Potential impacts of emission control policy on the vehicle to grid environment: a novel approach

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Abstract: Environmental conditions strained the existing transportation network to replace its conventional gasoline-based engines by electric vehicles (EVs) to reduce its share in pollution. EVs promise a potential solution, but they fail to motivate end users because of their inherent drawbacks. Utilisation of EVs in vehicle-to-grid (V2G) environment is expected to boost EVs penetration but will burden the conventional power generations for their energy demand. For improvement of the environmental conditions, it is likely that the authorities will come up with a strict emission control policy. This study demonstrates the effects of emission policy on the V2G environment. The proposed problem is modelled as a multi-objective optimisation problem. Non-dominated-sorting-based genetic algorithm (NSGA-II) is used to solve this problem. This study also demonstrates a long-term impact analysis of a system consisting of a V2G market, end users and EVs by considering time variance in EVs penetration and vehicles’ performance degradation. This analysis can help in planning and formulating the future V2G market.

1 Introduction

Increase in global energy demand will adversely affect the environment with 10% expected an increment in air pollution by 2040. The current environmental condition leads to global warming, airborne diseases, premature deaths etc. In India alone, about 0.59 million people prematurely died due to air pollution in the year 2012 and 3 million die annually on a global level [1]. This statistical data is just a glimpse of environmental degradation effects on humans. Therefore, a cleaner substitute to fulfill the energy demand becomes mandatory.

The transport sector alone shares more than 50% of total emission followed by industries around 26% and the least by the power generation sectors which constitute only 14% [1, 2]. Pollution from industries and power sectors has an indirect effect on humans since they are generally installed at the outskirts of cities, i.e. away from people's habitat. Whereas the transportation sector is a part of humans' lifestyle and its local emission has an immediate effect on humans. Cutting down the pollution from the transport sector has become of prime importance due to its direct impact on humans, and it also holds the most significant share of emission sources. One of the widely accepted emission reduction strategies is to replace the conventional internal combustion engines (ICEs)-based vehicles with electric vehicles (EVs).

EVs are capable of reducing emissions, but they have their own limitations and drawbacks. Their travel distance is based upon the energy storage limits which are very expensive to expand. Storage units not only need regular maintenance but also degrade upon usages at a much faster rate than ICEs. Cost, lifespan and distance travel limitation are some significant restrictions on EV technology acceptance by users. Furthermore, the emission reduction capability of EVs is under question since it relies on the electrical energy supply from conventional sources which are mainly coal-based generation systems. Even if, battery electric vehicles replace ICE-based vehicles, there will be no vibrant benefit of emission reduction. Such replacement of technology will only shift the point-of-emission from the transport sectors to the power generation sectors.

Integration of renewable resources such as solar, wind, tidal is expected to become a vital part of the future smart grid. However, they are intermittent. With the help of vehicle-to-grid (V2G) technology, EVs can act as a storage system for renewable energy sources and give the stored energy back to the grid [3–6]. Smart operation of vehicles’ fleet in the V2G environment can reduce both the system operating cost and emission [7].

Regardless of EVs’ infinite potential, the current operating condition makes this technology impractical in the present situation [8]. EVs rely on the grid for their transportation purpose. Due to uncertainty, EVs go for random charging which causes a stability problem. Numerous works have been proposed in the literature to solve this problem. The most common proposals are an application of centralised and decentralised modes of control [9, 10]. An indirect approach such as real-time pricing scheme control has also been used [11, 12]. Further, a concept of aggregator [13, 14], i.e. an agent in an electricity market on behalf of EVs' users who negotiates with the utility companies for EVs' services on a commission basis is introduced in the V2G market and expected to remove users' concern of V2G operation. However, most of these approaches involve security risk of users' privacy breach due to large data acquisition and individual monitoring of vehicles and users.

To promote green substitutes of ICEs, governments provide subsidy on production and electrical fuel price (FP). The grant provided to users on EVs usage reduces operating/running cost as compared to ICEs. Due to a rapid increase in EVs penetration and the proposed involvement of V2G market, it is least likely that governments will allow profit on the resale of subsidised electrical energy. Therefore, it is expected that V2G market operating and running cost of EVs will cost more than conventional ICEs [15].

In this paper, authors analysed the V2G market impact on the environment while incorporating practical hindrances involved in its application. The simulation of vehicles' fleet under probabilistic environment is done by generating random samples of vehicles' location, speed, grid availability etc. Bayesian analysis is done to find the nature of probability distribution of vehicles' fleet in the transportation network. Pricing mechanism is utilised to control the vehicle power demand in an uncontrolled fleet operation of vehicles. In this paper, authors assumed that all EVs are plug-in hybrid electric vehicles (PHEVs) and their running cost is more than ICE-based vehicles due to unsubsidised electricity market. While simulating a V2G model, authors have taken care of battery degradation, PHEVs sales and penetration level in market and power demand growth over a 5-year time span. Further, our present work can predict the real potential of PHEVs for emission reduction capability while maintaining a profit margin in the V2G market.
The main contributions of this paper are as follows. A novel approach to incorporate the shortfall of V2G technology while determining its long-term impact on the system is proposed. An uncoordinated V2G structure with an indirect cost-based control system is intended to minimise the risk of privacy and security of users who are part of V2G. A long-term analysis of V2G fleet is also done to see the impacts.

The organisation of this paper is as follows. Section 2 explains the modelling of vehicles and V2G electric market. The proposed multi-objective optimisation problem is defined in Section 3. Section 4 gives the details of the case study and the simulation results. At last, the paper concludes with final remarks and future scope in Section 5.

