Plug-in Vehicles and Renewable Energy Sources for Cost and Emission Reductions

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***Abstract*—Electricity and transportation industries are the main sources of greenhouse gas emissions on earth. Renewable energy, mainly wind and solar, can reduce emission from the electricity industry (mainly from power plants). Likewise, next generation plug-in vehicles which include plug-in hybrid electric vehicles (PHEVs) and electric vehicles (EVs) with vehicle-to-grid capability, referred to as "gridable vehicles" (GVs) by the authors, can reduce emission from the transportation industry. GVs can be used as loads, energy sources (small portable power plants) and energy storages in a smart grid integrated with renewable energy sources (RESs). Smart grid operation to reduce both cost and emission simultaneously is a very complex task considering smart charging and discharging of GVs in a distributed energy source and load environment. If large number of GVs are connected to the electric grid randomly, peak load will be very high. The use of traditional thermal power plants will be economically and environmentally expensive to support the electrified transportation. The intelligent scheduling and control of GVs as loads or/and sources have great potential for evolving a sustainable integrated electricity and transportation infrastructure. Cost and emission reductions in a smart grid by maximum utilization of GVs and RESs are presented in this paper. Possible models, including smart grid model, for GV applications are given and results are presented. The smart grid model offers the best potential for maximum utilization of RESs to reduce cost and emission from electricity industry.**

***Index Terms*—Cost, constraints, emission, gridable vehicles, load leveling, optimization, plug-in electric vehicles, renewable energy, smart grid, solar farm, wind farm.**

I. Introduction

THE alarming rate, at which global energy reserves are depleting, is a major worldwide concern at economic, environmental, industrial and societal levels [1]. The power and energy industry represents a major portion of global emission, which is responsible for 40% of the global CO_2 production followed by the transportation industry (24%) [2]. Climate change caused by greenhouse gas (GHG) emissions is now widely accepted as a real condition that has potentially serious consequences for human society and industries need to factor this into strategic plans [3]. The use of renewable energy may become attractive, especially if customers would have to pay not only for the cost of generation but also for transmission, distribution and the indirect cost of environmental clean-up and health effects [4]. Researchers are working toward generating more energy from resources that can be cost-effective and do not contribute to climate change or have adverse environmental impacts [5].

Partial solutions to the depletion of energy reserves and increase in emissions are (a) the integration of distributed renewable energy sources, and (b) the deployment of next generation plug-in vehicles on the roads which include plug-in hybrid electric vehicles (PHEVs) and electric vehicles (EVs) with vehicle-to-grid (V2G) capability, referred to as "gridable vehicles" (GVs) by the authors. V2G technology has been described in [6]. It is an energy storage technology that has capability to allow bidirectional power flow between a vehicle's battery and the electric power grid. It increases the flexibility for electric power grid to better utilize intermittent renewable energy sources (RESs). With V2G, the state of charge of a vehicle's battery can go up or down depending on the revenues and grid's demands.

Different forms of energy integration and R&D policy are discussed in [7]. A technical report from National Renewable Energy Laboratory (NREL) has reported that there are significant reductions in net CO_2 emissions from plug-in hybrid electric vehicles (PHEVs) [8]. The combination of fluctuating high oil costs, concerns about oil security and availability, and air quality issues related to vehicle emissions are driving interests in PHEVs. The economic incentive for owners to use electricity as fuel is the comparatively low cost of fuel. Considering cost advantages, a study by the US Electric Power Research Institute (EPRI) found a significant potential market for PHEVs [9]. However, use of PHEVs will increase the load on the electric power grid. If peak load is increased much, it is essential to install new power plants to supply the peak load, which may be very costly. Electrification of the transportation industry will need not only the re-structuring of present gasoline stations but also the modification of present electricity infrastructure.

PHEV and EV researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [10-21]. Their goals are to educate about the environmental and economic benefits of PHEVs and EVs, and to enhance the product market. PHEVs and EVs cannot alone solve the emission problem completely, as they need electric energy which is one of the main sources of emission. Therefore, success of practical application of PHEVs and EVs with V2G capability to achieve emission and cost reductions greatly depends on the maximum utilization of RESs.

A dynamic optimization approach is needed to optimize time-varying resources such as RESs and GVs in a complex smart grid. Then a successful bridge can be made between the

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electricity and transportation infrastructures.

The primary contributions of this paper are as follows: 1) Intelligent and flexible operations of gridable vehicles either as loads, sources or energy storages; 2) Illustration of the effectiveness of gridable vehicles in a smart grid with RESs; and 3) The maximum utilization of RESs through the use of gridable vehicles to reduce cost and emission in a smart grid.

The rest of the paper is organized as follows. The problem formulation for bridging the electricity and transportation industries is presented in Section II. For maximum utilization of resources and minimization of cost and emission, an intelligent optimization method is described in Section III. Simulation data and results are presented and discussed in Section IV. Finally, the conclusion is given in Section V.

II. Problem Formulation

In the proposed model: (1) renewable energy sources, mainly wind and solar, are used to reduce emission from the electricity industry; (2) GVs are used to reduce emission from the transportation industry; (3) GVs are smartly used as loads, energy storages and small portable power plants (S3Ps); (4) parking lots are used as virtual power plants (VPPs); (5) an on-board GV computer system communicates with utility to get real-time electricity pricing and convey vehicle battery's state of charge (SoC) and vehicle owner's preferences. Based on all the above system capabilities and features, an optimization method generates an intelligent schedule for proper decision, control and smart operations that uses GVs to maximize the usage of RESs in order to reduce both electricity cost and emissions from the electricity and transportation industries.

