# CONSIDERING IMPACTS OF PLUG-IN ELECTRIC VEHICLES IN PLANNING OPTIMAL HYBRID SYSTEMS

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## *ABSTRACT*

*This paper proposes a stochastic-heuristic optimization approach for planning hybrid active systems or micrograds. Optimal sizing of such systems could be a challenging task particularly in presence of plug-in electric vehicles (PEVs). The presented case study deals with optimal sizing of an autonomous wind-fuel cell hybrid power system under impacts of PEVs. The stochastic part of the presented approach carefully considers a realistic level of variability and inter-dependence structure for PEVs net load as well as wind power generation. Using a particle swarm optimization (PSO) embedded in the stochastic modeling offers a set of optimal sizes. Then, the planner would be able to use statistical indices and come to a decision that is advisable to be optimal with a greater confidence.*

## INTRODUCTION

Controllable electricity loads and storage devices have the potential to significantly and inexpensively increase the reliability of power systems, especially in hybrid systems with variable, unpredictable generation from renewable sources. Otherwise than the load-side management, planning sufficient storage capacity is of a primary importance in assembling an autonomous micro-grid. So far, hybrid systems are preferred; in which a wind farm and/or a photovoltaic field are coupled to some storage equipment such as batteries or hydrogen-based systems. On the other hand, interest in electric transportation, particularly plug-in electric vehicles (PEVs), has increased dramatically in recent years [1]. One of the main potential utility benefits from PEVs includes the use of vehicle batteries as distributed storage. Therefore, as the design of a hybrid autonomous power system requires a number of subsystems to be considered, accurate representation of PEVs impacts on power distribution of such systems should also be considered.

Sufficient understanding and representation of PEV load variations such as daily load shape as well as locational displacement have not fully addressed in traditional system planning methods. Indeed, PEV characteristics along with the anticipated high penetration of stochastic energy flows spatially distributed throughout the stand-alone micro-grids should be optimized by using hybrid stochastic-heuristic simulation methods in the planning stage. In addition to the high penetration of stochastic

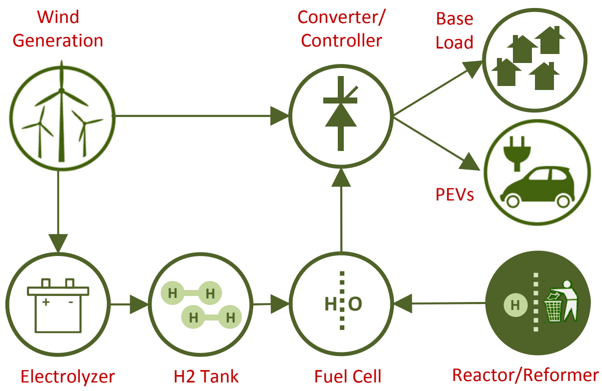


**Fig. 1. A diagram of the hybrid system under study; both the generation side and the load side are distributed.**

behaviors within such systems, there is a strong dependence structure between load, generation and storage variable behaviors over a year. An advanced stochastic modeling of the system requires multivariate uncertainty analysis.

In order for considering the impacts of both PEVs and wind power variation, this paper proposes a hybrid simulation procedure to the problem of optimal sizing for a hybrid autonomous power system. The developed algorithm consists of a subroutine by a particle swarm optimization (PSO) embedded in a multivariate stochastic simulation.

The use of a stochastic simulation (Monte Carlo approach) is necessary for the variability of PEV load whilst settling on a multivariate modeling style is to capture the dependence structure of the planning dataset. It is employed the **planning for net load** concept [2] in the context of this multivariate stochastic analysis. The whole method intended to capture both spatial and temporal diversity of PEV integration as customers in varied locations purchase PEVs of varied types and charge them differently.