2 Mathematical modelling

V2G operation in a smart grid requires substantial data acquisition and monitoring. Since EVs’ utilisation profile is random and time variant, a common probability density function (PDF) lacks to grasp the inner picture of practical hindrances such as vehicles’ movement before and after working hours and on holidays [12]. Therefore, authors suggest that a stochastic PDF is more suitable than a standard PDF for a day.

In this paper, authors are interested to find the probabilistic behaviour of operating cost, emission, V2G energy and the battery status of EVs during their lifetime in a V2G environment. Thus, the analysis is subjected to three main determining factors such as probabilistic drive profile, operating points in the trade-off characteristics of cost and emission from users’ point of view and the optimal V2G operation.

2.1 Time quantisation

The period of analysis is split into $N$ intervals by a quantised slot of $\delta T$ [16]. Quantisation operation ensures that vehicles do not alter their operating states such as charging, discharging and inert within the committed period of $\delta T$. Their state change request will only be permitted after the current time interval. This helps the grid operator reorganise vehicles for the next time slot. Users can disconnect their vehicles at any moment of the time interval by sending a disconnection request. There may be a delay in accepting users’ disconnection request due to their commitment.

A large $\delta T$ will increase the delay in state change which will cause dissatisfaction among V2G registered users. The $\delta T$ is selected based upon the assumption that the users’ behaviour should be least affected if they opt for V2G operation. Any delay in V2G operation should be same or similar to the maximum delay that a vehicle’s user can tolerate in non-V2G operation, i.e. conventional ICE vehicles usage. The V2G operational time lag can be considered as a similar 3–6 min [17, 18] time delay occurring in refuelling at petrol/gas station in conventional ICE vehicles usage. Considering the vehicle fuelling time delay as the deciding criterion, authors assume the quantisation time $\delta T$ as 5 min with 288-time steps in a one-day simulation.

2.2 Mobility profile

2.2.1 Vehicle availability: Considering working days case, any vehicle can undergo the transition as given in Fig. 1. In morning hours, vehicles are expected to be parked at homes and make a transition to workplaces/offices via road. Similarly, vehicles will depart for homes in evening time which will increase the on-road population of vehicles. Therefore, a usual rush hour for a vehicle fleet can be identified as morning and evening. Noon and night time are off-peak periods since vehicles are parked in parking areas at the office places and homes, respectively. A sudden jump in vehicle population on the road usually occurs before and after working hours. The average distance justifies the above hypothesis by travelled data of German transportation as reported in [19].

Let $\mathcal{N}$ denotes the set of vehicles registered for V2G operation with the fleet size $N := |\mathcal{N}|$. The number of vehicles ($X := [\mathcal{X}]$) connected to the grid can be considered as a time-variant variable. Since an exact trend of EVs' availability is not known, authors perform a Bayesian analysis to generate the vehicles samples. Initial samples are generated by the acceptance–rejection method given in [20] for vehicles location. The prior ($X_{\text{grid}}$) distribution for analysis is assumed to follow a beta distribution (1). The likelihood distribution ($X_{\text{veh}}$) is considered to follow an exponential distribution (2) based upon queueing M/M/C model [21]. The number of arrival and departure for M/M/C model is estimated from initial samples. Finally, a posterior (3) distribution ($X_{\text{post}}$) is constructed using empirical Bayesian analysis [22] and used to generate random sample population of vehicles' availability and their location in the network

$$X_{\text{pri}} \sim \text{Beta}(\alpha, \beta)$$

(1)

$$X_{\text{veh}} \sim \exp(\lambda)$$

(2)

$$X_{i}(\theta) \propto X_{\text{pri}}(\theta)X_{\text{veh}}(\lambda|\theta)$$

(3)

2.2.2 Speed profile: Once on road vehicles’ population and location are determined, the next thing is to compute vehicles' kinematics. Let $\mathcal{N}_{\text{veh}}$ is a set of mobile vehicles used in transportation at any moment of time slot $i$.

$$\mathcal{N}_{\text{veh}} \subseteq \mathcal{N}, \ \forall i \in \{1, 2, \ldots, i_{\text{max}}\}$$

(4)

Considering $N_{\text{veh}} := \lfloor N_{\text{veh}}\rfloor$ is the number of vehicles on road at any time interval, i.e. $N_{\text{veh}} \leq N$. Distance travelled ($D_{(i)}$) by $k$th vehicle is generated by data reported in [19]. The speed profile (5) of the vehicle fleet is formed by generating sets of random numbers $[0,1)$ which satisfy (6). $V_{\text{veh}}$ is vehicle’s speed restriction in its operating area. The average acceleration (Acc) of $k$th vehicle at $i$th time interval is determined by (7)

$$V_{l,k} = r[0, 1]V_{k,\text{max}}$$

(5)

$$N_{\text{veh}} \times D_{\text{avg}} = \sum_{k = 1}^{\text{max}} r[0, 1]V_{k,\text{max}} \delta T$$

(6)

$$\text{Acc}_{l,k} = \frac{V_{k,l} - V_{k,l-1}}{\delta T}$$

(7)

2.3 Vehicle kinetic model

The vehicles considered in this research are PHEVs. The drivetrain of hybrid vehicles consists of two power sources, one is a battery-stored electrical energy source, and another one is a gasoline-based ICE. Hybrid vehicles are costly, but they have benefits of both pure battery-powered EV and ICE. Due to the dual availability of drive mechanisms, two different types of fuel consumption rate and behaviour need to be considered.