The output of a solar photovoltaic (PV) panel given by (1) depends on the area of PV panel A, solar insolation $\mu(t)$ and the efficiency of the PV panel β.

$$P_{pv}(t) = A\beta\mu(t) \tag{1}$$

A wind turbine model is somewhat more complex due to its mechanical nature. Generally, the power output of a wind turbine is proportional to the kinetic energy, air density, etc. contained in the wind as given in (2) where α is the Albert Betz constant, $\rho(t)$ is air density, A is area swept by turbine rotor, and $v(t)$ is wind speed. Other parameters of wind turbine include cut-in wind speed, cut-out wind speed and rated wind speed, and typical values are 3.5 m/s, 25 m/s and 14 m/s respectively. Precise values can be obtained from manufacturer's data sheet for the respective units.

$$P_{wind}(t) = 0.5\alpha\rho(t)Av(t)^3 \tag{2}$$

Wind and solar energy may not meet all the load demand and thus requiring conventional units to supply the unmet demand. Wind and solar energy is emission free. However in electricity and transportation industries, the amount of carbon dioxide released is proportional to the amount of carbon in the fuel and the quantity of fuel burnt. Thus, a generation plant or vehicle that burns a carbon-intensive fuel, will generate more carbon dioxide at increased levels of operation [22]. Other types of emissions (SO_2, NO_X, etc.) are also produced from electric power and transportation industries. For environment friendly power generation, emission should be measured and minimized.

For the study in this paper, a linear approximate model is used to calculate emission from vehicles in transportation industry as follows:

$$\mathcal{EC}_i(L_i, e_i) = L_i \times e_i \tag{3}$$

where $\mathcal{EC}()$ is emission function, L_i is the length of travel by vehicle i in mile and e_i is emission per mile from vehicle i.

However, a non-linear accurate (complex) model is available for power systems. Typically emission is expressed as a polynomial function and its order depends on desired accuracy. In this study, quadratic function is considered for the emission curve [23] as follows:

$$\mathcal{EC}_i(P_i(t)) = \alpha_i + \beta_i P_i(t) + \gamma_i P_i^2(t) \tag{4}$$

where α_i, β_i and γ_i are emission co-efficients of unit i.

Fuel cost of a thermal unit is typically expressed as a second order function of generated power of the unit.

$$\mathcal{FC}_i(P_i(t)) = a_i + b_i P_i(t) + c_i P_i^2(t) \tag{5}$$

where a_i, b_i and c_i are positive fuel cost co-efficients of unit i.

The start-up cost for restarting a decommitted thermal unit, which is related to the temperature of the boiler, is included in the model as follows:

$$\mathcal{SC}_i(t) = \begin{cases} h\text{-}cost_i, & \text{if boiler temperature is higher} \\ & \text{than a threshold} \\ c\text{-}cost_i, & \text{if boiler temperature is lower} \\ & \text{than a threshold} \end{cases} \tag{6}$$

where $h\text{-}cost_i$ and $c\text{-}cost_i$ are hot start cost and cold start cost of unit i respectively, and $c\text{-}cost_i \geq h\text{-}cost_i$.

In a system with GVs operating as loads or S3Ps, power supplied from distributed generations must satisfy the load demand $D(t)$ and the system losses, which is defined as

$$\sum_{i=1}^{N} P_i(t) + P_{pv}(t) + \sum_{j=1}^{N_{V2G}(t)} \xi P_{v_j}(\Psi_{pre} - \Psi_{dep}) + P_{wind}(t) = D(t) + Losses, \quad \text{if GVs are S3Ps} \tag{7}$$

$$\sum_{i=1}^{N} P_i(t) + P_{pv}(t) + P_{wind}(t) = D(t) + Losses + \sum_{j=1}^{N_{V2G}(t)} \xi P_{v_j}(\Psi_{dep} - \Psi_{pre}), \quad \text{if GVs are loads} \tag{8}$$

where $P_i(t)$ is output power of unit i at time t; Ψ_{pre}/Ψ_{dep} is present/departure SoC; P_{v_j} is power of vehicle j; ξ is system efficiency; $N_{V2G}(t)$ is number of GVs connected to the grid at hour t; and N is number of units.

Only 'registered' GVs are considered for smart operations. 'Registered' GVs are vehicles whose owners have opted for their vehicles' batteries to participate in V2G transactions. All registered vehicles N_{V2G}^{max} take part in smart operations during a predefined scheduling period H.

$$\sum_{t=1}^{H} N_{V2G}(t) = N_{V2G}^{max}. \tag{9}$$

To maintain system reliability, adequate spinning reserves are required.

$$\sum_{i=1}^{N} P_i^{max}(t) + P_{pv}(t) + \sum_{j=1}^{N_{V2G}(t)} \xi P_{v_j}(\Psi_{pre} - \Psi_{min}) + P_{wind}(t) \geq D(t) + Losses + R(t), \quad \text{if GVs are S3Ps} \quad (10)$$

$$\sum_{i=1}^{N} P_i^{max}(t) + P_{pv}(t) + P_{wind}(t) \geq D(t) + Losses + R(t) + \sum_{j=1}^{N_{V2G}(t)} \xi P_{v_j}(\Psi_{dep} - \Psi_{pre}), \quad \text{if GVs are loads} \quad (11)$$

where $P_i^{max}(t)$ and $R(t)$ are maximum output limit of ith unit at time t considering ramp rate and spinning reserve of the system at time t respectively.

Each unit has generation range, which is represented as

$$P_i^{min} \leq P_i(t) \leq P_i^{max}. \quad (12)$$

Depletion of storage up to a certain minimum level (Ψ_{min}) and charging up to a maximum level (Ψ_{max}) are ensured by (13) to prevent loss of battery life.

$$\Psi_{min} P_{v_j} \leq P_{v_j}(t) \leq \Psi_{max} P_{v_j}. \quad (13)$$

In the proposed model, emissions (4) and generation costs (5)-(6) are considered as the objective of smart grid and load balance (7)-(8), registered vehicles (9), reliability reserve (10)-(11), generation limit (12), state of charge, system efficiency, parking lot limitation, etc. are constraints.

