand. The water cooling facility is also schedulable among its three operating indices or tasks. The cold water yield and electricity demand by the operating points of the WCS are presented in Table 2.

Moreover, the industry is aided by oxygen and water storage units which act as reserve for OGS and WCS, respectively. These reserves of constrained size, stores oxygen or cooling water in case extra generation is carried out. The reserves supply the same whenever there is insufficient generation, provided that they contain enough amount of oxygen or water to supply. The constraints related to oxygen and cooling water storage systems are defined as follows:

\[
\begin{align*}
OS & \leq OS \leq OS^* \\
WS & \leq WS \leq WS^*
\end{align*}
\]

(8)

(9)

where OS and WS refer to amount of stored oxygen and cooling water in cubic meter for a given time slot, respectively. OS and WS refer to minimum reserve to be maintained while OS and WS refer to maximum capacity of respective reserve storage systems. The numerical values of the above-mentioned constraints are as follows: \( OS = 2000 \text{ m}^3 \), \( WS = 150 \text{ m}^3 \), \( OS^* = 18,000 \text{ m}^3 \), \( WS^* = 850 \text{ m}^3 \).

The industry is also assumed equipped with reserve energy storage system, BESS and a non-schedulable energy generation system, photovoltaic (PV) panel. Constraints over the state of charge of BESS operation are as follows:

\[
\begin{align*}
\text{SoC}^\text{IN} & \leq \text{SoC}_\text{IN} \leq \text{SoC}^\text{IN}( = 0.9) \\
\end{align*}
\]

(10)

where \( \text{SoC}^\text{IN} \) refers to state of charge of the BESS at industry at any considered instance of time. While \( \text{SoC}^\text{IN}( = 0.2) \) and \( \text{SoC}^\text{IN}( = 0.9) \) refer to minimum and maximum limits of \( \text{SoC}^\text{IN} \) to be maintained, respectively. The capacity of the considered BESS is 6000 kWh with maximum power rating of 1500 kW. On the other hand, the PV panel installed at the industry is assumed to generate power invariably as shown in Fig. 3 for the study period of 24 h.

The load scheduler at the IN determines the operation schedules after receiving electricity price profile from DSO/VSO and also schedules the charging and discharging action of BESS. The load scheduler also effectively utilises the oxygen and water storage systems so as to use them at appropriate instances. The whole schedule is determined while satisfying the constraints of various systems and the net output demand of oxygen from the industry in order to minimise the operational cost. The overall representation of the IN depicting the schedulable and non-schedulable tasks is shown in Fig. 4.

In this paper, the industry considers the following objective function to be optimised so as to reduce the operating cost over 24 h of operation.

Objective function:

\[
\begin{align*}
\min \quad & \sum_{\beta = 1}^{N_\text{ogs}} \left[ \sum_{o = 1}^{N_\text{ogs}} E_{\text{gen}, \beta, TO} + \sum_{w = 1}^{N_\text{wcs}} E_{\text{w}, TW} + \gamma(h) \cdot \text{BESS}^\text{IN}_{\max} \right] \\
& - E_{\text{GS}, h} + EP(h)
\end{align*}
\]

(11)

The above described objective function is subject to following constraints:

\[
\begin{align*}
\gamma(h) & = \begin{cases} -0.25 \leq \gamma(h) < 0 & \text{when discharging} \\
0 < \gamma(h) \leq 0.25 & \text{when charging} \end{cases} \\
\sum_{\beta = 1}^{N_\text{ogs}} O_{\text{gen}, \beta, TO} + \beta \times OS & = \text{oxygen demand} \quad (12) \\
\sum_{w = 1}^{N_\text{wcs}} W_{\text{w}, TW} + \delta \times WS & = \text{WCS demand} \quad (13)
\end{align*}
\]

Such that:

\[
\text{WCS demand} = \sum_{w = 1}^{N_\text{wcs}} W_{\text{w}, TO}
\]

(15)

\[
\beta = \begin{cases} -1 \leq \beta < 0 & \text{filling the oxygen storage} \\
0 < \beta \leq +1 & \text{consuming from oxygen storage} \end{cases}
\]