2.3.1 ICE fuel and emission profile: Vehicle fuel ($\bar{F}$) and emission ($\bar{E}$) rate prediction require instantaneous kinematics variables. The dependency on rates is also related to driving characteristics. Numerous models are available in literature such as MOBILE and EMFAC large-scale models, to characterise the fleet
structure. An averaged over time-discretisation interval model is implemented on vehicles profile to obtain their fuel consumption and emission. The approach of the prediction model is based upon the look-up table given in [23]. Using the tabled data sheet, a non-linear 2D-interpolation is applied to frame the kinematics dependent fuel consumption rate and emission rates. The emission from ICE due to its fuel consumption is a composite mixture of carbon monoxide (CO), hydrocarbons (HC) and nitrogen oxides family (NOx). Based upon the instantaneous speed and acceleration data, the information regarding its fuel and emission rates are obtained by interpolating with the help of tabulated data. Cubic splines method is applied for data interpolation and out-of-bound values rounded-off to the nearest neighbours.

2.3.2 Vehicle degradation: With the utilisation of a vehicle, its life and performance degrade with time. The key factors that affect the vehicle's life are mechanical wear and tear, weather and EVs' battery cyclic degradation. EVs have a much lower lifetime in comparison to ICEs because the batteries of EVs degrade at a much faster rate in contrast to other parts of vehicles.

In this work, a battery-based EVs' annual degradation model is used. It can be written as sum of battery's degraded state and current year degradation ($\Delta D_{Bat}$,year) as

$$D_{Bat,k,year} = D_{Bat,k,year-1} + \Delta D_{Bat,k,year}$$

Such that,

$$\Delta D_{min,k} \leq \Delta D_{Bat,k,year} \leq \Delta D_{max,k}$$

Decay rate of a battery ($\Delta D$) is restricted by its upper and lower limits as in (9) due to restriction on battery's charging/discharging rates and its cyclic operation. Vehicles from the same operating area are expected to have similar drive profile. Therefore, is assumed that the vehicles' degradation due to mobility is same for all users. For V2G penetration, it is required that the users are least affected. Hence it is further assumed that the vehicles' utilisation pattern will not be affected if they are registered under V2G market. Thus, the battery degradation due to vehicles mobility will not change but an additional decrease in battery life will occur when it participates in a V2G market.

For the simulation of PHEVs over their lifetime, an empirical vehicle degradation function is applied. Assumptions used for EVs' battery are that it will provide 5 years’ service in PHEVs and need a replacement when it is degraded below 50% of its maximum capacity, i.e. below an economical usage limit. Under such assumption, the constraints on $\Delta D$ can be written as

$$\sum_{year=1}^{\infty} \Delta D_{Bat,year} \leq 0.5$$

Therefore, the upper limit on $\Delta D$ is set as 10%. The lower limit on $\Delta D$ is assumed as 5% based upon the previous assumption of an unaffected users' drive pattern in a V2G market and the users from the same locality having similar drive profile. The parameters like a number of charge/discharge cycles, operating weather conditions and self-degradation are random and their prior knowledge is not possible. To introduce randomness in the vehicles' degradation profile, authors used a uniform distribution to generate the decay factor ($\Delta D$) within its upper and lower limits.

2.3.3 EV energy profile: The electrical part of PHEVs produces drive energy by converting the chemical energy stored in the battery into an electromechanical form. Expected drive distance of EVs depends upon the maximum storage capacity, present energy value and the vehicles' kinematics. Thus, vehicle mileage model depends upon battery performance and drive kinematics. The battery of EVs is modelled as a capacitor equivalent [24] model. It is assumed that the terminal voltage of battery follows the capacitor's exponential governing equations. The instantaneous energy ($E_{cap}^{up}$) of a capacitor [25] is proportional to capacitance ($C$) and square of capacitor's terminal voltage ($V(t)$) as following:

$$E_{cap}^{up} \propto (C \times V(t)^2)$$

Further, the EVs battery degradation is approximated as a fall in capacitance value [26] with time. The instantaneous energy of discharging battery is modelled regarding $D$ and maximum energy as a capacitive discharge model as given in (13),

$$E_{Bat}^{dis} = \left(1 - \frac{D_{Bat}}{D_{Bat,year}}\right) \times E_{Bat,year} \times e^{-(t,t_{k,1})}$$

$E_{Bat,year}$ is the energy state of kth vehicle battery at time $t$. $D_{Bat,year}$ denotes battery degradation parameters which subsequently depends upon battery cycles and operating time.

$t_{k,1}$ is a kinematics-dependent parameter which depends upon the mobility state of the vehicle. Due to the lack of an exact model for EVs in literature, authors used an empirical model derived from the sweet spot operation of ICE. According to the sweet spot empirical model, the vehicle will have maximum efficiency when it operates within 10% of an efficient range. In case of EVs, the battery energy consumption rate increases with a deviation of vehicles speed from its optimal and expected range of travel. Therefore, $\frac{dR_{expected}}{dV}$ of a fully charged EV at a given speed ($V$) is approximated by a fourth-order polynomial curve as given in (14), where $a_k$ to $a_0$ are the coefficients of curve-fitting parameters.

$$R_{expected} = a_kV^4 + a_1V^3 + a_2V^2 + a_3V + a_4$$

$$\frac{dR_{expected}}{dV} = 4a_kV^3 + 3a_1V^2 + 2a_2V + a_3$$

The rate of change of expected distance with vehicle's velocity is given by (15), i.e. expected time of travel. Thus, EV's kinematics time constant ($t_{k,1}$) can be written as proportional to expected time of travel as in (16).