Therefore, the typical objective (fitness) function for cost-emission optimization in a smart grid environment would be

$$\min_{I_i(t), N_{V2G}(t)} \mathcal{TC} = \mathcal{W}_c \times \text{(Fuel + Start-up)} + \mathcal{W}_e \times \text{Emission}$$
$$= \sum_{i=1}^{N} \sum_{t=1}^{H} [\mathcal{W}_c(\mathcal{FC}_i(P_i(t)) + \mathcal{SC}_i(1 - I_i(t-1))) + \mathcal{W}_e(\psi_i \mathcal{EC}_i(P_i(t)))] I_i(t) \quad (14)$$

subject to (7-13) constraints.

$I_i(t)$ and $N_{V2G}(t)$ are decision variables for on/off state of units and number of GVs connected to the grid at time t respectively. ψ_i is the emission penalty factor of unit i. Weight factors $\mathcal{W}_c$ and $\mathcal{W}_e$ are used to increase flexibility of the system.

III. Cost and Emission Optimization

An optimization method is required to intelligently handle large number of GVs in a smart grid for maximum utilization of RESs in order to reduce both cost and emission to an optimum level. Particle swarm optimization (PSO) is used to minimize cost and emission in this study. PSO is a bio-inspired algorithm based on the behavior of flock of birds and school of fish, and has similarities to other population based evolutionary algorithms [24]. Each potential solution, called a particle, flies in a multi-dimensional search space with a velocity, which is dynamically adjusted according to the flying experience of its own and other particles. Binary and integer PSOs are used in order to reduce the search space dimension in this optimization problem. Generating units and GVs are represented by binary and integer numbers respectively. Binary PSO is used to determine the optimal on/off states of conventional generating units. Integer PSO is used to determine the optimal number of GVs in the constrained system. This approach provides a balance between local and global search abilities, and finds an optimal solution for cost and emission reductions.

PSO is an iterative method where the velocity and position of each particle is calculated as follows:

$$v_{ij}(k+1) = [v_{ij}(k) + c_1\, rand_1\, (pbest_{ij}(k) - x_{ij}(k)) + c_2\, rand_2\, (gbest_j(k) - x_{ij}(k))][1 + \frac{-Range}{MaxIte}(Ite - 1)]. \quad (15)$$

Binary PSO for generating units:

$$I_{ij}(k+1) = x_{ij}(k+1) = \begin{cases} 1, \text{if } U(1) < \frac{1}{1+\exp(-v_{ij}(k+1))} \\ 0, \text{otherwise.} \end{cases} \quad (16)$$

Integer PSO for GVs:

$$N_{V2Gj}(k+1) = x_{ij}(k+1) = \text{round}(x_{ij}(k) + v_{ij}(k+1)). \quad (17)$$

Here I_{ij} and x_{ij} are matrices of sizes $(H \times N)$ and $(H \times N + 1)$, respectively. However, N_{V2Gj} is a column vector of $(H \times 1)$ integers that reduces dimension and it is assigned to the last column of matrix x_{ij}. Particle's best position $pbest$, global best position $gbest$, velocity v, position x, accelerating parameters c_1 and c_2, particle number i, problem dimension j and iteration index k are standard terms of PSO [24]. Ite, $MaxIte$ and $U(1)$ are current iteration, maximum number of iterations, and a uniform number between 0 and 1, respectively. In the above velocity equation (15), first term indicates the current velocity of the particle (inertia term); second term presents the cognitive term of the particle where the particle changes its velocity based on its own private thinking and memory; and the third term is the social part where the particle changes its velocity based on knowledge derived from the interaction with other particles in the swarm.

Flowchart for minimization of cost and emission using GVs and RESs in a smart grid is given in Fig. 1. At hour t, if schedule is $[I_1(t), I_2(t), \ldots, I_N(t), N_{V2G}(t), P_{pv}(t), P_{wind}(t)]^T$

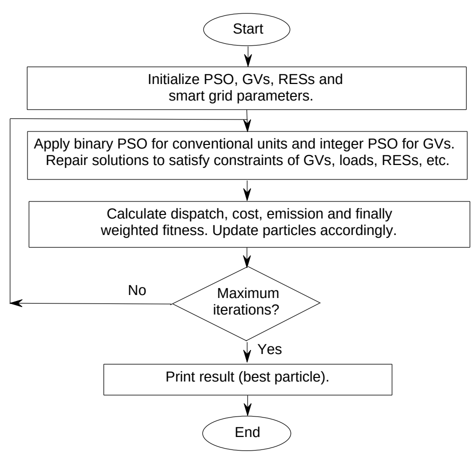

Fig. 1. Flowchart for minimization of cost and emission using GVs and RESs in a smart grid.

then power to/from vehicles is $\xi N_{V2G}(t)P_{v_i}(\Psi_{pre} - \Psi_{dep})$; sign of $N_{V2G}(t)$ indicates load/source; and the remaining demand $[D(t) + \xi N_{V2G}(t)P_{v_i}(\Psi_{pre} - \Psi_{dep}) - P_{pv}(t) - P_{wind}(t)]$ is met from conventional running units of the schedule $[I_1(t), I_2(t), \ldots, I_N(t)]^T$ with dispatch computed using Lambda iteration.

IV. Results and Discussions

A simulation study of an independent system operator (ISO) of 10-unit system with 50,000 registered GVs is carried out in this study. Load demand and unit characteristics of the 10-unit system are collected from [25]. Estimated emission coefficients and plant (generators) data are given in Tables I and II respectively. Two models are investigated to show the effect of GVs in the electricity and transportation industries.

- Case 1 (load leveling model): GVs are charged from conventional generation using load leveling optimization.
- Case 2 (smart grid model): GVs are charged from RESs as loads and discharged to the grid as sources.

Parameter values used in this study are:
average vehicle battery capacity, E_v = 15 kWh; total number of vehicles of a city = 50,000 (estimated); charging-discharging frequency = 1 per day; scheduling period = 24 hours; departure SoC, Ψ_{dep} = 50%; system efficiency, ξ = 85%; for PSO, swarm size = 30, iterations = 1000 and accelerating parameters c_1 = 1.5, c_2 = 2.5, $Range$ = 0.4.