(16)

\[
\delta = \begin{cases} -1 \leq \delta < 0 & \text{filling the water storage} \\
0 < \delta \leq +1 & \text{consuming from water storage} \end{cases}
\]

(17)

where \( E_{\text{gen}, TO} \) refers to energy consumed by OGS \( o \) through operating index TO, \( E_{\text{w}, TW} \) refers to energy consumed by WCS \( w \) through operating index TW. Here \( N_\text{ogs} = 4 \) and \( N_\text{wcs} = 3 \) refer to total number of OGSs and WCSs, respectively. While \( \gamma(h) \) represents the ratio of charging/discharging rate to maximum power rating of the BESS at hour \( h \). These parameters are later
determined using meta-heuristic techniques, whereas BESS\textsubscript{max} \((= 6000 \text{kWh})\) refers to maximum capacity of BESS, EGS\textsubscript{In}(h) refers to energy generation at industry at hour \(h\). EP(h) represents the electricity price at hour \(h\). oxygen\textsubscript{demand}(\(= 16,000 \text{ m}^3\)) represents the oxygen generation expected at each hour uniformly throughout the day. Oxygen generated by OGS \(o\) through task index TO is represented as Ogen\textsubscript{o,TO} and WD\textsubscript{o,TO} represents cooling water demand by OGS \(o\) through operating task index TO. The total cooling water demand by the systems at an instance is represented by WCS\textsubscript{demand}. \(W_c,TW\) represents cooling water generated by WCS \(w\) through task index TW. The amount of oxygen stored is represented as OS. Finally, \(\beta\) and \(\delta\) represent the fraction of available oxygen and water systems to be dispatched or stored.

This paper employs meta-heuristic approach to schedule the operation of OGS, WCS and BESS over 24 h. Bat optimisation algorithm (BOA) is used in this paper considering its advantages over other meta-heuristic techniques [22]. The BOA determines the optimal operating indices applicable to various systems in accord to the objective function defined in (11) while satisfying the various constraints discussed in (13) and (14). Specifically, BOA determines for each of 24 h the optimal pair of \(o\)-TO, \(w\)-TW and \(\gamma(h)\) in terms of previous explanation of the constraints, where \(o\) refers to the OGS unit concerned while TO refer to the operating index or task varying from 1 to 3. Similarly, \(w\) refers to the concerned WCS and TW refers to the operating index or task of WCS varying from 1 to 3.

The employed BOA assumes a population of 20 bats, i.e. probable solutions which organised similarly as shown in Fig. 5. Each bat is updated over the iterations to reach the most optimal solution. The BOA is programmed according to the standard algorithm presented in [23].

The industrial operation scheduled is estimated for every price profile received from the VSO. The operation schedule corresponding to initial and final price profile is analysed in Section 4.

### 3.2 Charging station

Another entity constituting the system is the CS. The considered CS consists of 100 charging slots of power rating 30 kW each, which allows EV owners to charge or discharge. The CS communicates with the DSO to get estimated price profile for time span of 24 h. The CS then determines the charging and discharging price to offer to the customers during every time interval. Schematic representation of the CS is depicted in Fig. 6. The charging prices are fixed in view of maximising the net income to the CS owner.

Due to the varying prices, EVs at CS may change their decision to charge or discharge. For example, if the charging price at the CS is increased then some of the EVs may choose to discharge instead of charging, or vice versa. This enables the CS to vary power demand by changing prices, hence DR. The CS is also equipped with BESS and PV panel. The constraints related to BESS are as follows:

\[
\text{SoC}_{CS} \leq \text{SoC}_{CS} \leq \text{SoC}_{CS}
\]  

(18)

where \(\text{SoC}_{CS}\) refers to state of charge of the BESS at the considered time instance, whereas \(\text{SoC}_{CS}\) refers to minimum state of charge to be maintained while \(\text{SoC}_{CS}\) refers to upper limit of state of charge. Numerical considered values for \(\text{SoC}_{CS}\) and \(\text{SoC}_{CS}\) are 0.2 and 0.9, respectively, whereas the PV panel is expected to produce power according to the bar chart as shown in Fig. 7 during the study period.