2.4 V2G energy exchange model

When a vehicle is connected to the grid, it will either go for charging, discharging or supporting ancillary services by keeping its battery energy as an active power reserve. For charging, similar kinematics-dependent capacitive discharge model but with modification of battery time constant are used as given in (17) and (18), respectively.

$$E_{Bat,t_{1,1}} = \left(1 - \frac{D_{Bat}}{D_{Bat,year}}\right) \times E_{Bat,year} \times (1 - e^{-t/t_{k,1}})^2$$

$$E_{Bat,t_{1,1}} = \left(1 - \frac{D_{Bat}}{D_{Bat,year}}\right) \times E_{Bat,year} \times e^{-(t,t_{k,1})}$$

where $T_{cha,1}$ and $T_{cha,1}$ are the lower and upper time limit to charge an empty battery to its lower ($E_{Bat,t_{1,1}}$) and upper limit ($E_{Bat,year}$), respectively. The charging time of a battery can be defined as $T_{cha} = T_{cha,1} - T_{cha,1}$. Similarly, for discharging process $T_{dis,1}$ and $T_{dis,1}$ are the upper and lower limit of time to discharge from its maximum energy state to its $E_{Bat,1}$ and $E_{Bat,1}$, respectively. The charging time of a battery with time $t_{cha,1}$, $t_{cha,1}$ and $t_{cha,1}$ are fraction of lower and upper limit of Kth vehicle's battery to its maximum energy capacity $E_{Bat,year}$, respectively. Using charging and
discharging (17) and (18), the charging \( τ_{\text{cha}} \) and discharging \( τ_{\text{dis}} \) time constant can be written as in (19) and (20), respectively.

\[
τ_{\text{cha}} = \frac{T_{\text{cha}}}{\log((1 - \sqrt{\theta_{\text{cha}}})(1 - \sqrt{\theta_{\text{U}}}))} \quad (19)
\]

\[
τ_{\text{dis}} = \frac{T_{\text{dis}}}{\log(\sqrt{\theta_{\text{cha}}}/\sqrt{\theta_{\text{U}}})} \quad (20)
\]

### 2.5 ICE fuel pricing

Cost of operation of a PHEV in an ICE mode is modelled as per unit of fuel consumed. In a domestic market, gasoline FP is dynamic only in the long run. An average, the FP remains constant for a few days to months. Thus, a constant ICE fuel cost model is applied, i.e., the price of petroleum price in the Indian domestic market as of 16 June 2016.

### 2.6 V2G energy market

V2G is a power market structure in which the grid is supporting vehicles that get financial gain for their services to the network which includes smart charging, providing active power to the grid and ancillary support services to utility companies. Development of a practically applicable market [27, 28] structure is one of the most crucial technological hindrances in the advancement of V2G technology. Thus, a market structure is necessary for V2G operational analysis.

For understanding V2G energy market, Let \( N_{\text{j}} \) is a set of parked EVs at any moment of time \( i \)

\[
N_{\text{j}} \subseteq N, \quad ∀i \in \{1, 2, \ldots, i_{\text{max}}\} \quad (21)
\]

\( N_{\text{cha}}, N_{\text{dis}}, \) and \( N_{\text{int}} \) are sets of charging, discharging and inert vehicles, respectively. The \( N_{\text{cha}}, N_{\text{dis}}, N_{\text{int}} \subseteq N_{\text{j}} \) are mutually exclusive hence

\[
N_{\text{cha}} \cup N_{\text{dis}} \cup N_{\text{int}} = N_{\text{j}} \quad \cap N_{\text{cha}} \cap N_{\text{dis}} \cap N_{\text{int}} = \emptyset
\]

The V2G market used here has three pricing schemes which are as follows.

#### 2.6.1 Buying price (BP): Vehicle charges its battery from grid power for which the user has to pay for per kilowatt hour of energy consumed during charging process which is defined as a buying price. When the system is charging demand increases, i.e. during peak hours, the user demand will increase, and supply of energy will become low. Hence the BP will increase with total load \((10, 29, 30)\) stress \((D_{\text{cha}} = D_{\text{load}} + D_{\text{cha}}, ∀i)\), where \(D_{\text{load}}\) and \(D_{\text{cha}}\) are system load and vehicles’ fleet charging demand, respectively.

\[
D_{\text{cha}} = \sum_{k \in N_{\text{cha}}} D_{\text{cha}, k} \quad (22)
\]

Therefore, the buying price in the V2G market will be restricted by the following constraint:

\[
\text{BP}^{\text{i}}(D_{\text{cha}}^{\text{i}}) < \text{BP}^{\text{i}}(D_{\text{cha}}^{\text{i}}) \quad ∀i \in \{1, 2, \ldots, i_{\text{max}}\} \quad (23)
\]

#### 2.6.2 Selling price (SP): The price at which the vehicle’s user will sell energy to the grid or the rate at which utility company will buy electricity from the users. Vehicles active power discharge \((\text{Dis})\) to the power-grid provides payback to users at the rate of per kilowatt hours of energy.