For practical applications, the number of GVs in an electric power network can be estimated analytically based on the number of electricity clients (customers) in that network. An estimate of GVs from residential electricity clients may be computed as follows:

$$\begin{aligned} N_{GV} &= Q_{V2G}V_{REC}N_{REC} \\ &= Q_{V2G}V_{REC}X_{RL}D_{min}/AV_{HLD} \end{aligned} \quad (18)$$

$$AV_{HLD} = AV_{MEC}/(30 \times 24) \quad (19)$$

TABLE I
Generator Emission Co-efficients

Unit	α_i (ton/h)	β_i (ton/MWh)	γ_i (ton/MW^{2}h)
U-1	10.33908	-0.24444	0.00312
U-2	10.33908	-0.24444	0.00312
U-3	30.03910	-0.40695	0.00509
U-4	30.03910	-0.40695	0.00509
U-5	32.00006	-0.38132	0.00344
U-6	32.00006	-0.38132	0.00344
U-7	33.00056	-0.39023	0.00465
U-8	33.00056	-0.39023	0.00465
U-9	35.00056	-0.39524	0.00465
U-10	36.00012	-0.39864	0.00470

TABLE II
Plant Size and Maximum Capacity (1,662 MW) of 10-unit System

	U-1	U-2	U-3	U-4	U-5
P_i^{max}(MW)	455	455	130	130	162
P_i^{min}(MW)	150	150	20	20	25
	U-6	U-7	U-8	U-9	U-10
P_i^{max}(MW)	80	85	55	55	55
P_i^{min}(MW)	20	25	10	10	10

For example: the minimum load, D_{min}, in the 10-unit benchmark system considered in this research is 700 MW [25]. It can be taken that the average monthly electricity consumption, AV_{MEC}, of a domestic home is about 1,500 kWh [26]. Thus average hourly electricity load of a residential client, AV_{HLD}, is 2.0833 kW. If we assume that percentage of residential loads in the power network, X_{RL}=30%, the total number of clients in the region N_{REC}, is 100,801.6 and it can be rounded to 100,000 for simplicity. It is reasonable to assume that in the future, V_{REC}=1, i.e., on average there will be one GV per residential electricity client, and Q_{GV}=50%, i.e. 50% register to participate in the process. Thus, N_{GV} from (18) is about 50,000 and this is a reasonable number of vehicles to be considered on the 10-unit benchmark system for our simulation studies.

If 50,000 GVs are connected to the grid randomly, in the worst case an excess of (50,000×15kWh=) 750 MWh energy will be needed for the small system of a city (or at least 375 MWh if 50% departure SoC is considered). No optimization is carried out since the charging-discharging process is totally random (random model). In such a system, peak load will be approximately 50% more in the worst case, thus, such a system is practically not feasible.

Case 1 (load leveling model): As the random system is not feasible, the next possible solution is load leveling. It is estimated that average distance driven with a vehicle is about 12,000 miles per year [26], thus a vehicle covers an average distance of 32.88 miles/day. It is assumed that an EV can run 4 miles/kWh. Therefore an EV needs about 8.22 kWh/day. Study on load forecasting including GVs is not done yet. So an approximate linear model is shown here. Extra energy needed for only 50,000 vehicles is (50,000×8.22 kWh =) 411 MWh in a small system each day. If GVs are charged randomly from the existing power system, in the worst case (if all vehicles are charged at peak hour only) peak load will be increased by 411 MW which is too high for a small system where 50,000 GVs belong to residential customers of the system. It is logical that a system may not have sufficient capacity to meet this extra peak load. Besides load increases by about 10% each year. In this case, it is necessary to install new units to meet the new load from GVs, which is costly and time consuming. However, an intelligent scheduling of GVs can soften the problem by leveling the load demand intelligently. GVs can be used and are promising as load leveling devices in the electricity industry.

Load curve of the standard 10-unit system has both peaks and valleys (see Fig. 2). According to the load curve, demand is relatively low during hours from 1st to 9th and from 22nd to 24th (total 12 hours). GVs can be charged from the grid

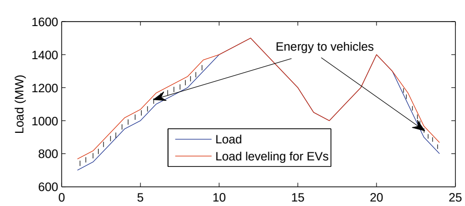

Fig. 2. Load leveling for GVs.

TABLE III
EMISSION FROM 10-UNIT SYSTEM (WITHOUT GVS AND RENEWABLE SOURCES)

Time (H)	U-1 (MW)	U-2 (MW)	U-3 (MW)	U-4 (MW)	U-5 (MW)	U-6 (MW)	U-7 (MW)	U-8 (MW)	U-9 (MW)	U-10 (MW)	Emission (ton)	Demand (MW)
1	455.0	244.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	682.70	700.0
2	455.0	295.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	754.72	750.0
3	455.0	265.0	0.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	772.80	850.0
4	455.0	364.9	0.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	944.86	950.0
5	455.0	285.0	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	865.39	1000.0
6	455.0	385.0	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	1049.96	1100.0
7	455.0	410.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1130.46	1150.0
8	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1241.00	1200.0
9	455.0	455.0	130.0	130.0	104.9	0.0	25.0	0.0	0.0	0.0	1272.40	1300.0
10	455.0	455.0	130.0	130.0	162.0	0.0	25.0	10.0	0.0	0.0	1332.61	1400.0
11	455.0	455.0	130.0	130.0	162.0	0.0	25.0	55.0	35.1	0.0	1355.50	1450.0
12	455.0	455.0	130.0	130.0	162.0	0.0	47.9	55.0	55.0	10.0	1387.29	1500.0
13	455.0	455.0	130.0	130.0	162.0	0.0	25.0	10.0	0.0	0.0	1332.61	1400.0
14	455.0	455.0	130.0	130.0	104.9	0.0	25.0	0.0	0.0	0.0	1272.40	1300.0
15	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1241.00	1200.0
16	455.0	309.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	930.24	1050.0
17	455.0	260.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	853.61	1000.0
18	455.0	359.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1022.56	1100.0
19	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1241.00	1200.0
20	455.0	455.0	130.0	130.0	162.0	0.0	0.0	10.0	10.0	10.0	1370.45	1400.0
21	455.0	455.0	130.0	130.0	119.9	0.0	0.0	10.0	0.0	0.0	1281.70	1300.0
22	455.0	385.0	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	1049.96	1100.0
23	455.0	315.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	851.03	900.0
24	455.0	345.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	842.33	800.0
Total emission = 26,078.589 tons Total running cost = $558,372.08 (fuel cost plus start-up cost)												

