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RESEARCH ARTICLE

OPTIMAL PLACEMENT AND SIZING OF ELECTRIC VEHICLE CHARGING INFRASTRUCTURE USING DC POWER FLOW MODEL

Zhaohong Wang[a*], Han Lin[b], Jiahan Wen[b], Yang Xia[c], Chenghan Wen[d]

[a]Integra Credit, Chicago 60603, USA
[b]Faculty of Applied Science & Engineering, University of Toronto, Toronto M5S1A4, Canada
[c]Meta LLC, New York 10003, USA
[d]School of Applied Science & Engineering, Columbia University, New York 10027, USA
[*]Corresponding Author Email: zhaohongwang714@gmail.com

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ABSTRACT

With the burgeoning interest in electric vehicles (EVs) due to their sustainable attributes, concerns arise regarding the electrical grid's capacity to handle the consequent rise in electricity demand from charging stations. Ontario's aspiration to ensure that 5% of all vehicle sales are electric by 2020, driven by the province's Climate Change Action Plan, accentuates these concerns, particularly with the potential rise in fossil fuel power generation. This study delves into the optimization of generator outputs and the strategic placement and sizing of EV charging stations in Ontario. The goal is to curtail overall generation costs, adhering to the demand, generation, and transmission constraints. Through the utilization of a representative system, modeled after the IEEE 34-node test feeder due to data unavailability, the research explores Ontario's power dynamics over a 24-hour period in 2020. The findings provide insights into ideal locations and dimensions for charging stations, while also quantifying the environmental ramifications of the increased electrical grid load. This paper offers a comprehensive strategy to mitigate grid stress while bolstering EV infrastructure efficiently.

KEYWORDS

Electric Vehicle; Infrastructure; Vehicle Charging; Strategy

1. INTRODUCTION

In recent years, there has been a notable rise in electric vehicle (EV) interest. The growing popularity of EVs can be largely attributed to their environmental benefits and sustainability. However, concerns have emerged regarding the impact of widespread EV adoption, particularly the increased electricity demand resulting from the operation of charging stations.

Ontario has set a goal of having 5% of all vehicle sales be electric vehicle sales by 2020 (Ministry of the Environment, 2015). This goal was created to help the province meet its greenhouse gas emission goals outlined in Ontarios 5-Year Climate Change Action Plan (Ministry of the Environment, 2015). However, the electrical grid stress caused by the charging stations required to power these electric vehicles may result in a substantial increase of fossil fuel power generation.

This project aims to investigate the optimization of generator outputs and charging station placement and sizing in Ontario, to minimize overall generation costs while satisfying demand, generation, and transmission constraints. A system is created to analyze Ontarios generation output, power flow, and load draw over a day in 2020. These results are aggregated to determine optimal placements and sizing of charging stations, and to determine the overall environmental impact caused by charging station loading on the electrical grid throughout the day.

2. ONTARIO REPRESENTATIVE SYSTEM

2.1 Overview

Unfortunately, data on Ontario's distribution grid (with bus interconnections, line lengths, line impedances, etc.) were not available online, so a representative system was used for this optimization problem. The basis of the representative model is the IEEE 34-node test feeder (Anderson et al., 2018). This model was chosen based on its thorough documentation and appropriate system complexity. A visualization of the final system can be found in Fig. 1.

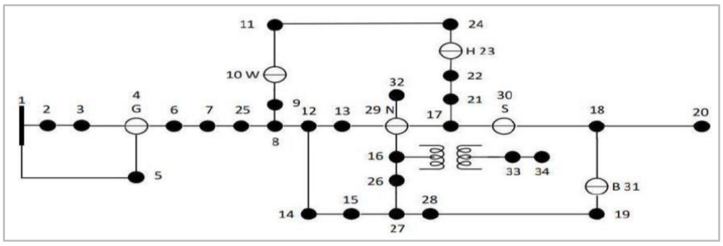

Figure 1: Overview of the system's node structure (Generators are identified as white nodes with the first letter of the generation type next to the node. Node 1 is defined as the slack bus.)

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3. Power Generation

To simplify power generation, the system features 6 generators, representing Ontario's primary energy sources: nuclear, hydro, gas, wind, solar, and biofuel. Nuclear and hydro generators are strategically placed at nodes with multiple line connections due to their significance in the system, while the remaining generators are evenly distributed.