In a dynamic cost market, \( SP^{\text{i}} \) at \( i^{\text{th}} \) time will be direct functionality of total load stress \((D_{\text{dis}}^{\text{i}} = D_{\text{load}} - D_{\text{cha}}, ∀i)\) on the network which is an instantaneous sum of non-vehicular load and V2G discharge power of vehicles.

\[
D_{\text{chi}}^{\text{i}} = \sum_{k \in N_{\text{cha}}} D_{\text{dis}, k} \quad (24)
\]

When there is an abundance availability of V2G discharge power, the utility will be willing to pay at a lower rate as in (25) and the rates will be decided by demand-supply equilibrium.

\[
SP^{\text{i}}(D_{\text{dis}}^{\text{i}}) \leq SP^{\text{i}}(D_{\text{dis}}^{\text{i}}) \quad ∀i \in \{1, 2, \ldots, i_{\text{max}}\} \quad (25)
\]

#### 2.6.3 Ancillary price: It is the price paid to the user by the utility company for providing an active power reserve. The ancillary price (AP) is rated for reserve power that can be promptly available for the commitment period of the vehicle. The reserve revenue incentive will motivate the users to use energy for the V2G market purpose even if the selling profit margin is low.

The grid-connected vehicles can serve as a system active power reserve by fulfilling the immediate demand from the grid. Reserve capacity of the fleet will be determined by the amount of energy stored in EVs battery over and above its threshold limit \((\Phi)\) which restricts the complete depletion of battery. The reserve energy available at any moment of time \( i \in \{1, 2, \ldots, i_{\text{max}}\} \) is defined as

\[
E_{\text{i}}^{\text{Anc}} = \sum_{k \in N_{\text{cha}}} (E_{\text{i}}^{\text{Bat}, k} - \Phi E_{\text{i}}^{\text{Bat}, k}) \quad (26)
\]

The AP at any moment of time should be a decreasing function of vehicles’ stored energy availability as defined in (27)

\[
AP^{\text{i}}(E_{\text{i}}^{\text{Anc}}) < AP^{\text{i}}(E_{\text{i}}^{\text{Anc}}) < E_{\text{i}}^{\text{Anc}} \quad ∀i \in \{1, 2, \ldots, i_{\text{max}}\} \quad (27)
\]
HC and NOx released per unit of fuel consumed in $\delta t$ time of operation. 

Minimise

$$f_{\text{Cost}} := \sum_{i=1}^{m} (\mu_i C_{\text{ICE}} + (1 - \mu_i) C_{\text{V2G}})$$  \hspace{1cm} (28)$$

$$f_{\text{Emission}} := \sum_{i=1}^{m} (\mu_i E_{\text{CO}} + E_{\text{HC}} + E_{\text{NOx}})$$  \hspace{1cm} (29)$$

where

$$C_{\text{V2G}} = \lambda \text{Char}_k (1 - \text{Dis}_k) (1 - \text{Anc}_k) (E_{\text{Bat}} - E_{\text{Bat},i-1}) BP$$

$$C_{\text{ICE}} = (\hat{F}_{i,k} - \hat{F}_{i-1,k}) FP$$

Such that,

$$\mu_i, \text{Char}_k, \text{Dis}_k, \text{Anc}_k \in (0, 1)$$

$$\text{Char}_k + \text{Dis}_k + \text{Anc}_k = 1; \forall i, k$$

$$E_{\text{Bat}} \leq E_{\text{Bat},U} \text{ if } \text{Char}_k = 1$$

$$E_{\text{Bat}} \geq \Omega_{\text{Bat},U} \text{ if } \text{Dis}_k = 1,$$

$$\text{BP} \geq \Omega_{\text{BP}} \text{ if } \text{Anc}_k = 1.$$  \hspace{1cm} (35)$$

During V2G discharging, the PHEV should not be discharged completely since the vehicle utilisation for transportation purpose is random and its exact prior knowledge of utilisation is not possible. Therefore, the V2G operation should take care of such contingency of vehicle depletion by restricting the PHEV to discharge below a threshold value ($\Omega$) as given in (35). Similarly, the reserve or ancillary support for instantaneous discharging is also restricted by the threshold of reserve ($\Phi$) as given in (35).

### 3.2 Optimal points

Authors of this paper are mainly interested in finding the all possible optimal points on which PHEVs can be operated. In a multi-objective problem, there is no single optimal solution instead there is a set of solutions called Pareto-optimal front. A system can operate on all optimal solutions based upon the trade-off points between different objectives. Therefore, as a first step, objective functions (28) and (29) are simultaneously minimised to find the Pareto-optimal front.

Once the Pareto front is known, the modelling of the government policy on emission can be done. For this, let us consider a sample search space as shown in Fig. 2. The line ABCD is a Pareto front, and all the bubbles are the feasible solutions. The points A and D are the independently optimised objectives cost and emission with values $C_{\text{min}}$ and $E_{\text{min}}$, respectively. PHEVs’ users will always try to maximise their profit by minimising the operating cost. Thus, the users will attempt to operate their vehicles near the critical point A which gives the maximum profit. However, the operating point cannot be fixed at a particular point. Therefore, the possible samples of the operating point will be near point A and be restricted by line $C_1 C_2$, which defines the maximum operating cost that a user is interested to bear on the sacrifice of profit. On the Pareto front, AB segment defines the possible operating region (III) where authors call as cost-oriented operation since sample solutions are near the minimum cost point. When the government changes its policy and implements an upper cap on emission to control the pollution level which is represented by line $E_2 E_2'$; the operating point will shift from A to B, and the possible operating samples will be less than the emission cap. Similarly, the user’s operating cost will also shift from $C_1$ to $C_2$ and be constrained by the boundary condition $C_2 C_2'$. The operating region II is a trade-off zone concerning objective functions. On the next level, if the upper cap on emission is further reduced from $E_2$ to $E_1$, then new region (I) of operation will be CD and called as emission oriented. The different levels of operation can be implemented for any number of levels, but in this work, only three regions are considered.