TABLE IV
EMISSION FROM 10-UNIT SYSTEM WITH 50,000 GVS CONSIDERING LOAD LEVELING

Time (H)	U-1 (MW)	U-2 (MW)	U-3 (MW)	U-4 (MW)	U-5 (MW)	U-6 (MW)	U-7 (MW)	U-8 (MW)	U-9 (MW)	U-10 (MW)	Emission (ton)	Demand (MW)
1	455.0	279.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	730.32	734.3
2	455.0	329.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	813.02	784.3
3	455.0	299.2	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	824.73	884.3
4	455.0	399.2	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1018.17	984.3
5	455.0	319.2	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	921.58	1034.3
6	455.0	409.3	130.0	130.0	0.0	0.0	0.0	0.0	0.0	10.0	1136.81	1134.3
7	455.0	444.2	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1213.37	1184.3
8	455.0	455.0	130.0	130.0	64.2	0.0	0.0	0.0	0.0	0.0	1238.08	1234.3
9	455.0	455.0	130.0	130.0	119.2	20.0	25.0	0.0	0.0	0.0	1303.70	1334.3
10	455.0	455.0	130.0	130.0	162.0	42.4	25.0	0.0	0.0	0.0	1325.06	1400.0
11	455.0	455.0	130.0	130.0	162.0	80.0	25.0	0.0	10.0	0.0	1358.07	1450.0
12	455.0	455.0	130.0	130.0	162.0	80.0	0.0	55.0	10.0	10.0	1390.00	1500.0
13	455.0	455.0	130.0	130.0	162.0	47.8	0.0	10.0	0.0	10.0	1360.57	1400.0
14	455.0	455.0	130.0	130.0	119.9	0.0	0.0	10.0	0.0	0.0	1281.70	1300.0
15	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1241.00	1200.0
16	455.0	309.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	930.24	1050.0
17	455.0	260.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	853.61	1000.0
18	455.0	359.9	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1022.56	1100.0
19	455.0	455.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	1241.00	1200.0
20	455.0	455.0	130.0	130.0	162.0	0.0	0.0	10.0	10.0	10.0	1370.45	1400.0
21	455.0	455.0	130.0	130.0	119.9	0.0	0.0	10.0	0.0	0.0	1281.69	1300.0
22	455.0	455.0	130.0	0.0	94.2	0.0	0.0	0.0	0.0	0.0	1179.83	1134.3
23	455.0	349.2	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	913.60	934.3
24	455.0	379.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	911.39	834.3
Total emission = 26,860.578 tons Total running cost = $567,844.98 (fuel cost plus start-up cost)												

during the off-peak hours to level the demand. Load resulting from GVs can be automatically scheduled by intelligent agents operating on GVs and interacting with other utility agents based on real-time electricity pricing available to GVs through smart meters. An additional 411 MWh/day is needed to supply the 50,000 GVs which can be equally distributed (411 MWh/12= 34.25 MWh at each hour) over the off-peak hours to level the demand without increasing the peak load (see Fig. 2).

Based on an average distance of about 12,000 miles driven with a vehicle in a year and an average emission from a vehicle of 1.2 lb/mile, the emission from a vehicle is estimated to be 14,400 lbs (12,000$\times$1.2) using (3). The total emission from 50,000 mechanical vehicles is therefore 720,000,000 lbs (326,678.766 tons).

First, emission is calculated for the 10-unit system with standard input data of power plants, emission co-efficients and load demand without considering GVs and RESs. PSO is used to calculate the schedule, load dispatch, and corresponding cost and emission. Results are shown in Table III. Then cost and emission are calculated considering load demand from 50,000 GVs and leveling the extra load. These results are shown in Table IV. From Tables III and IV, excess emission is 781.989 tons (26,860.578 tons - 26,078.589 tons) from power plants to supply energy to the 50,000 GVs during 24 hours. So excess emission is 285,425.985 tons (781.989 tons $\times$ 365) per year (on the other hand 326,678.766 tons from transportation sector). However, lower system efficiency

