Charging Analysis of Ground Support Vehicles in an Electrified Airport

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***Abstract*—Within a fully electrified airport, no fossil fuels would be used on the grounds. This includes the electric load of the building along with any indoor and outdoor operations such as the ground support vehicles servicing the jets on the runway. This paper focuses on the analysis of airside ground support vehicles and their plug-in charging requirements. Following the modeling proposal for such an airport and its ground support vehicles, this work describes a charging algorithm created to service each vehicle type efficiently. The simulation-based experiments for a synthesized airport model show numerically and graphically how this algorithm optimizes vehicle performance and minimizes operating costs by managing various parameters in Monte Carlo simulations. The results of the simulations are analyzed and discussed from an efficiency perspective according to the design variables using Pareto optimality.**

***Index Terms*—Electrification, airport, Monte Carlo, Pareto front, electric vehicle charging, ground support vehicles, optimization**

I. Introduction

With automotive electrification becoming a reality, the aviation industry is also making strides into more or all electric aircraft [1], [2]. While all electric aircraft may not be in the near future, a prerequisite of such innovation is electrified airport infrastructure [3]. All major airports currently have a set of ground support vehicles on the airside, which interact with the planes as they complete their flying and servicing cycles. Most of these existing vehicles are gasoline or diesel vehicles. Changing these fossil fuel vehicles to plug-in electric vehicles is a key way in which an airport moves towards electrification.

As a fully electrified fleet of ground support vehicles is realized, a number of challenges arise. The biggest challenge pertains to the significantly longer charging time compared to refueling conventional fossil-fueled vehicles. Another central issue involves the increased burden on the electric grid, including both rises in steady-state loads and dynamic disturbances.

Overcoming the extended charging time and minimizing the load on grid components requires thorough system planning and sufficient backup vehicles. To optimize the system, the ground support vehicles must be charged under intelligent scheduling based on variable pricing and required airplane support at peak and off-peak times. A smart scheduling system of charging, similar to one used with fleets of on-road vehicles, is required due to the large number of vehicles in service. This system can benefit from reduced off-hour electricity rates while putting less strain on physical components of the grid and ensuring its stability [4]–[7].

This paper designs a system that addresses the above issues, using a synthesized model of one terminal at a medium to large-sized international airport. A Monte Carlo simulation along with the Pareto front analysis will show the effect of various factors on the systems performance as well as the efficacy of an optimization algorithm. At the end of the paper we present the overall conclusions and closing arguments.

II. Electrified Airport Model

The proposed electrified airport model consists of the general electrical load of the airport, the ground support vehicles and the vehicle chargers where their use is governed by a scheduling algorithm to determine usage and charging times. This charging algorithm is designed to minimize the total number of electric vehicles required and the amount of gas vehicles used if electric vehicles are unavailable. The adjustable parameters of this model include the number of each type of ground support vehicle, number of chargers, charging algorithm weights, and maximum target load of the facility.

In addition, the system has a number of other variables that are not adjustable but are factors that affect system performance. The largest factor is the base load of the airport. This includes any other electrical load on the property that is not vehicles charging such as lighting and heating. The charging algorithm will keep the total electrical load of the facility at or below the max target load. A sample of the airport load with random noise is shown in Figure 1. The number of planes entering the terminal is determined randomly according to a uniform random distribution. During peak hours, an exponential random distribution is also summed to simulate potentially higher traffic.

The ground support vehicles are split into three categories: A, B, and C. Class A vehicles are typical on-road vehicles. These vehicles are used to transport fuel, food, deicing fluid, and people around the airport property. Class B vehicles are high-powered tug tractors that are responsible for pushing the plane back from the gate. Class C vehicles are small, low power tug tractors that handle cargo.