The hourly maximum and minimum power outputs of these generators was determined depending on their power source. The average nominal costs of operation (including capital, material, and shutdown costs) for each power source (2) were found in (Ontario Energy Board, 2017). These costs were adjusted based on each generators power output (see Figure. 2). The amount of equivalent CO2 emissions produced from each generation source per kWh was found in (Schlmer et al., 2014). Both values were used as a basis for the system cost function, with the gCO2eq/MW values also being used to determine the environmental impact of increased generation caused by the charging station loads.

Table 1: Cost Bases for Generation

	Nuclear	Hydro	Gas	Wind	Solar	Biofuel
$\theta_2(\$/kWh)$	0.069	0.058	0.205	0.173	0.48	0.131
θ_1/θ_2	0.7	0.9	0.7	1	1	0.7
θ_3/θ_2	1.3	1.8	1.3	1	1	1.3
gCO_2eq/kWh	12	24	490	11	41	230

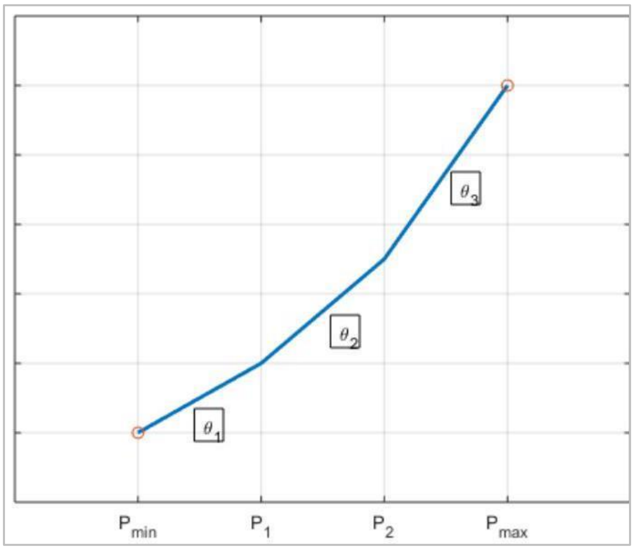

Figure 2: Visualization of generation cost adjustment with respect to output (P_1 and P_2 and taken to be and between P_{min} and P_{max}, while the slope s is located in Table 1)

3.1 Load Distribution

The overall demand load was also found by averaging hourly IESO data from Mar. 23-27, 2018. This was done so that the system load would adequately match the overall generation capability. This load was first distributed with a constant probability distribution function throughout all 34 nodes in the system. The nodes were then equally split into either commercial or residential loads. The loads were adjusted based on the varying distribution of power between commercial and residential loads throughout the day (Andersen et al., 2017).

3.2 Transmission Lines

The impedances, lengths, and configurations of the lines were found in (Anderson et al., 2018). To have the system closer resemble a transmission grid rather than a distribution grid, lines were added between nodes 1 and 5, 11 and 24, 13 and 29, and 19 and 28. The flow limits of the lines were determined by scaling the total system load according to the maximum number of transmission lines at each node to make the optimization feasible. The operating voltage of the system was chosen to be the highest in Ontario (500kV), as we would be analyzing power flow at the highest level. Thus, the per unit voltage base was chosen to be 500_{kV} while the per unit power base was chosen as the commonly used 100MW. All other per unit bases were derived from these bases. Lines losses were considered by squaring the per unit power flows, multiplying by per unit resistance of the respective line, and adding the resulting power loss, times cash cost per unit energy, to the objective.

4. Charging Stations

The number of electric vehicle charging ports required in this system was determined based on the estimated number of electric vehicles currently in Ontario, as well as the expected growth in electric vehicle sales by 2020. At the end of 2017, there were approximately 47,800 electric vehicles on the road in Canada (Schmidt, 2018). In the past 4 years, Ontario has accounted for approximately 40% of all Canada-wide electric vehicle sales (Schmidt, 2018). This means that about 40% of these 47,800 electric vehicles are currently on the road in Ontario. Given the recency of most electric vehicle sales, it can be assumed that very few of these vehicles will be scrapped in the near future. Thus, we assume that this base number of 19,120 vehicles will remain in 2020. A total of 284,000 passenger vehicles were sold in Ontario in 2015 (Ministry of the Environment, 2015). Assuming total vehicle sales remained constant, but electric vehicle percentage sales increased from 1.6% in 2017 to 2.4%, 3.5% and 5% in 2018,2019, and 2020 respectively, then the total number of electric vehicles in Ontario is expected to reach about 50,008 in 2020.