TABLE V
SMART GRID SCHEDULE AND DISPATCH OF GENERATING UNITS, RESSs AND GVS AS LOADS AS WELL AS SOURCES

Time (H)	U-1 (MW)	U-2 (MW)	U-3 (MW)	U-4 (MW)	U-5 (MW)	U-6 (MW)	U-7 (MW)	U-8 (MW)	U-9 (MW)	U-10 (MW)	V2G/G2V (MW)	Solar (MW)	Wind (MW)	Emission (ton)	Cap. (MW)	Demand* (MW)	Reserve (MW)
1	455.0	150.0	107.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-22.96	0.00	10.54	634.02	1063.0	700.0	363.0
2	455.0	161.8	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-19.09	0.00	22.27	660.66	1059.1	750.0	309.1
3	455.0	255.1	130.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-15.66	0.00	25.50	759.21	1055.7	850.0	205.7
4	455.0	231.6	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	-22.16	0.00	25.50	792.42	1192.2	950.0	242.2
5	455.0	259.6	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-25.15	0.00	25.50	853.11	1357.1	1000.0	357.1
6	455.0	352.0	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-17.52	0.00	25.50	1006.84	1349.5	1100.0	249.5
7	455.0	398.4	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-14.08	0.09	25.50	1104.13	1346.1	1150.0	196.1
8	455.0	388.7	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	28.32	17.46	25.50	1082.68	1360.3	1200.0	160.3
9	455.0	427.0	130.0	130.0	25.0	20.0	25.0	0.0	0.0	0.0	31.07	31.45	25.50	1222.69	1528.1	1300.0	228.1
10	455.0	455.0	130.0	130.0	89.6	20.0	25.0	0.0	0.0	10.0	23.77	36.01	25.50	1326.22	1575.8	1400.0	175.8
11	455.0	455.0	130.0	130.0	130.8	20.0	25.0	10.0	10.0	0.0	20.56	38.06	25.50	1370.34	1627.6	1450.0	177.6
12	455.0	455.0	130.0	130.0	120.4	20.0	25.0	10.0	10.0	10.0	73.10	35.93	25.50	1397.80	1735.1	1500.0	235.1
13	455.0	455.0	130.0	130.0	97.6	20.0	25.0	0.0	0.0	10.0	15.03	36.78	25.50	1328.32	1567.0	1400.0	167.0
14	455.0	441.9	130.0	130.0	25.0	20.0	25.0	0.0	0.0	0.0	16.76	31.59	24.82	1259.44	1513.8	1300.0	213.8
15	455.0	414.4	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	15.08	9.70	20.74	1140.81	1347.1	1200.0	147.1
16	455.0	303.8	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-21.43	12.92	14.62	920.10	1353.4	1050.0	303.4
17	455.0	271.8	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-37.33	0.00	25.50	870.35	1369.3	1000.0	369.3
18	455.0	357.2	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-16.27	0.00	19.04	1017.07	1348.3	1100.0	248.3
19	455.0	370.2	130.0	130.0	25.0	20.0	25.0	0.0	0.0	0.0	19.34	0.00	25.50	1095.30	1516.3	1200.0	316.3
20	455.0	455.0	130.0	130.0	106.2	20.0	25.0	10.0	0.0	0.0	50.73	0.00	18.02	1328.15	1602.7	1400.0	202.7
21	455.0	455.0	130.0	130.0	34.4	20.0	25.0	0.0	0.0	0.0	24.98	0.00	25.50	1291.24	1522.0	1300.0	222.0
22	455.0	354.1	130.0	130.0	25.0	0.0	0.0	0.0	0.0	0.0	-15.59	0.00	21.42	1010.95	1347.6	1100.0	247.6
23	455.0	220.2	130.0	130.0	0.0	0.0	0.0	0.0	0.0	0.0	-35.22	0.00	0.00	779.14	1205.2	900.0	305.2
24	455.0	150.0	118.7	130.0	0.0	0.0	0.0	0.0	0.0	0.0	-56.28	0.00	2.55	705.51	1226.3	800.0	426.3

Solar farm size = 40 MW (250,731.33 m^2)
Wind farm size = 25.5 MW (17 wind turbines and 1.5 MW each)
Total running cost = \$553,172.03 (fuel cost plus start-up cost)
Total emission = 24,956.688 tons

Notes: Demand* does not include the load of GVs; positive and negative values of V2G/G2V indicate discharging and charging, respectively.

and higher network losses will increase the emission from power plants. So in load leveling model, significant emission reduction is not guaranteed, as emission will be shifted from transportation sector to power system. Modern technologies for mileage-efficient GVs and modern emission absorption techniques for power plants can reduce emission in this model. Usually the overall efficiency of GVs (23.1%) is higher than that of conventional vehicles (12.6%) considering fuel energy that drives the wheels. The same as emission, net operation cost will not be significantly decreased in the load leveling model, as operation cost will be shifted from the transportation industry to electricity industry. However, transportation fuel price is more volatile and the proposed model reduces dependency on it, which is very important in the present world.

Case 2 (smart grid model): A smart grid consists of RESs, GVs and conventional generating units. In this study, solar insolation data are collected from NREL's Solar Radiation Research Laboratory (SRRL) in Golden, CO [27] for the solar farm model. Wind speed data are collected from the National Wind Technology Center (NWTC) in Boulder, CO [28] for the wind farm model. Figs. 3 and 4 are used to estimate a realistic wind farm and solar farm size for the analysis presented in this study. However for a given location, this can be formulated and solved using an optimization algorithm to find a near-optimal size based on data of wind speed and solar insolation over a period of time.

For a small city of 50,000 GVs, at least (50,000×15 kWh =) 750 MWh wind and solar energy is needed to get the maximum benefit of the GVs for reducing cost and emission. If the energy ratio from wind and solar is 2:1, i.e. 500 MWh comes from wind and 250 MWh from solar. This assumption is based on there is sufficient wind speed and solar insolation profiles for the location studied.

From (1) and Fig. 3, area A of the solar farm is calculated as follows:

$$A\beta[\mu(t=1)+\mu(t=2)+\ldots+\mu(t=24)] = 250 \text{ MW} \quad (20)$$

where solar insolation $\mu(t=1)$, $\mu(t=2)$, …, $\mu(t=24)$ are extracted from Fig. 3 and standard value of PV panel efficiency β is 16%. Thus, area A of the solar farm is 250,731.33 m^2 from (20). Considering 1,000 W/m^2 maximum solar insolation and 16% efficiency, the maximum capacity of the solar farm is ≈40 MW.

On the other hand, for the output of the wind farm, the power curve for General Electric 1.5 MW turbine model 1.5sle [29] under ideal conditions is approximated and used to determine the output of the wind farm based on the wind speed. First $P_{wind}(t=1)+P_{wind}(t=2)+\ldots+P_{wind}(t=24)$ is calculated for a single 1.5 MW turbine during 24 hours using the wind speed curve (Fig. 4) and manufacturer data sheet of power curve [29]. It is 30.06 MWh for a single 1.5 MW turbine during 24 hours and for the wind speed data. However, this model needs 500 MWh from wind and thus a wind farm of (500/30.06=16.63 ≈) 17-turbine is needed for this model.

