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# Dynamic forecasting, optimization and real-time energy management of gridable vehicle – a review

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***Abstract*— This paper investigates the concept of the new generation smart power grid that includes gridable vehicles and renewable energy sources. Here it is analyzed the feasibility of developing a real-time dynamic stochastic optimization approach that will result in a combined cost-emission reduction by the maximum utilization of clean energy sources. The concept in this paper is look at a gridable vehicle (GV) as a small portable power plant (SP3) and a smart parking lot (Smart Park) as a virtual power plant (VPP). After an extensive investigation of existing literature review, it is recommended that a dynamic stochastic optimization (DSO) approach can be used to automatically schedule and coordinate non-stationary sources to get full benefits of renewable energysources (RESs) such that (1) load demand can be leveled; (2) cost and emissionwill be reduced; (3) reserve and reliability of a smart grid can be increasedwhen millions of new loads, e.g., GVs, are to be integrated.**

***Keywords*— Smart grid; renewable energy; vehicle grid; optimization; dynamic forecasting**

## I. INTRODUCTION

The worldwide energy reserves are running down to the alarming rate, which is a major international concern at economic, ecological, manufacturing and society levels [1]. And with the concern is escalating over global climate changes, policy makers are advancing the renewable energy sources (RESs) as a means of meeting emissions reduction goals. A gridable vehicle (GV) is a modified version of the plug-in hybrid electric vehicle or an electric vehicle (EV) that can bring about a revolution in the energy and transportation sectors. To be economical, and have environmental and societal impacts, next generation vehicles (gridable vehicles) should have capability to charge and discharge from the grid in an intelligent manner that maximizes the utilization of RESs. Furthermore, a major portion of global emission represented in the power and energy consumption in the industrial sector, in which 40% of the global CO2 production occurs. Transportation sector is responsible for 24% [2]. The projected costs of an escalating climate change are to the extent that 20% of the global domestic product (GDP). Nevertheless, these costs could be restricted to just about 1% of GDP by taking the proper measurements [3]. In Addition, Climate is also changing due greenhouse gas emission. And it is now extensively acknowledged as a real condition that has likely serious effects for human society. Therefore, it is essential for industries to put this factor into their concerns as well as their strategic plans [4]. Therefore, environment friendly modern planning is essential. And the new energy plan encourages us to deploy the electric vehicles on the road. Not mentioning the huge electric vehicles are charged from present electric grid randomly, the peak load will be very high. Thus it will result economically and environmentally expensive especially if thermal power plants remain the major source of electric energy. PHEV and EV researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [5-11]. Their goals are to educate about the environmental and economic benefits of PHEV and EV, and to enhance the product market. However, power system reliability consists of system security and adequacy. A smart power system is adequate if there is a sufficient power supply to meet customer needs with minimum cost and emission. PHEVs, by themselves, cannot solve the emission problem completely, because they need electric power which is one of the main sources of emission. Therefore, success of practical application of PHEVs and EVs greatly depends on the maximum utilization of renewable energy so that the goal of cost-emission reduction is achievable. However, the integration of GVs with RESs in a smart grid with the appropriate control technology has the potential for cost-emission reduction.

Therefore, by using the smart grid it maximizes the utilization of renewable energy; improves reliability and security; and provides sufficient customer choice and affordability as seen in figure 1. Where A,B,C, E: RESs; D: Emissions proportional to energy taken from thermal power plants; F: GV as a small portable power plant (SP3), load or energy storage; G: Smart parking lot (SmartPark) as a virtual power plant (VPP), bulk load or bulk energy storage; H: An information and communication device (ICD) in a GV to interact with a distribution center. Distribution center carrying out real-time dynamic stochastic optimization for cost and emission reduction A true smart grid with GVs and RESs will be a complex system in a dynamic environment. Traditional static optimization methods cannot meet the requirements of a smart grid in real-time. Such a smart grid calls for dynamic stochastic optimization techniques to achieve in real time cost and emission reductions. With real-time dynamic stochastic optimization of a smart grid consisting gridable vehicles, conventional generating units and RESs, smart grid and electrified transportation infrastructure will become a reality.