Two common ratios exist for defining the number of electric vehicles charging ports required in a region: population to charger ratio and vehicle to charger ratio (International Council of Clean Transportation, 2017). To determine the number of chargers to be expected in our system, the vehicle to charger ratio will be used, as that will better account for the large influx of predicted electric vehicles in the near future. In Canada, there are currently between 10-15 electric vehicles per charging port (International Council of Clean Transportation, 2017). Our system assumes the upper bound of charging ports, so a 10:1 ratio of electric vehicles to charging ports was used. This means there are 5,000 charging ports to be placed in our system.

The power level of the chargers was all chosen to be Level 2 at 19.2kW (Yilmaz and Krein, 2013). While some Level 3 chargers will inevitably be installed - with more being added as time progresses - there will likely not be many by 2020. Our system will consider units of 19.2kW chargers, with their percentage usage varying throughout the day. The year averaged energy draws per hour from was used to determine the fractional power draw from all chargers at each hour of the day (Jiang and Tian, 2016) .

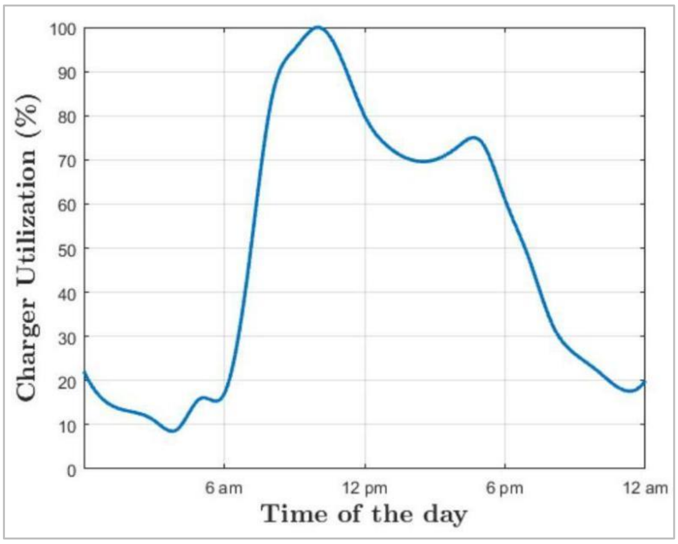

Figure 3: Change in fractional charger load throughout the day

5. Optimization Problem Definition

The model is defined by defining total system cost as the objective function while introducing constraints from practical power grid system and EV chargers.

5.1 Objective Function

Economic dispatch cost functions and transmission loss functions (2) and (3) are nonlinear functions which are linearized by line segment approximation. Pollutant emission has been converted into cost by introducing the CO_2 treatment coefficient to simplify the multi-objective problem into a single objective problem (4). The compensation function (5) has been added to promote matching of the EV charger distribution pattern with the system load distribution. In real life, heavy loads usually indicate higher day-time population density and implies larger usage of electrical vehicles.

Overall objective function

$$MinE^{\pm} = (1b) + (1c) + (1d) + (1e) \tag{1}$$

Cost for power generation

$$\sum_{k=1}^{6}\sum_{t=1}^{24} PGC_k \times PGA_{k,t} \tag{2}$$

Cost for transmission losses

$$\sum_{l=1}^{37}\sum_{t=1}^{24} \left(FPU_{l,t} / VPU\right)^2 \times RPU_l \times TPC \tag{3}$$

Cost for CO_2 emissions

$$\sum_{k=1}^{6}\sum_{t=1}^{24} PGA_{k,t} \times \delta_k \times CCO \tag{4}$$

Compensation for load matching EV charger placement

$$\left\| \frac{\beta \sum_{i=1}^{24} LSL_{n,t}}{24} - EVC_n \right\|_1 \times EPC \tag{5}$$

For these purposes of this work, the following definitions are valid:

E	expected system cost over the planing horizon ($)
k	electricity-conversion technology, with k=1 for nuclear, k=2 for hydro, k=3 for gas, k=4 for wind, k=5 for solar, k=6 for biofuel.
t	hour of the day ∈ {1,2, … ,24}
l	transmission line number ∈ {1,2, … ,37}
δ_k	emission coefficient of CO_2 equivalent for generation technology in question
PGC_k	cost for generating power ($/p.u.)
$PGA_{k,t}$	power generation amount for technology k during hour t (p.u.)
$FPU_{l,t}$	line flow through line I during hour t (p.u.)
RPU_l	line resistance (p.u.)
VPU	system voltage level (p.u.)
TPC	loss cost ($/p.u.)
β	load to charger conversion ration
$CCP_{k,t}^{\pm}$	operation cost for CO_2 treatment ($/ton)
EPC	EV charger placement compensation
$LSL_{n,t}$	local system load (p.u.)
EVC_n	number of charger at node n

5.2 Constraints

Equations (6) and (7) depict the fundamental equilibrium constraints for power flow optimization while (8) and (9) are the constraints from practical power generation and transmission. The CO_2 emission constraint (10) originates from our environmental impact reduction objective and the limit is derived by scaling the Ontario governments 2020 CO_2 emission goal to be compatible with our system power generation level (Ministry of the Environment, 2015). The total number of EV chargers (11) is decided by the total predicted future electrical vehicle count and the ratio of chargers to vehicles. Limits for the minimum number of EV charger at each station (12) is introduced to justify the high capital cost of station construction. Non-negativity constraints are imposed on the decision variables and integer constraints are necessary for the number of EV chargers at each bus.

Constraint of total power demand

$$\sum_{k=1}^{6} PGA_{k,t} = \sum_{n=1}^{34} LSL_{n,t} + EVTL, \forall t \tag{6}$$

Constraint of local power demand

$$LPGA_{n,t} - PIJ_{n,t} = LSL_{n,t} + EVC_n \times EVL_t, \forall n, t \tag{7}$$

Constraint of power generation limit

$$PGL_{k,t}^{-} \le PGA_{k,t} \le PGL_{k,t}^{+}, \forall k, t \tag{8}$$

Constraint of transmission capacity

$$TLC_{l,t}^{-} \leq FPU_{l,t} \leq TLC_{l,t}^{+}, \forall l, t \tag{9}$$

Constraint of CO_2 emission

$$\sum_{k=1}^{6}\sum_{t=1}^{24} PGA_{k,t} \times \delta_k \leq COL \tag{10}$$

Constraint of EV charger quantity

$$\sum_{n=1}^{34} EVC_n = 5000 \tag{11}$$

Constraint of local EV charger quantity limit

$$EVN_n^{-} \leq EVC_n \leq EVN_n^{+}, \forall n \tag{12}$$

Nonnegativity constraint

$$PGA_{k,t}, LPGA_{n,t}, EVC_n \geq 0, \forall k, n, t \tag{13}$$

Integer constraints

$$EVC_n \in \mathrm{Z}, \forall n \tag{14}$$

$EVTL$	total EV load (p.u.)
$LPGA_{n,t}$	power generation amount per node (p.u.)
$PIJ_{n,t}$	power injection per node (p.u.)
EVL	EV charger load per charger coefficient (p.u./charger)
COL	CO_2 emission limit per day (ton)
$PGL_{k,t}^{\pm}$	power generation limits
$TLC_{l,t}^{\pm}$	transmission line limits
$EVN_n^{\pm}$	charger quantity limits

5.3 DC power flow

For the system in question, we applied the DC power flow model. The model is described by the equations below. XPU definition

$$XPU = X\frac{100 \times MW}{(500 \times kV)^2} \tag{15}$$

Susceptance matrix

$$BPU = A^t \times XPU^{-1} \times A \tag{16}$$

Injected power equation

$$PIJ = BPU \times \theta \tag{17}$$

Flow equation

$$FPU = XPU^{-1} \times A \times \theta \tag{18}$$

X	line reactance matrix (Ω)
XPU	line reactance matrix in p.u. (p.u.)
BPU	line susceptance matrix in p.u. (p.u.)
A	adjacency matrix
θ	angle vector (rad)

5.4 Solver

Due to the integer number of EV chargers constraint introduced by (2i), the solver intlinprog is used for mixed-integer optimization. In addition, the demand input is the real-time 24-hour demand data which expands all the decision variables with a time dimension of 24. The goal of this optimization is to solve for the optimal EV charger location distribution which results in the lowest system cost over an entire day. Therefore, only EVC (the number of chargers at each station) has no time dimension. The model has been constructed under the MATLAB YALMIP code environment and no additional solvers are involved.