The optimal sizing problem is investigated for a wind-fuel cell hybrid system (Fig. 1) having an arbitrary level of penetration with PEVs. Using of hydrogen in the hybrid system provides a higher reliability. Optimization of all modeling outcomes using PSO algorithm results in a cluster of optimal sizes which provides a wide knowledge of all possible upshots stemming from multivariate PEVs/wind uncertainty. The final mostly optimal sizes can then be calculated based on the relevant statistical moments of the size sets. These sizes are advisable to be optimal with a greater confidence. This study is performed utilizing a dataset for a real site in Iran.

## HYBRID ACTIVE SYSTEM WITH ELECTRIC VEHICLES

The hybrid system involves some wind turbines, some fuel cells, some electrolyzers, and some hydrogen tanks and assumed to be an autonomous small power system according to Fig. 1. The system's power output should meet the demand and the costs are minimized. The objective function and operation strategies for this grid-connected hybrid system are somewhat identical to the autonomous system of [3]; so, they are not fully described in this short paper to keep focus on the main issue. The main difference is adding some PEVs to the consumers' load share.

Optimized solution is achieved by minimizing total system costs throughout the whole of its useful lifespan (20 years), when those costs are referred to or updated for the initial investment; that is called **Net Present Cost** (*NPC*). The *NPC* of the *n*-th component can be calculated via below equation:

$$NPC_n = N_n \times \{CC_n + RC_n \times K_n + OMC_n \times APW(IR, R)\} \quad (1)$$

Where, $N_n$ is the number/rating, $CC_n$ is the capital cost, $RC_n$ is the replacement cost, and $OMC_n$ is the operation and maintenance cost, all for *n*-th equipment ($n$=1,2,…,4 represents wind turbine, fuel cell, electrolyzer, and hydrogen tank, respectively). Moreover, $R$ is the project's lifespan, and $IR$ is the so-called **real interest rate** that is assumed 0.08. Other parameters, $APW$ and $K$ are **annual payment present worth** and **single payment present worth**, respectively, defined as

$$APW(IR, R) = \frac{(1+IR)^R - 1}{IR \times (1+IR)^R}, \quad K_n = \sum_{j=1}^{y_n} \frac{1}{(1+IR)^{j \times L_n}}, \quad (2)$$

where, $y$ is the number of times each component replaced and $L_n$ is the lifespan of each component. Therefore, based on the definition of *NPC* by (1) along with the constraints [3], a classic form of the multi-objective optimization problem could be written as

$$\begin{aligned}
&\underset{x}{\text{Minimize}} \quad \sum_n NPC_n \\
&\text{with respect to} \quad N_n \\
&\text{subject to} \quad N_n > 0 \\
&\qquad 0 \le E_{\tan k(i)} \le E_{\max} \\
&\qquad P_{wt_comv(i)} + P_{fc_conv(i)} = P_{load(i)} / \eta_{conv} \\
&\qquad P_{fc_conv(i)} \le N_{fc} \times P_{fc}
\end{aligned}$$

Indeed, the weighted sum method, used here consisting sum of the individual system devices' NPCs, is one of the most common methods for solving multi-objective optimization.

Considering PEVs' aggregated load in this problem could be presented by inserting its impacts on the net load of the system through a multivariate modeling of its behaviour. The net PEV loads provide an indication of the basic impacts on utility load patterns and provide some quantitative information such as the change in utility load factor, such as the need for additional capacity. Moreover, system load is variable; besides, renewable generation varies.

Distribution systems currently are designed under the assumption of power flow from a substation to end-use loads. Depending on the penetration level, PEVs can cause a reversal of power flow through the distribution system, and this is the likely source of problems. Correlated load and PEVs' controlled behavioural scenarios are needed to predict the maximum amount of reverse power flow.

On the other hand, distribution network rely on a "coincidence factor of loads" for sizing all of the system's components. Indeed, the loads are not likely to operate deterministically simultaneous, and the planner takes advantage of this by sizing the component for the expected coincident load rather than the maximum load [2]. The probability of coincident operation of PEVs is much higher, because there are some specific times in which the customers would like to plug-in their vehicles. Anyhow, the actual electricity demands associated with PEV controlled charging are quite modest compared to normal electricity demands. Controlled charging would even create additional benefits as some kind of a demand side management programs. Such a controlled charging yet, with 5% randomness is employed in this paper. The net load of the hybrid system with and without PEVs is illustrated in Fig. 2 by two histograms.