Results in a smart grid model with wind, solar and GVs are shown in Table V, where GVs are operated as loads as well as sources. Solar energy is available only at day time from 7am to 4pm and wind energy is available most of the time. According

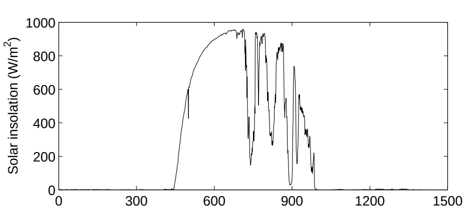

Fig. 3. Average solar insolation in a day taken for the analysis in this study.

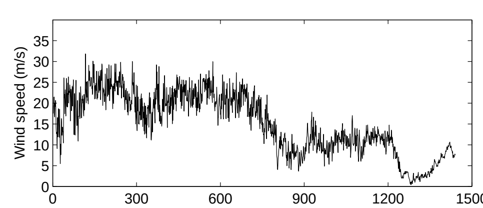

Fig. 4. Average wind speed in a day taken for the analysis in this study.

TABLE VI
SUMMARY OF DATA AND RESULTS

Item	Value
Average distance covered by a vehicle	12,000 miles/year
Number of registered GVs per city (assumed)	50,000
Average distance covered by GVs per kWh	4.00 miles
Energy needed by a GV per day	8.22 kWh
Energy needed by 50,000 GVs per day	411 MWh
Typical off-peak load duration of a day	12 hours
Extra demand for GVs per off-peak hour	34.25 MWh
Typical percentage time a GV is parked (gridable)	95%
Average emission of a vehicle	1.2 lb/mile
Emission from 50,000 vehicles (transportation industry) over a year	326,678.766 tons
Case 1: Load Leveling Model	
Extra emission from power plants for 50,000 GVs during one day	781.989 tons
Extra emission from power plants for 50,000 GVs over a year	285,425.985 tons
Case 2: Smart Grid Model	
Emission reduction from power plants for 50,000 GVs and RESs per year	409,493.865 tons
Total emission reduction from power plants and transportation sector for 50,000 GVs and RESs per year	736,172.631 tons
Total operational cost reduction from power system and transportation sectors for 50,000 GVs and RESs per day	$179,072.95 (at least)
Estimated Capital Cost for RESs	
Extra energy needed for the smart grid model	750 MWh per day
Wind energy and solar energy ratio (location dependent)	2:1
Capital cost of wind power	1.0 $/W
Capital cost of solar power	5.0 $/W
Solar farm size (based on some assumption of average solar insolation)	40 MW
Wind farm size (based on some assumption of average wind speed)	25.5 MW
Total capital investment in power system for the smart grid model	$225.50 million

to Table V, GVs are charged from the grid at off-peak load during 1st-7th, 16th-18th and 22nd-24th hours. On the other hand, GVs are discharged to the grid at peak load during 8th-15th and 19th-21th hours. So, GVs are operated as loads and storages mainly at night from 10pm to 7am; they are operated as sources during working hours from 8am to 3pm; and rest of the time from 4pm to 9pm, they are operated as loads or sources depending on the system demand. According to the results, maximum amount of power (73.10 MW) is discharged to the grid as V2G at the peak load hour (12th hour). However, amount of power for V2G and grid-to-vehicle (G2V) is not linearly proportional to the demand, as cost and emission are non-linear with respect to power output, and PSO optimizes both cost and emission under constraints here.

In Table V, emission is 24,956.688 tons and cost is $553,172.03 when 50,000 GVs are considered in the 10-unit system during 24 hours in the smart grid. On the other hand, emission is 26,078.589 tons when GVs are not considered in the same system (Table III). Thus, GVs reduce (26,078.589 tons - 24,956.688 tons =) 1,121.901 tons emission per day or 409,493.865 tons per year from power plants in the 10-unit small system with RESs. Besides 50,000 GVs will replace 50,000 conventional vehicles and it is already calculated that emission is 326,678.766 tons from the 50,000 vehicles. So 50,000 GVs will reduce total 736,172.631 tons (409,493.865 tons + 326,678.766 tons) emission each year from electricity and transportation industries.

Fuel cost is highly volatile. The benchmark fuel cost co-efficients that are used in this simulation, are old. Thus present cost co-efficients are higher, as current fuel cost is scaled up since the last decade. According to the results, the system can save at least ($567,844.98 - $553,172.03=) $14,672.95 per day in the 10-unit small system. It will also save running cost from the transportation industry. It is assumed that mileage of a light weight vehicle is 20 miles/gallon and present gasoline price is $2/gallon. So, transportation cost will be reduced by (50,000×(32.88 miles / 20 miles)×$2 =) $164,400 per day for the 50,000 GVs. Thus the smart grid model with RESs can reduce at least ($14,672.95 + $164,400 =) $179,072.95 from electricity and transportation industries daily. Results are summarized in Table VI.

Emissions from power plants are shown in Fig. 5 at each hour. Most of the time emission is low when GVs are considered in the smart grid model except at peak load (12th hour) and off-peak load (17th hour). In smart grid model, GVs are operated as loads to store energy at off-peak hour (17th hour) and thus total load is higher when GVs are included at 17th hour in the smart grid. On the other hand, at peak load emission is slightly higher because of higher emission rates of small plants, constraints, overall cost-emission minimization,

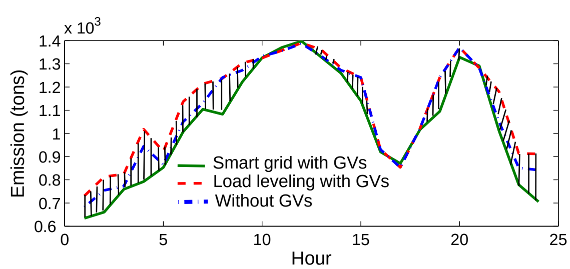

Fig. 5. Emission with and without GVs.

stochastic optimization method, etc. However, it is already described that total emission is reduced more in the smart grid model compared to the load leveling model and it is shown by the area between the red and green lines in Fig. 5.