There are certain assumptions to be considered with respect to the CS, which are listed as follows:

- Vehicles connected to the charging ports remain connected throughout the time slot, i.e. 1 h while charging or discharging at constant power.
- Discharging price offered to the EVs is 90% of charging price.
- Total number of EVs to be present at the CS is same as shown in Fig. 8 during the considered study period of 24 h. It is typical for a day and may vary for a different choice of study period.
- When the prices are varied by the CS, the EV owners respond to change in price by changing decision to charge or discharge based on the charging decision model shown in Fig. 9. Here, delp(h) refers to the deviation of charging price as compared to the grid electricity price. From the plot it is observable that not >20% of the vehicles deviate from their dispatch action. When there is an decrement in the charging price, i.e. delp(h) is negative, then the number of charging cars increases by a factor of charging decision multiplier, and vice versa.

The proposed CS employs BOA to determine the appropriate price deviation \(\Delta EP(h)\) from grid price throughout the study period of 24 h as well as to schedule the BESS in order to maximise net income in response to changing grid electricity price. The objective function considered by the CS is given as
at hour $h$ while, $\text{NEV}_{\text{dch}}^h$ represents number of EVs discharging at hour $h$. $\text{CP}_h$ and $\text{DP}_h$ represent charging and discharging prices offered to EVs at hour $h$. $\text{BESS}_{\text{max}}^h (\text{W})$ refers to maximum capacity of BESS at the CS while $\text{EGS}_{\text{ch}}^h (\text{h})$ represents energy generation at CS at hour $h$.

At the CS, BOA is employed to determine the optimal $\Delta \text{EP}(h)$ w.r.t. grid price $\text{EP}(h)$, such that the objective of the CS to maximise all-day income is fulfilled as in (19). Along with $\Delta \text{EP}(h)$, BOA also determines suitable schedule of BESS in order to increase the net income without violating the BESS constraints. The charging price offered to EVs is calculated as

$$\text{CP}_h = \text{EP}(h) + \Delta \text{EP}(h)$$  \hspace{1cm} (21)$$

Such that: $\Delta \text{EP}(h) \in [-0.2 \times \text{EP}(h), 0.2 \times \text{EP}(h)]$.

The population matrix is formed as shown in Fig. 10. Here the population size is taken as 20. While rest of the optimisation technique functions as that referred to in industrial scheduling. The results so obtained are presented and analysed in Section 4.

### 3.3 Aggregated residential loads

The third type of consumer considered in this paper is an aggregate of numerous residential loads. The load consumption pattern is illustrated in Fig. 11 for this consumer type. Normally, as observed the residential loads have lesser schedulable loads as compared to non-schedulable loads. Therefore, the scope of DR is limited for this type of loads when compared to other loads considered in this paper. Although the introduction of advanced metering infrastructure has enabled users to take informed decision and optimise their usage. The success is limited due to lack of participation or awareness of users in general.

The residential consumers are motivated for DR techniques solely due to monetary benefits. The objective function to perform DR for residential loads can be formulated as

$$\min \left\{ \sum_{h=1}^{24} \sum_{r=1}^{N_{\text{res}}} E_{h,r} \times \text{EP}(h) \right\}$$  \hspace{1cm} (22)$$

where $E_{h,r}$ represents the energy consumed by individual residential load $r$ among a total of $N_{\text{res}}$ during hour $h$. $\text{EP}(h)$ represents the electricity price during hour $h$.

### 4 Results analysis and discussions

This section illustrates the strength of the proposed mechanism. The scheduled load consumption patterns through DR for individual consumers as well as aggregate of the system are presented. Initial and final schedules w.r.t. price profiles, for all consumers and the respective optimisations performed are compared.