Mathematically, the operating points of different regions based upon policy are defined as follows. Let us consider $\mathbb{R}^m$ as Pareto-metric space defined as ordinate (emission in this case) in Euclidean search space. It is sliced by the system functions $f_1, f_2, f_3, f_4$ and transformed as $f_1: \mathbb{R}^m \rightarrow \mathbb{R}^m, f_2: \mathbb{R}^m \rightarrow \mathbb{R}^m$ and $f_3: \mathbb{R}^m \rightarrow \mathbb{R}^m$ such that $m1 \approx m2 \approx m3$. Considering the three points $y_1, y_2, y_3 \in \mathbb{R}^m$; the three economic operating regions can be identified as $P_1, P_2$ and $P_3$ for emission oriented, trade-off and cost oriented, respectively, as given in (36)–(38).

$$P_1 = \{y_1 \in \mathbb{R}^m \mid y_1 > y_2, y_1 > y_3\} = \emptyset$$  \hspace{1cm} (36)$$

$$P_2 = \{y_2 \in \mathbb{R}^m \mid y_2 > y_3, y_2 < y_3\} = \emptyset$$  \hspace{1cm} (37)$$

$$P_3 = \{y_3 \in \mathbb{R}^m \mid y_3 < y_1, y_3 < y_2\} = \emptyset$$  \hspace{1cm} (38)$$

Let $\mathbb{P}_k$ be the $k$th user’s Pareto set. $\mathbb{P}_k \in \{1, 2, 3\} \subseteq \mathbb{P}$ is a feasible set for different economic(e) norms. Based upon emission cap restriction, users are free to operate at any operating point $p_k \in \mathbb{P}_k$, $\forall e \in \{1, 2, 3\}$. Therefore, the operating point is decided by randomly selecting a point from the feasible Pareto sets $\mathbb{P}_k$.

### 3.3 Simulation: data formation

This study consists of two major parts which are data formation and their analysis. Based upon the samples and optimal operating points, annual and lifetime data is formed.

One of the most significant problems of a dynamic market is that users need to share their vehicles’ and personal utilisation data with utility companies. Data sharing involves security breach and burdens the communication channel. If the amount of individual energy shared during V2G is minimal, the users will avoid such a complicated market structure. To attract the end users, the system must involve an aggregator, i.e. a third-party negotiator who takes the market risk and compensation. Since the energy price structure is dynamic, continuous monitoring of vehicles and users’ activity profile is needed for market operation. Due to security issues and complex operations of the market, users will be demotivated from registering their vehicles for V2G.

Thus, a simple and widely accepted market structure is inevitable for motivating the users towards V2G. In this paper, authors used a day-ahead market which is widely accepted in the

![Different operating economies](image-url)
unit commitment process. Based upon the historical data of system demand, the utility companies issue a price structure for the predicted demand. The day-ahead pricing schemes will help the users to locally optimise their vehicles’ utilisation themselves. The proposed market structure is not optimal from the grid perspective, but at the present development stage of V2G, authors feel that users’ motivation is more important than the idealised grid operation.

The price scheme is defined concerning grid supportive strategies. Higher buying price at peak hour in comparison to an off-peak hour is applied to demotivate users to charge EVs at peak hour. An empirical pricing system based upon the deviation of demand from its mean is adopted in this paper as given in Fig. 3. The requirement of valley filling and peak-swapping strategies determines the selling and buying price which is defined as a fraction of base price. The steps involved in determining market pricing as follows:

**Step 1:** The estimated load demand is normalised with its mean demand in 24 h.

**Step 2:** Power demand deviation limit from the mean point is set for morning period, peak time and evening period separately.

**Step 3:** A minimum buying price rate is set by the system operator. Below this minimum price, it is uneconomical for the grid to sell electricity to users.

**Step 4:** Similarly, a maximum buying price rate is set beyond which it is uneconomical for users to buy electricity from the grid.

**Step 5:** When the normalised demand is less than the minimum power limit (set in Step 2) then the buying price rate is saturated to the lowest rated which is determined in Step 3. Similarly, for the demand greater than the maximum limit (determined in Step 3), the BP is set at the maximum rate as set in Step 4.

**Step 6:** The selling price rate at other time period is set by linearising the points between two consecutive saturation periods.

**Step 7:** Selling price is set as a fraction of the buying price curve.

**Step 8:** The ancillary price rate is set as flat rate for 24 h schedule.

The deviation from mean demand is set as 0.7, 0.8 and 1.5 for morning, evening and peak hour, respectively. Minimum buying rate is set as 1.0 and the maximum is set as 1.6. The selling price is formed by setting base price as 70% of the buying price curve. The ancillary services’ price is assumed at 10% of the base price which attracts EVs to remain connected to the main grid.

The first part of the study is aimed to find the possible operating points of PHEVs with the trade-off between their operating cost and emission based upon the government policy. Each possible random drive profile of the vehicles is subjected to three economic conditions as in (36)–(38).

Use of day-ahead market pricing scheme will simplify the V2G market operation where a user need not share his/her data with either utility or other users. Since the market price is known a priori, the users can plan to maximise their vehicles’ utilisation to reach the required objective, i.e. profit. Local optimisation can be done at each user end to provide better or near optimal operating point. Operation of each user is independent since their power demand does not affect the price (SP, BP and AP). Any change in kth user demand does not affect the profit of another user. Each user will locally optimise their greedy operation strategy to maximise their profit or minimise their operating cost while satisfying the emission constraint.