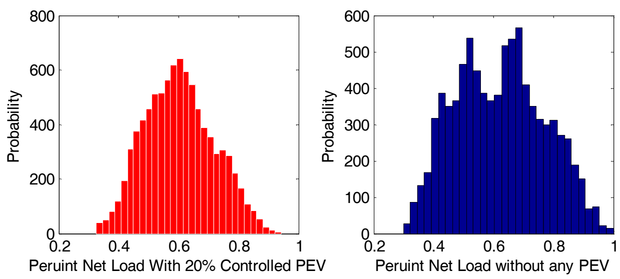


**Fig. 2. System net load distribution. The partially controlled charging is assumed when considering PEVs.**

Modeling dependence structure of the planning data set (net load within two scenarios and wind speed) is illustrated in Fig. 3 in the form of an autocorrelation matrix. Each pixel set gives the correlation between two

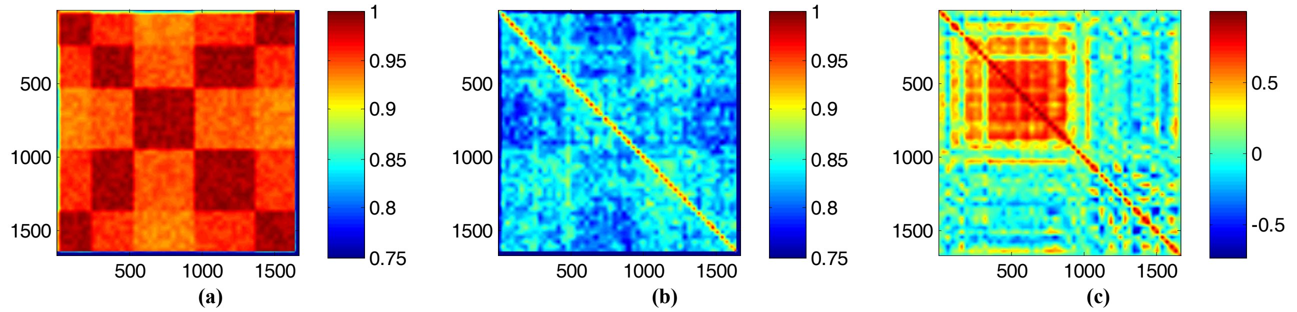


**Fig. 3. Modelled dependence structure of the planning data set over a year: (a) Net load without any PEV demand; (b) Net load with 20% partially controlled PEV demand assuming DSM; and (c) wind speed. Such a multivariate modeling could be used to capture the impacts of PEVs and wind power in the planning/sizing stage.**

horizons, and hence ones for each horizon on the diagonal. It is also interesting to note that the annual/seasonal pattern of load and wind speed is revealed considering Fig. 3 (note the distinguishable square areas); which conforms to an accurate modeling as presented. These probabilistic models allow for simulating above-mentioned characteristics which are employed by the proposed stochastic algorithm in the next section.

## AN OUTLINE OF THE STOCHASTIC-HEURISTIC ALGORITHM

The general outline of the presented analysis is illustrated by a flowchart in Fig. 4. The scenarios are considered in a