6. Results and Analysis

6.1 Load And Optimal Generation

Hydro is almost always maximized due to its low combined capital and carbon cost. However, the high price put on operating hydro at its maximum power output is able to prevent it from being permanently maxed out. This makes the hydro power output more realistic, as the reserves in hydro stations can't sustain constant maximum power output. Nuclear remains relatively constant throughout the day, as per its operation restrictions, and gas and biofuel are able to perform peaking during periods of high demand. One anomaly in our results, however, is that biofuel is not turned off during the middle of the day when it isn't required. This result contrasts the reality in Ontario, where biofuel is not often utilized unless there is a strong necessity.

6.2 Station Placement And Sizing

The placement and sizing of the stations (Figure. 4) seems to generally match the load distribution. We can see that the stations are placed in areas with high daily

loads, which is expected due to our focus on placing chargers in/near high energy consumption nodes. This ensures public chargers will be more readily available for charging during the day. We also notice a spike in charger placement at the hydro generation bus due to price advantage

6.3 Cost Analysis

The costs of the optimized system with the EV chargers installed is displayed in Table II. The system was run again with no EV chargers installed, to define baseline pollutant production. The resulting difference shows that adding 5,000 EV chargers to the system produced an additional 320 tons of CO2 equivalent pollutants per day.

	Generation Cost ($1000's/day)	Pollutant Cost ($1000's/day)	Pollutant Produced ton CO_2 eq/day
w/	37,982	630.6	12,612
w/o	37805	614.6	12,292

To compare with this, we can look at the total emissions saved by driving electric vehicles instead of fossil fuel vehicles. The emissions produced by driving an electric and fossil fuel vehicle in Ontario are about 422

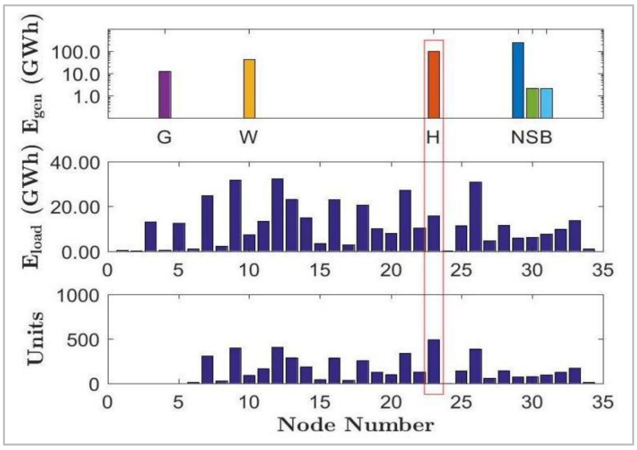

Figure 4: Distribution of the EV chargers per node (bottom), with generation outputs (top) and load distributions (middle) for comparison

kgCO2eq/year and 4,192 kgCO2eq/year respectively (Kopperson and Kubursi, 2014). Given the number of electric vehicles in 2020 is expected to be 50,000, then the amount of emissions saved from replacing fossil fuel vehicles with electric vehicles on the road is approximately 516.4 tons of CO2 equivalent pollutants per day. This means that our system justifies the replacement of fossil fuel vehicles with electric vehicles solely on an emissions production basis. However, when taking into consideration the costs it would take to install, operate, and maintain these charging stations, the tradeoff may not be as attractive financially.

7. Conclusions and Future Work

We were able to create a statistical analysis and construct a model that was loosely representative of Ontarios transmission grid. The model was put under limits that were derived from the provinces generation, load, transmission characteristics, and greenhouse gas emission goals, and was able to configure an optimal distribution of charging stations throughout the model based on total system cost. The resulting hourly generation patterns and charger distribution followed trends that emulated realistic scenarios. The final result of the model justified the shift from fossil fuel vehicles to electric vehicles, solely based on the emissions saved from vehicle operation versus the emissions produced to charge these vehicles given our generators current capacities. This model could potentially be used for actual charger distribution planning in the future, especially if a more accurate system model was available. Also, in future models, there will be more patterns being considered to improve the model accuracy such as climate factors, seasonality and geographical data (Koeva, 2022).Significant improvements that would be made with a better model include accurate placement and limits of generators, loads, and transmission lines; more accurate generation cost functions; better identification of residential and commercial nodes.

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