Each drive profile is solved for its multi-objective Pareto sets to identify a large number of solutions within the Pareto-optimal front. The conventional weighting sum method for solving the multi-objective problem requires prior knowledge of scaling factors and the problem needs to be solved with differently and a large number of weight values to obtain a smooth Pareto set. It suffers from high computational costs due to a large number of individual optimisation calls. Since the optimisation problem is independent of users’ instantaneous demand, the problem can be easily vectorised and solved using a parallel computation technique. Therefore, a non-dominated sorting genetic algorithm (NSGA-II) [31] is used in this paper. It is a compelling computational technique which can provide a non-dominated Pareto front in a single run. Authors used NSGA-II to simultaneously minimise the objective functions (28) and (29). Flowchart of the data generation algorithm is given in Fig. 4.

### 4 Case study and results

A case study is carried out for prediction of operating cost, emission and V2G support capabilities of vehicle’s fleet. For V2G pricing schemes, the base price of electricity is considered as $0.20 per kilowatt hour as an unsubsidised energy rate. A model study is done on the expected PHEVs stock availability [32] in India with fleet size as 1000. It is assumed that 25% PHEVs compounded annually replacing ICE conventional vehicles. Further, an initial PHEV penetration of 40% is considered as a threshold for V2G technology implementation. Each year fraction of new PHEVs are added to the fleet, thus a heterogeneous mixture of vehicles operating at life edges as shown in Fig. 5. The vehicles’ samples were generated based on the fleet distribution and mobility profile as explained in Section 2. Each sample is optimised considering the fitness of cost and emission to find the operating point samples. The ICE model of PHEVs is taken as Geo-Prizm vehicle [23].

The Pareto generation and its sample analysis require substantial computation. To reduce the computational time, vectorisation and parallel processing [33] techniques have been used. Complexity and extensive data analysis were done using grid computing with master bench: Intel i5/8 Gb RAM and Intel Dual-
Xeon E5-2697 v4, 64 Gb, 72 cores as slave nodes. Hierarchy of case study is distributed in three sub-sections namely the identification of mean operating cost and tailpipe emission with their PDFs, the effects of PHEVs on grid power demand profile and the analysis of total emission which includes tailpipe and pollution from the power plant for finding the true potential of PHEVs for emission reduction application.

4.1 Effect on operating cost and tailpipe emission

The operating cost and emission of PHEVs fleet on per day basis were calculated to find and visualise the effect of different operating economies. Authors are mainly interested to find the benefit or loss due to replacement of conventional vehicles with future smart grid supported V2G technology PHEVs. Therefore, emission and cost results are normalised with the data of same sample assuming all vehicles are conventional ICES only. Normalised/fractional cost is defined as the ratio of operating cost per day of current fleet structure to the fleet containing only ICES. Similarly, normalised/fractional emission is ratio of current fleet to conventional fleet emission on per day basis.

The fractional cost and emission samples fitted on normal distribution are given in Figs. 6 and 7 for year 1. An increment of 20% operating cost and 39% emission reduction is observed in case of emission oriented operation. Thus, it can be concluded that users will be burdened by higher operating cost when PHEVs are subjected to emission reducing policy. A trade-off operation of fleet leads the system into profit, i.e. V2G operation becomes profitable but the emission reduction capability PHEVs fleet is reduced by 9% in first year and reduced by 30% potential in the fifth year of operation. The cost-oriented operation provides maximum profits out of V2G operation and reduces the fleet operating cost by 37% in comparison to pure ICE-based fleet but the emission reduction capability is diminished to 15% only.

The operating cost in year 5 for emission oriented case is increased by 28% as in Fig. 8 which is more than year one, because of vehicle degradation. In the trade-off zone of operation, the profitability of fleet is increased to 19% and the emission is decreased to 40%. The cost-based operation shows that the V2G operation can provide profit by cutting the operating cost by 48% and has the potential to reduce the tailpipe emission by 30% as in Fig. 9.

In year 1 analysis, all the PHEVs under consideration are new with zero degradation. Therefore, the results in Figs. 6 and 7 provide us the insight of maximum benefit that can be harvested from PHEVs. However, year 2 onwards vehicles are degraded, and only a fraction of PHEVs are new and operating with low potential.

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The detailed results from year 1 to 5 for cost and emission under different operating policies are given in Table 1.

In emission-oriented economies, the pollution control policies are strict. Therefore, the users have less option to trade-off the emission objective to minimise their cost. Similarly, in cost-oriented economies, the users will always try to operate in the minimum cost zone since the emission restriction is relaxed where the users can easily trade-off the operating points across different emission values. Hence the deviation of cost samples is minimum in cost-oriented economies for year 1 and 5 as 0.00430 and 0.00388, respectively, in Figs. 6 and 8. Similarly, the emission samples are also subjected to government policy on pollution. Therefore, the deviation of emission is minimum in emission-oriented economy ($\sigma = 0.00259$) and maximum in cost-oriented operation($\sigma = 0.00368$) in fifth year samples. Nonetheless in first year, such trend is not observed due to a large fraction of ICE vehicles which are not participating in the V2G market. Therefore, the trend of emission deviation following the economic operation will only be valid if the EVs share the majority in vehicle’s fleet.