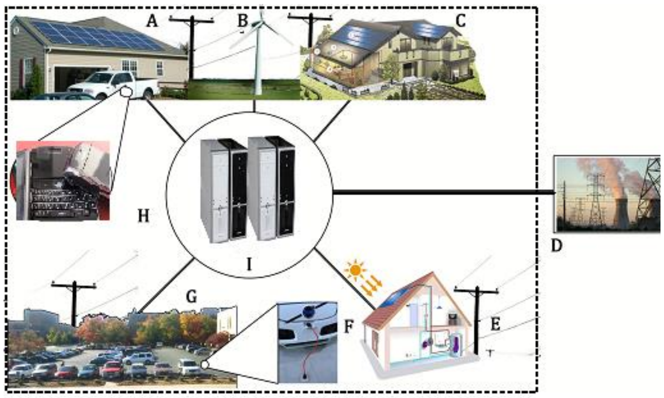


Figure 1. A smart grid with gridable vehicles and renewable energy

## II. CLIMATE CHANGES

Climate change is the largest element of environmental change, as it covers the globe and extends to time horizons beyond the lifetimes of the people alive today. Currently U.S. carbon emissions rises to 6 billion tons, and if business as usual continues, it will grow 6.4 billion by 2020. In most of the countries, new energy plan calls for implementing an economy-wide cap-and-trade program to reduce greenhouse gas emissions 80% by 2050. It is obvious that advanced technologies are needed today to reduce carbon footprint of individual activity while accelerating worth of existence.

The power and energy industry represents a major portion of global emission, which is responsible for 40% of the global CO2 production followed by the transportation sector (24%) [2,12]. The amount of carbon dioxide released is in direct proportion to the amount of carbon in the fuel and the quantity of fuel burnt. Thus, a generation plant that burns a carbon-intensive fuel will generate more carbon dioxide at increased levels of operation [13] . Other types of emissions (SO2, NOx, etc.) are also produced from power generation systems and transportation sector.

In accordance with the International Energy Agency (IEA), effectively executed energy efficiency measurements could provide up to 80% of avoided GHGs while considerably rising security of supply (G8 Summit, 2007) [14] . The development of intelligent technologies for energy-efficiency, maximum utilization of renewable energy and efficient road transportation will both soften negative effects of the climate change on the economy and enhance energy security

## III. RENEWABLE ENERGY SOURCES

The use of renewable energy sources 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 cleanup and health effects [15]. Secured and reliable power systems must have enough generation to meet the time-varying demand each day. In addition, they must also have enough reserve to deal with unexpected contingencies. Stimulated by recent technological developments and increasing concern over the sustainability and environmental impact of conventional fuel usage, the prospect of producing clean and sustainable power in substantial quantities from RESs arouses interest around the world. Energy prices, supply uncertainties, and environmental concerns are driving the United States to rethink its energy mix and develop diverse sources of clean, renewable energy. The nation is working toward generating more energy from domestic resources — energy that can be cost-effective and replaced or renewed without contributing to climate change or major adverse environmental impacts [16]. And by using the smart grid along with these renewable energy sources as seen in figure 1 above Where The smart grid should be flexible and allow GVs to charge/discharge from/to the grid when they are parked both in their small home garages which is A in Figure 1 or in a Smart Park which is G in Figure 1 above. A vehicle on-board information and communication device (ICD) is needed on each GV to communicate with a distribution center that performs dynamic stochastic optimization in a real-time which is H in Figure 1 above. Vehicles are mostly parked than on the road. The ICD in a vehicle will communicate current operating state of the vehicle (standby, engine assist or charging/discharging batteries), charging-discharging efficiency, available time, etc. to the DSO system using some encrypted codes and receive critical smart grid status to make its local decision when parked intelligently.