Every vehicle in the system has a number of attributes in the "vehicle matrix" which includes the vehicles' state of

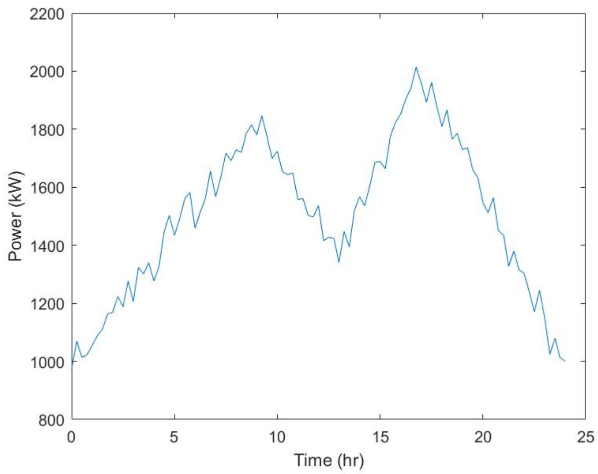

Fig. 1. Sample airport baseline load with random noise

charge (SOC), availability, current activity, vehicle type and tag number. The SOC is initially set randomly by a random uniform distribution. Availability is calculated for an entire class of vehicles and is defined by the number of vehicles that could be used to immediately service planes divided by the total number of vehicles in that specific class. For each time step, each vehicle is ranked and then reordered according to the attributes within the vehicle matrix. Vehicles with low SOC and availability have high ranks and thus have charger priority over other vehicles. The ranking function is defined as

$$Rank = (1 - SOC) \cdot W_{SOC} + (1 - A) \cdot W_{\text{Avail}} \tag{1}$$

where W is the charging weights, and A represents the availability:

$$A = \frac{\text{Class X Vehicles with SOC>0.5}}{\text{Total Vehicles in Class X}}. \tag{2}$$

This method of ranking each vehicle forces the algorithm to give vehicles with low SOC and availability precedence over vehicles that are closer to fully charged as well as having similar vehicles ready to be used.

The number of planes coming in at the given time step determines how many of each vehicle class are required. When there are not enough electric vehicles available at a time step to cover all the required jobs, gas vehicles are used. The number of vehicles required per plane is shown in Table I. The number of gas vehicles required at the given time step is the difference of the required number of vehicles minus the amount of available vehicles according to (3) where $N_{\text{gas},X}$ is the number of gas vehicles used in a given class, $N_{\text{elec,required},X}$ is the number of required electric vehicles in a given class per plane, and P represents the number of planes at the time step.

Class A vehicles have the added constraint that if five or more planes enter the terminal at the same time, five class A vehicles are required to account for the potential of having to move people to the terminal if there are no open gates at the time.

TABLE I
NUMBER OF REQUIRED VEHICLES TO SERVICE EACH PLANE ENTERING THE TERMINAL

Vehicle Class	A	B	C
Number of Vehicles Required	3 (5)	1	3

$$N_{\text{gas},X} = (N_{\text{elec},X,\text{required}} \cdot P) - N_{\text{elec,avail}} \tag{3}$$

The algorithm then checks how many vehicles can charge by dividing the difference of the max electrical load and current airport load by the load one vehicle charging would require. This is shown according to (4) where $N_{\text{charge,max}}$ is defined as the maximum number of vehicles that can charge at the time step and $Load_{\text{charge,1 vehicle}}$ is defined as the amount of power required to charge the vehicle during the time step.

$$N_{\text{charge,max}} = \frac{Load_{\text{max}} - Load(t)}{Load_{\text{charge,1 vehicle}}} \tag{4}$$

Finally, the SOC of each vehicle in service is updated. If the vehicle is charging, the SOC increases by the amount of energy the charger provides it during the time step in terms of SOC. This is shown in (5). If the vehicle is servicing a plane, the SOC decreases by the amount of energy expelled to complete the task in terms of SOC as shown by (6).

$$SOC_{\text{final}} = SOC_{\text{initial}} + SOC_{\text{charge}} \tag{5}$$

$$SOC_{\text{final}} = SOC_{\text{initial}} - SOC_{\text{service}} \tag{6}$$

If the SOC of a vehicle is charged and surpasses 100%, the amount of energy added to the vehicle is averaged over the time step and the overage is subtracted from the charge rate. The SOC is then set to 100% and the vehicle will no longer charge.

Once the time step is complete, the model moves to the next time step and repeats the process for the remaining time steps. Each set of parameters is run for three separate days each with random inputs that are consistent between each varying set of parameters. In the end, the total amount of gas used is calculated by equating the electrical energy that would have been used if electric vehicles were available to amount of energy within gasoline and averaged over the 3 days that are simulated.