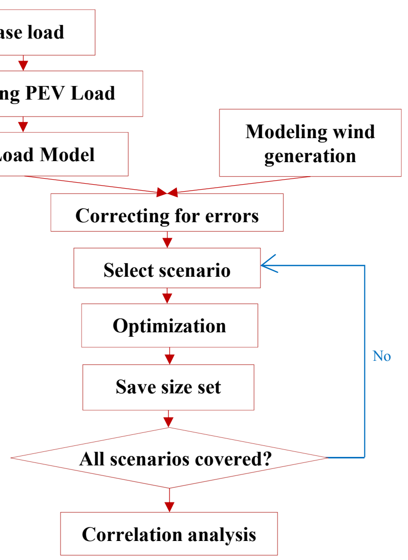


**Fig. 4. Flowchart of the proposed hybrid approach.**

weekly time horizon. By the time the net load probabilistic model considering impacts of PEVs is obtained and corrected for bias and standard errors, each scenario is fed into an optimization loop to calculate the most optimal size set for that scenario. Doing this for all scenarios results in a cluster of optimal sizes that could be further analyzed by a correlation analysis.

It should be mentioned that the multivariate modeling in the previous section is able to provide a large number of scenarios. These scenarios, all together, represent the long-term behaviour of the PEV load and wind time series considering uncertainty and could be used for planning purposes. This provides a **scenario-based forecasting**. The application of point forecasting methods in this paper (even the methods that consider uncertainty) is irrelevant because of both the consideration of PEVs and the long-term planning.

## RESULTS

The results of the whole stochastic optimization process using 12,000 samples/scenarios are depicted by Figs. 5 (a)-(f) as the distribution of optimal point differences between the scenarios with 20% PEV penetration and scenarios with no PEV. The latter case is identical to those considered in [3] by just considering the load model in Fig. 3(a). The optimal sizes of the wind turbine, electrolyzer, hydrogen tank and fuel cell for the scenarios with no PEV are equal to 89, 2330, 3140, and 470, respectively; and the optimal cost is $16.16M. These quantities would be changed when considering 20% PEV load demand according to Figs. 5(a)-(f). Assume the mean values are used as optimal decision, then, comparing two cases with and without PEVs shows an improved optimal solution with a lower total cost when there are some PEVs in the system. This is understandable since the PEVs assumed to be used in a somewhat controlled manner to improve DSM indexes.

Any decision other than using mean values could be made based on more advanced analyses of the results. Another illustration of the results could be some kind of a matrix plot in Fig. 6 which reveals any correlation between every planning parameter. From the statistical point of view, such information could be very useful to investigate the relationships between different optimal points with which the final decision would be made.

Furthermore, the scatter plots in Fig. 7 shows the optimal cost and sizes of wind turbine, electrolyzer, tank and fuel cell from top to bottom, respectively for the 12,000 scenarios. The simulations of optimal cost have been sorted from the highest value to the lowest one. This order has been kept to plot other traces for size sets. As a case in point, these plots can be employed as some decision stuff like Pareto optimal movement. Pareto principal, as a well-known criterion in multi-objective optimization, utilizes Pareto optimal set to depict the trade-off between the objectives. The decision maker can then select the most preferred solution out of the Pareto optimal set.