The U.S. Energy Information Administration (EIA) estimates that U.S. electricity demand will grow by 39% from 2005 to 2030, reaching 5.8 billion megawatt-hours (MWh) by 2030. Penetration of renewable energy is increasing day-by-day to reduce cost and emission. The United States has target to supply 10% of national electricity demand from RESs by 2012. Energy efficient homes are highly encouraged to reduce electricity cost and emission. A smart house, which is off the grid and stand-alone power system (SPS) with RESs, is highly expected in near feature.

Weather influences both electricity consumption and renewable power generation. Renewable resources vary considerably from one location to another. In central renewable power systems, green sources are converted into electricity on the large scale. However, a distributed system is non-central, on- and off-grid systems. Inclusion of storage in the distributed generation system provides the user dispatchability of its distributed resources. Renewable power dispatch is addressed in [13, 17]. Voltage and frequency regulation up to a certain standard level is essential to use the distributed renewable power in the grid so that the utility interconnection functions properly. PHEVs with V2G technology are very promising for effective utilization of distributed renewable energy.

In [18], authors present a hybrid wind-solar power system for either autonomous or grid-linked applications. A linear programming-based approach was used to reduce the cost of electricity and emissions while meeting the load requirements in a reliable manner. This is possible by monitoring the operation of the autonomous/grid-linked systems and determining the energy availability from each of the system components. Results shown that the utilization of renewable energy can offer considerable economic and ecological credit compared to diesel generation.

An advanced power electronic interface that is scalable to meet different power requirements, with modular design, lower cost, and improved reliability, will improve the overall cost and durability of distributed and renewable energy systems [19]. The increase in the penetration of renewable energy in recent years has led to a number of challenges, for example, the coordination wind generation with other forms of generation and energy storage technologies while maintaining the existing level of security of supply. This calls for advanced technologies for real-time dynamic stochastic optimization to maximize the utilization of RESs and optimal energy storage.

## IV. Gridable Vehicles in Road Transportation

A technical report from National Renewable Energy Laboratory (NREL) has reported that there are significant reductions in net CO2 emissions from PHEVs [20]. The combination of fluctuating high oil costs, concerns about oil security and availability, and air quality issues related to vehicle emissions are driving interest in PHEVs. Considering cost advantages, a study by the Electric Power Research Institute (EPRI) found a significant potential market for PHEVs [21]. However, the use of PHEVs or GVs will increase electric load as mentioned before. If vehicles are charged randomly, peak load will be very high and it will become necessary to install new power plants to meet it, which is very costly. Electrification of the transportation sector will need modification of present gasoline stations and also will increase complexity in present power grid.

A primary investigation on the impact of PHEVs charging on the utility power system is reported in [22]. The investigation is mainly focused on the impact of the additional electrical load from PHEVs charging will have on primary energy source utilization and subsequent environmental air pollution (EAP) as emissions are transferred from vehicle tailpipes to power plants. This investigation made a comparison between two simulated scenarios. The first scenario is the business as usual scenario with no PHEVs and the second scenario included PHEVs. The tradeoff between lowering total EAP levels generated by traditional vehicles and increasing power plants EAP was the focus of the investigation.

Research in PHEV and EV has mainly concentrated on the successful integration of energy storage capabilities in vehicles to the grid [5-11, 23]. Profit based investigation for plug-in hybrid electric vehicles with V2G capability is reported in [24] and it has been shown that considerable amount of profit is possible after proper optimization. This encourages people to purchase plug-in hybrid electric vehicles changing the transportation sector to be cost efficient, emission free and health caring. Significant fuel savings in transportation is achievable by implementing a continuous updating process of rout suggestion with the help of real-time traffic data [25]. The impact of daytime recharging using solar arrays located at commuters' work sites is studied in [26] and this would convert large parking areas into solar recharge stations for commuters. Authors in [27] present basic design considerations for PHEVs including vehicle architecture, energy management systems, drive train component function, energy storage trade-offs and grid connections. In [28], the viability of the PHEV as a mobile energy storage unit connected to the power grid is examined from a power system perspective, involving an examination of practicality, reliability, short- and long-term economics, and alternative energy storage units. Authors have discussed current US hybrid and PHEV trends, summarized major national and state projects, the charging impact on the power grid, vehicle-to-grid technology (V2G) and so on in [29]. Four typical daily charging strategies are investigated, which are:

1. Uniform charging.
2. Home-based charging.
3. Off-peak charging and
4. Vehicle-to-grid charging in [30].

Emission issue is investigated in [31]. Balance between load and demand sides is investigated in [32] where V2G is considered with wind penetration varying from 0% to 100%.