Present capital costs for wind and solar power are about \$1/W and \$5/W respectively. So capital investment in power system for RESs is approximately (\$1$\times$25.50$\times 10^6$ + \$5$\times$40.00$\times 10^6$ =) \$225.50 million to get the full advantage of 50,000 GVs in the smart grid. However, it is expected per watt capital costs of solar and wind power will reduce in near future when mass amount of solar panels and wind turbines will be produced.

Number of vehicles connected to grid or amount of power transaction to/from the grid is not directly proportional to the load demand. Schedule of vehicles depends on non-linear price curves, emission curves, load demand, constraints, fitness function, balance between cost and emission, and so on. An intelligent optimization method, e.g. PSO can handle these factors efficiently. Fig. 6 shows an intelligent distribution using PSO for the system of 10-unit system and 50,000 GVs in the smart grid where GVs are charged/discharged to/from the grid to reduce cost and emission. Maximum number of vehicles (11,466) discharges to the grid at peak load at 12pm. Similarly maximum number of GVs is charged at off-peak load from 12am to 1am at night.

There is a trade-off between cost and emission optimizations. Depending on operator's demand, different weights can be assigned for cost and emission. Results are non-dominated, i.e., if cost is low, emission is high, and vice-versa. Table VII shows some non-dominated solutions in the smart grid. Minimum cost is \$551,977.83 where emission is relatively high. On the other hand, minimum emission is 24,818.964 tons where cost is relatively high.

Controllability of GVs is important, as today's vehicle owners with increase in fuel cost and emission taxations over time will start having more of electric and hybrid vehicles. It will be possible to control V2G/G2V nicely based on policies, incentives and rebates put in place by the government, utilities and gridable manufacturers. Utility may provide incentives/rebates on vehicle batteries in return for V2G participation. Under such conditions, vehicle use culture/habit will most likely change and GV owners will allow their vehicles to charge/discharge in recommended hours by the utilities. GVs embedded with advanced features for V2G/G2V operations will be attractive and the easiness will be additional factor for the culture change. Examples of these advanced features include the use as an automatic intelligent agent to

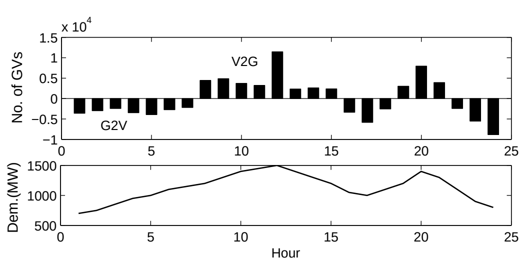

Fig. 6. Number of GVs charged/discharged at each hour in the smart grid.

TABLE VII
NON-DOMINATED SOLUTIONS FOR COST AND EMISSION OPTIMIZATIONS IN THE SMART GRID

Sl. No.	Cost (\$)	Emission (ton)
1	551977.83	25043.225
2	552461.92	25033.487
3	552524.27	25021.793
4	552574.41	24985.209
5	552686.01	24975.958
6	553097.86	24974.187
7	553118.16	24965.303
8	553131.38	24961.131
9	553172.03	24956.688
10	553811.96	24818.964

1) make charging decisions based on real-time pricing and 2) communicate with a utility agent on the GVs availability for V2G operations and state of battery charge needed at the departure time. It has been mentioned earlier that each day a vehicle covers an average estimated distance of 32.88 miles and thus takes roughly less than one hour of travel time. Therefore, it can be said that on an average basis a vehicle is on the road less than 5% of a day and it is parked more than 95% of a day, either in a parking lot or in a home garage. Vehicles can be charged/discharged during the 95% time of a day using an automatic intelligent agent when they are parked. It is difficult to determine whether a particular vehicle will be parked or on the road at a particular time. Thus in this model, an individual vehicle is not scheduled. However, it is possible to schedule a fleet of vehicles that will be charged/discharged to/from the grid at each hour. It is logical that most of the vehicles are parked and depending on the schedule, committed number of vehicles (not specific vehicles) is charged/discharged using an intelligent autonomous agent, as enough number of GVs are in parking lots or in home garages. Instead of considering an individual vehicle, aggregation of vehicles can solve the control problem of GVs. It is possible to control at least some percentage of GVs at a time and this percentage can be used as an upper limit constraint of the optimization system. Therefore recommended number of vehicles can charge/discharge to/from the grid. One vehicle may leave in the middle of the operation and in this case, it will be substituted by another vehicle in a 'parking' status.

V. CONCLUSION

The maximum utilization of renewable energy sources using gridable vehicles has been presented to illustrate cost and emission reductions for a sustainable integrated electricity and transportation infrastructure in this paper. Two possible models for GV applications have been studied and the smart grid model is a promising approach for GVs whereas the random mode is more or less not practical. The load leveling model does not guarantee significant cost and emission reductions. On the other hand, the smart grid model needs considerable amount of capital investment for RESs. This capital cost will vary depending on the location's solar insolation and wind speed profiles. Particle swarm optimization method has been used to generate the successful schedule and control of GVs in a smart grid. As the system complexity and shear size evolves, an advanced optimization method to track the dynamic behavior of RESs and GVs in a smart grid environment is needed. Furthermore, real-time pricing, and purchase and sale rates have to be considered in the scheduling, control and optimization of GVs in a smart grid.

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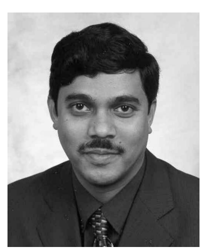

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