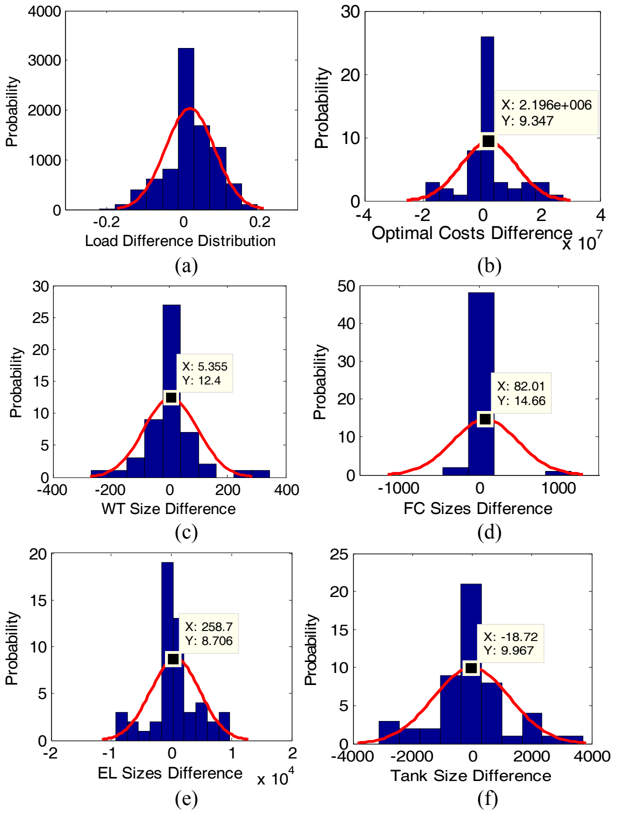


**Fig. 5. Probability distributions of differences when the results of scenarios without PEVs are subtracted from the results of scenarios with 20% PEV penetration.**

It is also inferable from Fig. 7 that if the decision maker decides to have perfect (unit) supply reliability, even with uncertainty, an overdesigned system would be necessary with an optimal cost of approximately \$30M (in case there is no PEV, this would be \$50M). Nonetheless, a worthwhile optimal selection would be the mean values of all scenarios at the cost of reducing the reliability, but to an acceptable level most of the time.

## CONCLUSIONS

A new strategy is proposed to take proper account of PEV proliferation in the optimal sizing problem for a stand-alone hybrid power system. A PSO-embedded stochastic simulation is developed and several statistical analyses are performed prior to and after the simulation aiming at realistic modeling of the wind power and load demand data. A set of optimal sizes are obtained as final outputs which is then analyzed to provide a measure for making the optimal decision. Other relationships could also be implied and might be used to help the decision maker in a more appropriate optimal system planning.

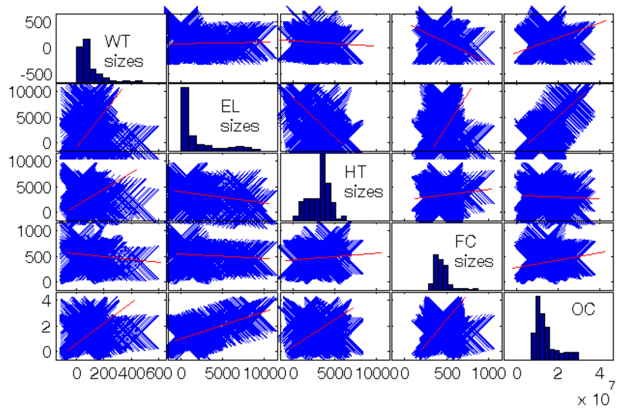


**Fig. 6. Visualizing the correlation matrix structure of results. The direction of correlation is depicted by red lines.**

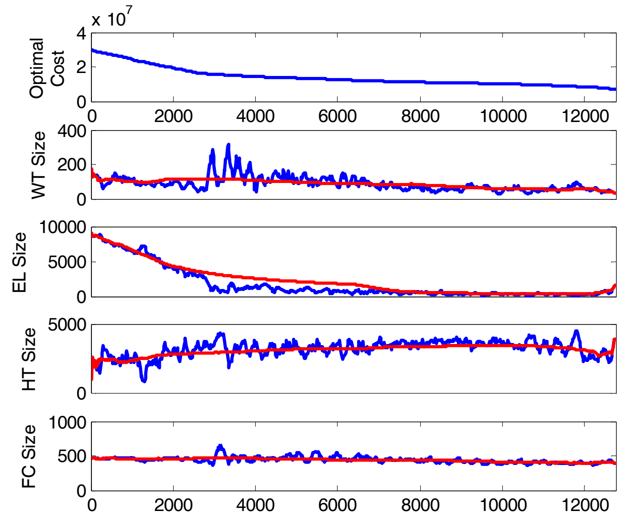


**Fig. 7. Simulated size sets for all 12,000 samples for the optimal cost, wind turbine, fuel cell, electrolyzer, and hydrogen tank respectively from top to bottom (red bold lines are a mean trend of data). The descending order of optimal cost has been kept for plotting optimal size sets.**

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