PHEVs, by themselves, cannot solve the emission problem completely, because they need electric power which is one of the main sources of emission. Gridable vehicles can be utilized for harnessing renewable energy, storage, transportation, and providing power for both residential and commercial customers. Maximum utilization of renewable energy and GVs with V2G capability, where the vehicle can discharge as well as charge, can contribute to solving the energy cost and emission problems. Real-time dynamic stochastic optimization for a smart grid with renewable energy sources and GVs can minimize cost, losses, emission and peak load; and spinning reserve and reliability of the electricity infrastructure will be increased. Besides, GV owners will have financial benefit, thus people will be interested in purchasing GVs.

## V. Static Optimization /Scheduling in Power Systems Operation

Static optimization is being used in power systems optimization, e.g., unit commitment (UC) scheduling, economic dispatch, maintenance scheduling, etc. The main objective of the power systems optimization is to reduce cost. Among the power systems optimization areas, UC mainly involves to properly scheduling of all available resources in the system and economic dispatch is a part of the UC scheduling where load is distributed among online resources. Additionally to accomplish a lot of system constraints, optimization methods should satisfy the forecast load demand computed beforehand, production range, least up/down time, restricted operating zone, ramp rate, transmission restraints, spinning reserve constraints, etc. periodically to ensure minimum total cost. Power systems optimization is a complex combinatorial optimization problem with both binary and continuous variables in non-stationary environment. The number of combinations of variables grows exponentially for a large-scale real problem.

A bibliographical survey on optimization of power systems reveals that numerous numerical optimization methods have been deployed over the last three decades. Among these methods, priority list methods [33] are very speedy methods; but they are extremely non-recursive. In terms of storage capacity Branch-and-bound methods [34-35] have the danger of insufficiency. Lagrangian relaxation methods [36-38] focus on seeking a suitable coordination technique for producing reasonable primal resolutions, at the same time reducing the duality gap. But it is difficult to obtain a feasible solution with these Lagrangian relaxation methods. The meta-heuristic schemes [39-50] are iterative in nature that can be used to explore both local and global optimal solution. But it depends on problem domain and time limit for execution.

Different general-purpose searching methods like genetic algorithm, evolutionary programming, tabu search, simulated annealing, etc. are used in meta-heuristic techniques for power system optimization. However, they are very sensitive during parameter selection process; possibility to be unbalanced between local and global searching capabilities and so on. Besides these, Particle swarm optimization (PSO) and ant colony optimization are two well recognized swarm inspired schemes in intelligent computational field. Inspired by the food-seeking behavior of real ants, Ant Systems, attributable to Dorigo et al., need huge memory like dynamic programming even for a moderate size of UC problem, and difficult to solve it in real-time and physical computer storage capacity. However, PSO is simple, and it requires less computation time and memory. It has good information sharing and conveying mechanisms. It makes balance between local and global searching abilities. Different variations of PSO are also available to solve different types of problems.

Power system researches have presented conventional UC problems in literature to minimize cost. They have not considered gridable vehicles in unit commitment problems to optimize both cost and emission, though these factors are important as discussed above. Emission in the traditional dispatch system is address by some researchers, however without considering gridable vehicles [51-53]. Besides, the above-mentioned optimization methods applied to power systems is static. In this proposal, gridable vehicles and RESs are included as time varying resources in a smart grid to minimize both cost and emission. This calls for real-time dynamic stochastic optimization techniques.