We considered three consumers of different types to validate the performance of the proposed mechanism of VSÖ. The optimisation starts with initially expected demand profile of the consumers and corresponding price profile. Over the iterative process of rescheduling loads and updating price, it is expected to achieve a balanced profile of demand and electricity price, which satisfies the objectives of all concerned entities with necessary tradeoff. Among the consumers, the industrial load proactively reschedules the load demand to reduce the net operating cost while meeting the production constraints. The industry at a particular hour chooses the best of OGS and WCS operating indices to engage along with the dispatch actions of the BESS, oxygen storage and water storage systems which optimises the net electricity cost over the considered day. The CS utilises DR to maximise its profit over a day of operation. Since the CS does not have any directly controllable load, it optimises the power transaction by motivating the EVs to change their dispatch action through variation in charging/ discharging costs. Along with, determining the charging cost the CS also optimally schedules BESS to further aid in optimising the demand schedule. The aggregated residential load is the third consumer considered. The residential load is motivated solely
towards reducing the net electricity bill. The aggregated profile of the residential loads is presented for analysis.

In Fig. 12, the convergence characteristic of the iterative process is presented. The iteration is stopped when convergence criterion is satisfied, i.e. \( \varepsilon \leq \varepsilon^* \). In this study, \( \varepsilon \) is taken as 15\%. It is observed in this plot that over the iteration the maximum change in electricity price reduces in magnitude w.r.t. that in the previous iteration.

The price profile presented in Fig. 13 shows the comparison between the initial and final price profile. It is observable that the final price profile turns out to be closer to the mean value at all hours as compared to the initial price profile. This indicates towards a fairly distributed load consumption pattern. The optimised schedules obtained for individual consumer units are compared w.r.t. initial and final price profiles.

Fig. 14 compares the demand profile of the industrial load after DR corresponding the initial offered price profile and final schedule after successive iterations of rescheduling with VSO. The profiles appear more to be shifted in time rather than towards mean load. This scenario effectively demonstrates the rescheduling process of the VSO. Here, the load demand of industry strategically shifts in the process to balance the overall system load towards the mean load and ultimately obtain a flatter demand profile in unison with other consumers. A completely flatten demand profile may not be possible due to operational constraints of the industry.

The industry was aided by a 6000 kWh BESS. The dispatch schedule of the BESS obtained by BOA is presented in Fig. 15. Observably, the distinction in schedules corresponding to initial and final price profile arises to suit the price profiles. The BESS while not violating the SoC limits, strategically charges during low price period and discharges during high price periods to reduce overall cost of operation.

The variation in the electricity demand at the CS is shown in Fig. 16. As compared to the initial load profile, the final load profile is observed to be less during most of the hours. The CS during consecutive iterations of VSO attempts to reduce its dependency on the grid and hence the net import by varying the charging price it offers to the EVs. Fig. 17 shows the dispatch schedule of the BESS at the CS of capacity 1500 kWh. The BESS schedule obtained by BOA optimisation allows the CS to charge the BESS during low price period. The BESS is then discharged during high price periods in order to reduce power import during such period.

Fig. 18 illustrates the charging prices offered to the EVs at the CS obtained using BOA. The CS offers the charging price such that the net income is enhanced. During low price period the CS to motivate more charging, lowers the prices and increases during high price period. Care is taken to not affect the dispatch action of >20% of the EVs. The EVs in return react to the variation in prices by changing their decision of charging or discharging according to the charging decision model shown in Fig. 9. In comparison to the number of EVs initially charging or discharging shown in Fig. 8, Fig. 19 shows the improvised count of charging or discharging vehicles.
It is evident that the increased number of discharging vehicles enables the CS to reduce power import from the grid. Moreover, referring to Fig. 16, due to decreased charging power requirement, a portion of the power output from the PV panel is exported to the grid which further adds to the net income.

Fig. 20 illustrates the effect of DR on the background residential load. The initial and final load profile does not vary by >10%. The background load demand curve although aiming towards a flattened profile does not show much deviation from initial curve as compared to that of CS and industry due to its inherent nature.

Fig. 21 clearly illustrates the effectiveness of the proposed method such that the suggested net system demand to be scheduled by the DSO is flattened as compared to the initial demand profile. From the SO's perspective, this load schedule is appreciable as peak and underloads are reduced than the initial profile.

