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# An integrated algorithm for evaluating plug-in electric vehicle's impact on the state of power grid assets

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ABSTRACT

Plug-in Electric Vehicles (PEV) exert an increasingly disruptive influence on power delivery systems with penetration surge in the past decade. Therefore, accurately assessing their impact plays a crucial role in managing grid assets and maintaining power grids' reliability. However, PEV loads are stochastic and *impulsive*, which means they are of high power density and vary in a fast and discrete manner. These load characteristics make conventional assessment methods unsuitable. This paper proposes an algorithm, which captures the inter-temporal response of grid assets and allows fast assessment through an integrated interface. To realize these advantageous features, we establish analytical models for two generic classes of grid assets (continuous and discrete operating assets) and recast their cost functions in the statistical settings of PEV charging. Distinct from simulation-based methods, the proposed method is analytical, and thus greatly reduce the computation resources and data required for accurate assessment. The effectiveness of the proposed algorithm has been demonstrated on a set of power distribution networks in Columbus metropolitan area, in comparison with the conventional assessment methods.

## 1. Introduction

The current electric power system has been increasingly penetrated with Plug-in Electric Vehicles (PEV). According to the International Energy Agency (IEA), over 750 thousand fleets of new PEVs were registered in 2016 alone, and the worldwide PEV penetration target is 30% of total market share by 2030 [1]. The power required to charge PEVs is provided at the distribution and potentially sub-transmission level (below 69 kV) of the grid [2]. PEV loads consume much higher power during charging. As Table 1 shows, at DC Level 2, it is possible to charge a 25 kWh battery pack in 10 min, which far exceeds the peak power demand for an average household in the U.S. Moreover, the power electronics-interfaced (PE-interfaced) configuration of PEV charger can ramp to full charging level almost instantaneously. For example, it only takes 7 s for a 2016 Ford Focus Electric to reach its full charging power after connecting to the grid.

Distinct from conventional loads, PEV loads are stochastic and *impulsive*, which means they are of high power density and vary in a fast and discrete manner. Prior works have shown that these load characteristics will result in negative impacts on the power grid, including disruptively varying voltage profiles along the feeder and overloading of service transformers [4,6–10]. This will consequently affect the operating state of grid asset and induce asset depreciation over the long term. With increasing PEV penetration and improving fast/ultra-fast charging technologies, it is critical for electric utilities to accurately quantify the impact of PEV loads on grid assets and plan for equipment replacement and infrastructure expansion accordingly, in order to ensure service reliability.

On assessing grid assets' response under high penetration of PEVs, existing studies fall into two categories: static analysis and Time-Series (TS) analysis. Most of the static analysis results in the consideration of maximum PEV loads induced by coincidental charging. For example, [11] shows that the energy losses can increase up to 40% in off-peak hours and the investment cost can increase up to 15% of total distribution network costs for a scenario of 60% PEV penetration level. In [12], the case study shows that both peak-to-average ratio (PAR) and loss increment are the big concern to the widespread use of PEVs due to the coincidence of daily peak load and charging activities. The shortfall of this approach is that only the worst cases are considered, and thus tend to overestimate the PEV's impact. Improving on this approach, other work, such as [13,14], considers the probabilistic distribution of PEV loads connected in the system. In [13], Roulette wheel selection concept is used to take various uncertainties into account, thus quantifies the congestion and security risk impact of PEV in the form of probabilistic distribution functions. While these assessments allow more accurate input of PEV charging, an inherent deficiency of the

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**Table 1**
PEV charging ratings and configurations. [1,3–5]

| Charging level | Input voltage and connection | Maximum power (kW) | Charging time | Typical use |
|---|---|---|---|---|
| AC Level 1 | 120 V 1-phase | 2 | 10~13 h | Private/Public residential/Commercial |
| AC Level 2 | 240 V 1-phase/3-phase | 20 | 1~4 h | |
| AC Level 3 | 240 V 3-phase | 43.5 | ~1 h | |
| DC Level 1 | 200~450 V 3-phase | 36 | 0.5~1.44 h | Public Commercial |
| DC Level 2 | 200~450 V 3-phase | 96 | 0.2~0.58 h | |
| DC Level 3 | 200~600 V 3-phase | 200 | ~10 min | |

*Note:* AC Level 3 and DC Level 3 are not yet finalized.

static analysis is embedded from the assumption of fixed grid configurations. Therefore, they cannot capture the inter-temporal response of grid assets. These deficiencies can be alleviated in TS analysis.