## VI. Dynamic Optimization

Dynamic programming deals with a search which tracks toward the back from final step, preserving in memory all suboptimal paths from any specified point to the end, until the initial point is achieved. The consequence of this is that the method consists high computational cost for most real problems. Adaptive critics designs (ACDs) are designs capable of optimization over time under conditions of noise and uncertainty. A family of ACDs was proposed by Werbos [54] as new optimization methods based on the combined concepts of reinforcement learning and approximate dynamic programming. For a given series of control actions that must be taken sequentially, and not knowing the effect of these actions until the end of the sequence, it is impossible to design an optimal controller or decision network using the traditional supervised learning techniques. The adaptive critic method determines optimal control laws for a system by successively adapting two networks, namely an action network (which dispenses the control/decision signals) and a critic network (which "learns" the desired performance index for some function associated with the performance index). These two networks approximate the Hamilton–Jacobi–Bellman equation associated with optimal control theory. The adaptation process starts with a non-optimal, arbitrarily chosen, control/decision by the action network; the critic network then guides the action network toward the optimal solution at each successive adaptation. During the adaptations, neither of the networks needs any "information" of an optimal trajectory, only the desired cost needs to be known. Furthermore, this method determines optimal control/decision policy for the entire range of initial conditions and needs no external training, unlike other techniques. Neural networks can be used as tools to implement the action and critic networks. The critic network learns to approximate the cost-to-go or strategic utility function at each step (the function of Bellman's equation in dynamic programming) and uses the output of the action network as one of its inputs, directly or indirectly. The cost-to-go function is given as follows:

$$J\big(x(t)\big) = \sum_{k=0}^{\infty} \gamma^k U(x(t+k)) \text{……………………(1)}$$

Where $\gamma$ is a discount factor for finite horizon problems ($0< \gamma <1$), $U(.)$ is the utility function or the local cost and is an input vector to the critic. Different types of critics have been proposed. For example, Watkins [55] developed a system known as Q-learning, explicitly based on dynamic programming. Werbos, on the other hand, developed a family of systems for approximating dynamic programming [54]; his approach subsumes other designs for continuous domains. For example, Q-learning becomes a special case of action-dependent heuristic dynamic programming (ADHDP), which is a critic approximating the function, in Werbos' family of adaptive critics. ACD family includes both dual heuristic programming (DHP) and globalized dual heuristic programming (GDHP). In which DHP approximates only the derivatives of the function J with respect to its states and GDHP approximates both J and its derivatives. Because any differentiable structure is appropriate as a building block, these methods do not involve entirely neural-network executions. The correlations among members of the ACD family have been formalized and presented in depth by Prokhorov [56]. Implementations of ACD in various applications of power systems are given in [57-64].

CEED has been studied by several researchers as a multi-objective problem using computational intelligence techniques such as non-dominated sorting genetic algorithm (NSGA-II) [65] and evolutionary programming [66]. Dynamic optimization strategies based on advanced computational intelligence techniques – the ACDs, have the potential to solve the CEED problem, with emphasis on CO2 reduction.

## Conclusion

The Combined Economic Emission dispatch (CEED) problem is a complex constrained optimization problem with many local optima. Whenever minimum cost of operation is taken as sole optimization objective, the corresponding emission level increases. Similarly, when minimum emission dispatch is taken as the sole objective, it results in higher operating cost. Therefore, both objectives are conflicting in nature and some weights must be assigned to obtain a non-inferior solution. Under such cases, the aim is to determine the trade-off surface, which is a set of non-dominated solution points, known as the Pareto optimal solutions. Every point on the Pareto front is an acceptable solution. Several classical optimization techniques are challenged by the nature of this problem and get trapped in a local minimum. In addition, the computational overhead is enormous as the search space grows with increasing number of power generation units. After an extensive investigation of existing literature review, it is recommended that a dynamic stochastic optimization (DSO) approach can be used to automatically schedule and coordinate non-stationary sources to get full benefits of renewable energy sources (RESs) such that (1) load demand can be leveled; (2) cost and emission will be reduced; (3) reserve and reliability of a smart grid can be increased when millions of new loads, e.g., GVs, are to be integrated.

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