Inclusion of VSO in the system has significant impact on the load consumption pattern of every consumer from individual as well as aggregated point of view. From previously presented results it is observable that the employed DR technique successfully improves the demand schedule in order to be economical for the consumers as well as flattens the demand profile to better suit the SO. Numerical proofs for the same are provided in Tables 3 and 4. In Table 3, variation in demand schedules of various consumers in response to changing price profiles is compared. Clearly, the mean of aggregated load of the system is observed to reduce along with the maximum deviation of the schedule from the mean value over the study period. The overall optimisation of demand schedule is achieved even though the industrial load does not follow similar pattern as the other consumers do. From Table 4, it is justified that the operation cost of industry during the instances of comparison goes on decreasing.

Table 4 compares the cost of operation and the net profit of the concerned entities over the study period. Operating costs for all entities without DR, with DR for initial and final price profiles are compared, and notable saving in terms of operating cost is observed at each stage as compared to the previous one. The operating costs of industry, CS and residential loads are observed to reduce by ~6, 45 and 7%, respectively, when compared for the same price before and after performing DR. The huge change in operating cost for the CS is observed as the effective load changes owing to changed decision regarding dispatch of EV owners, in reaction to offered charging price. Further, when comparing respective initial operating costs with that obtained after performing DR for final price reduction by ~6, 63 and 7% is observed for industry, CS and residential load, respectively. In aggregate reduction in operating cost by 4% is observed for initial price profile with and without performing DR, while 9% of reduction is observed when initial and final operating costs are compared. The presented incomes for CS are the optimal incomes owing to the applicable price profile. Observably, increase in income is noted after DR for the initial price profile by nearly 27%, but being suitable to overall system the price profile finally converges such that the CS manages 17% more income instead, as compared to the initial scenario. Hence, the proposed concept emphasises more on the collective benefit of the system along with individual benefits.

5 Conclusions
This paper presented a novel concept of VSO. The VSO enables the constituent entities in the considered system to perform DR to
foresee the impact of DR performed to the best of their interest through an iterative process. Each entity considered different primary objective to schedule their loads such as industry to reduce net operational cost, CS to enhance net income and DSO to uniformly distribute loads over considered time span. Through the results presented it was verified that these objectives were satisfactorily met. Moreover, at the end of the iterative process the load demand profile so obtained by each unit could directly be communicated to the SO. Such a load schedule would ensure reliable and secure operation of the system and also reduce burden on the generating systems during peak hours.

### 6 References

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### Table 3 Demand response assessment of system entities

|                     | Industry | Charging station | Residential load | Aggregated system |
|---------------------|----------|------------------|------------------|-------------------|
| without DR          | mean load, MW | 8.450            | 0.8848           | 14.879            | 24.2140 |
|                     | max. deviation from mean load, MW | 2.2603           | 1.3052           | 4.0406            | 6.4363  |
| DR for initial price| mean load, MW | 8.1593           | 0.5018           | 14.800            | 24.614 |
|                     | max. deviation from mean load, MW | 3.2547           | 1.227            | 3.1116            | 4.9150  |
| DR for final price  | mean load, MW | 8.2102           | 0.842            | 14.645            | 23.2019 |
|                     | max. deviation from mean load, MW | 3.0418           | 0.787            | 2.852             | 3.5298  |

### Table 4 Monetary assessment of system entities

|                     | Without DR for initial price, price, €/day | For initial price, price, €/day | For final price, price, €/day |
|---------------------|--------------------------------------------|----------------------------------|-------------------------------|
| industry operating cost | 4.87 × 10³                                    | 4.70 × 10³                     | 4.59 × 10³                    |
| charging station net income | 208.08                                      | 265.95                           | 245.25                        |
| charging station operating cost | 534.27                                      | 296.71                           | 196.45                        |
| residential load operation cost (aggregated) | 8.83 × 10³                                    | 8.70 × 10³                     | 8.25 × 10³                    |
| net system operating cost | 14.27 × 10³                                    | 13.71 × 10³                     | 13.04 × 10³                  |

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