TS analysis feeds load profiles in time series to power flow analysis and observes power grid's response. A few studies adopt TS analysis in PEV's impact evaluation, under deterministic or stochastic settings. Ref. [14] simulated four PEV charging scenarios, considering stochastic nature in charging start time, and thus concludes that a 20% level of PEV penetration would lead to a 35.8% increase in peak load for uncontrolled charging scenario. However, the results of these studies do not naturally fulfill utilities' needs of quantifying the long-term cost induced by PEV penetration. This is because (i) the existing studies are simulation-based, and thus the conclusions drawn cannot be generalized to other power systems; (ii) TS analysis only shows the electrical response (e.g., voltage, power, etc.), but grid asset depreciation could depend on response in other dimensions (e.g., winding temperature); and most importantly (iii) the load flow resulted from the TS analysis are taken in the form of annual average in the grid asset assessment [15], which makes PEVs' impulsive charging characteristics invisible. In other words, the load spikes caused by PEV charging can be easily averaged off in the assessment and shown harmless, while they could greatly reduce the lifetime of the grid assets in reality.

To address the above deficiencies, this paper proposes an algorithm to evaluate grid asset depreciation under PEV's penetration. The contributions of the proposed algorithm are twofold:

- It provides an approach to conveniently assess PEV's impact on grid assets. The PEV charging profiles are pre-processed through Monte Carlo Simulation (MCS), which ensures accounting of random charging patterns, fed into TS analysis and asset lifetime analysis. The outputs are presented through an integrated interface.
- Inter-temporal response of grid assets is considered. Compared to existing methods, which assess grid assets based on their average loading, the proposed algorithm considers assets' operating frequency and temperature variation. These factors could lead to significant differences in the assessment, as demonstrated in the numerical cases.

The above two engineering advantages are realized under a unified mathematical framework, in which we establish analytical models of two generic classes of grid assets (i.e., continuous and discrete operating assets) and recast their cost functions in the statistical settings of PEV charging. Distinct from simulation-based methods, the proposed method is analytical, and thus greatly reduce the computation resources and data required for accurate assessment.

The rest of the paper is organized as follows. Section 1 introduces the mathematical framework, the analytical models, and the updated cost functions of the grid assets. Section 2 demonstrates the effectiveness of the proposed algorithm on a set of power distribution networks in Columbus metropolitan area, Ohio. We further discuss the implications of grid assets' depreciation under different PEV charging settings. Finally, the proposed algorithm and its future applications are concluded in Section 3.

This paper assumes that the power grid operates in the steady-state. The dynamical response of grid assets is defined as the inter-temporal state change. This paper does not address the transient response (i.e., power quality issues) and voltage instability induced by PEV charging [16,17]. In the paper, "grid assets" and "power delivery equipment" are used interchangeably. In addition, although the proposed algorithm can be applied to any power systems, we only examine its effectiveness in simple settings, where mitigation on PEV charging is not applied. An exhaustive examination of PEV's impact on grid assets is out of the scope of this paper.

### 1.1. *Overview of proposed integrated algorithm*

The proposed integrated algorithm is outlined in Fig. 1. In general, the algorithm combines TS power distribution systems analysis with off-line asset impact assessment. TS analysis is deployed to feed the time-varying grid status to the analytical asset depreciation models. Distinct from existing methods, which approximate actual grid status with annual average values, TS analysis enables accurate evaluation of grid assets' inter-temporal response. MCS is deployed to reflect the stochastic PEV charging patterns in the power flow, which are feed to TS analysis. Based on the Central Limit Theorem, the loading levels output from TS under MCS will provide a more accurate assessment if more charging patterns are available.

### 1.2. *Total cost of ownership analysis in utility practice*

Grid assets can be classified into two categories based on their depreciation procedures: continuous loading equipment and discrete operating equipment. The former's depreciation rate depends on their thermal loading, while the latter's depends on their operating frequency. Examples are transformers, which depreciate faster under heavy loading, and voltage regulators (VR), which exhaust after operating for a certain number of times.

Total Cost of Ownership (TCO) analysis is commonly adopted by utilities to assess the long-term cost, comprised of fixed capital cost and operating depreciation, of power delivery equipment. The TCO of discrete operating equipment is conventionally evaluated independent of loading conditions. For continuous loading equipment, its TCO is exemplified by a transformer and expressed as (1), with terms expanded in (2)–(5) [18].

$$TCO = C_o + CL\cdot A + LL\cdot B, \tag{1}$$

where $C_o$ is the bid price (capital cost) in dollar of the transformer, the rest of the terms are operating cost in dollar. $CL$, $LL$ are transformer core loss and load loss provided by manufacturers, $A$ and $B$ are core loss and load loss factor,

$$A = DC + N\cdot PEC \tag{2}$$