### Table 1: Yearly mean data of normalised cost and emission under different government policy

| Year | Cases | Cost | Emission |
|------|-------|------|----------|
|      | I     | II   | III      | I        | II     | III      |
| 1    | 1.2065| 0.8586| 0.6329   | 0.6155   | 0.7095| 0.8474   |
| 2    | 1.2372| 0.8373| 0.5996   | 0.5119   | 0.6347| 0.8190   |
| 3    | 1.2569| 0.8237| 0.5814   | 0.3956   | 0.5537| 0.7847   |
| 4    | 1.2754| 0.8336| 0.5636   | 0.2752   | 0.4675| 0.7385   |
| 5    | 1.2866| 0.8181| 0.5266   | 0.1960   | 0.4061| 0.6996   |

(I), Emission oriented; (II), Trade-off and; (III), Cost oriented economies cases.

The operation of V2G is only supported when the grid support is facilitated by operation of PHEVs. The controlled activity of vehicle–grid interaction should be such that the total power demand curve reduces its peak requirement simultaneously increasing its demand valley. In this paper, authors used an indirect method to control the power demand profile by using dynamic pricing. This strategy facilitates the users to operate independently from the grid control and protect themselves from the potential cybercrimes. The validation of price-based control is done by checking the resultant average power profile of different samples. The power demand profile is taken from [34], which is assumed to be annually increasing by 20% due to increase in energy demand [35] but the profile shape remains same.

The resultant average power demand (including PHEVs) is compared with forecast power and given in Fig. 10 for year 1 to 5, respectively. It can be observed that profile shapes remain similar with extra peaks appearing in the V2G operation. Two critical time slots from 7:00 to 9:00 h and 19:00 to 20:00 h can be identified which are new peaks in demand profiles. Since these periods are post-peak periods from the transportation point of view, the vehicles will reconnect themselves to the grid.

When the system is operating as cost-oriented economies, the users prioritise PHEVs storage system for generating revenue by selling the stored energy when the grid is paying higher prices. Such effects can be seen in Figs. 10a–e. This is due to charging of vehicles at off-peak periods and discharging at a peak interval. A drawback of uncoordinated price-based fleet control mechanism fails to stabilise the surge power discharge in the grid for a revenue-generating purpose. Due to users greedy operation strategy to maximise its profit the reverse power flow becomes highly fluctuating between 7:00 to 9:00 h and 19:00 to 20:00 h.
dominating on peakiness of demand profile and converting into a valley. In the emission oriented operation, the vehicles mainly rely on battery energy since it helps to reduce the tail pipe emission but requires frequent charging. Due to this, the resultant power demand shifts upward except at peak schedule. Since the optimal operating points in the emission oriented operation have non-zero weight to operating cost, PHEVs can reduce cost by selling at the peak periods. The trade-off-based operation has potential to swap demand and fill the valley without creating a secondary peak. Although such anticipated result was only valid for year 1 and 2 operation and violated the peak demand constraint from third year of operation. The peak of demand depends upon the PHEVs penetration in V2G market compared to system size. If the number of PHEVs registered in V2G market is more, the capability of delivering energy to the grid will increase. This will also step up the charging demand with boom in randomness of charging/discharging requests from vehicles.

4.3 Effect on total emission control

The tailpipe emission control is useless if the global production of greenhouse gases is not reduced. The PHEVs green operation shifts the source of emission from the user end to the generating station. Thus, it has become mandatory to analyse the real effectiveness of emission control by PHEVs on a global basis. As the use of EVs increases, a coal-based power plant needs to burn more fuel to fulfil the extra power demand. Coal-based power plants are more efficient in producing per kWh of energy than individual ICEs which we compare as a small diesel generating sets. Emission/kWh of a coal plant depends upon its operating point on its cost curve of individual units which are fulfilling the total demand. Since the number of operating units is unknown, authors used an average emission rate data of units given in [36] which are 777.4333 g/kWh. For analysis of total emission, two scenarios such as constant power demand (CD) for periods of analysis and 20% annual increase in demand (ID) for different operating modes are considered. When emission from the power plant is also considered, the pollution control potential of V2G is drastically reduced as shown in Fig. 11. In a constant demand scenario with emission-oriented operation, the potential is drastically reduced to 6% in first year whereas tailpipe is decreased by 40%. Further, an extra 1% decrement in its potential is observed when the second scenario of 20% demand increment is considered. Similarly, it was expected that in fifth year, the tailpipe emission will reduce by 80%, 60 and 30% for different modes of operation. On the contrary, it is observed that the total emission reduction capability is diminished to 14, 11 and 5% for constant demand scenario and 7.5, 5.5 and 2.5% in demand increment scenario. A similar trend in reduction of emission control potential is also observed for other years in Fig. 11. The minimum 2.5% and maximum 14% of numeric figures in emission reduction appear very small as compared to the complexity of V2G technology that needs to be implemented to achieve such results. Here, authors assume that only conventional coal-based plant is the source of electricity. The integration of renewable green energy sources can easily increase the figures, but the true potential of PHEVs will not be visible in overall effects.

5 Conclusion

The present work shows that the EVs are highly capable of reducing the local pollution while providing profit to the users. However, PHEVs lose their green certification when the analysis includes their global effect on greenhouse gases. EVs under the
V2G market have some capability to reduce the total emission in the range of 2.5 to 14% but much lower than promised.

This work also shows the effect of government policies on emission control which directly affects the profit-making ability of the V2G market. If the profit observed in the V2G market does not seem to dominate, then the users may be indirectly discouraged to participate in the V2G market or in the worse situation the users may not switch to EVs from ICEs vehicles. Thus, the users’ motivation towards EVs for emission control requires some leniency in government policies so that the profit attraction of V2G indirectly helps in pollution control.

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