III. Simulation of an Electrified Airport

A Monte Carlo simulation estimates a solution to a problem by running many trials of a system that contains one or more random variables. By running many trials, the law of large numbers states that the average output of the simulation is a close approximation to the actual solution. We chose this type of simulation due to the stochastic nature of the inputs such as initial values in the vehicle matrix and the number of planes at any given time. A Monte Carlo simulation is also used because the model contains a large number of adjustable parameters that can significantly affect the results [8]. In this specific case, the Monte Carlo simulation allows the user to run many trials while changing the various parameters and analyzing how the system is affected by the changes between each trial.

The concept of the Pareto front is used to analyze the results of the Monte Carlo simulation and find any optima. The Pareto front is defined when no more design variables can be optimized without negatively influencing another variable of interest [9]. A simplified way to visualize the Pareto front is plotting simulation results as points, then the Pareto front is a cluster of multiple data points nearest to the ideal combination of design variables. The Pareto front is useful when there is not one clear solution, but when there are a large amount of data points in a multivariable optimization problem such as a Monte Carlo simulation of an electrified airport. In the case of the electric airport, the design goal is to spend the least amount of money on vehicles while also using the least amount of gas.

The Monte Carlo simulation is implemented in MATLAB code and has three main sections: initialization, time-step iterations, and output plotting. The constants of the simulation are set in the initialization section, which includes maximum and minimum number of vehicles and chargers, charge rates, battery data, and airport base electrical load.

The electrified airport model is implemented in the iterative stage. Here, the parameters are determined and inputted into a set of time step loops that simulate a day of operation. Each time step is defined as 15 minutes. The days are run multiple times with preset random values and attributes to ensure that the average of the random numbers guiding the system are as close to the true expected value as possible. Once the set number of days is run, the parameters change, and the days are run again. A flowchart of this algorithm can be seen in Figure 2.

Once all the trials are run, relevant figures are created that focus on the analysis of the system.

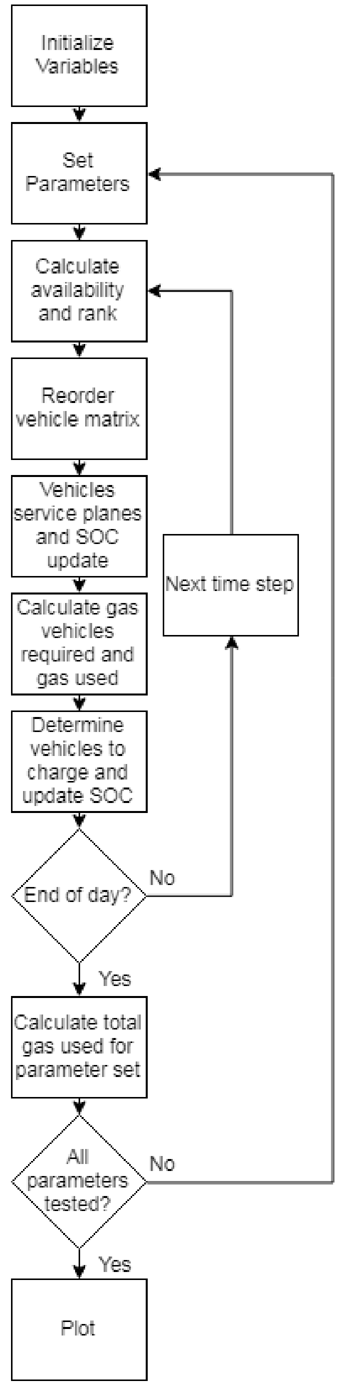

Fig. 2. Flowchart of the simulation algorithm.

IV. Results and Analysis

In order to run the optimization analysis, we impose a set of constraints on the system. These constraints drive the system to meet the design goal of controlling the overall electrical load of the facility as well as minimizing the overall cost of the system.

$$L_{\text{chargers}} + L_{\text{base}} < L_{\text{max}} \tag{7}$$

$$min[C] = f(N_A, N_B, N_C) \tag{8}$$

such that when

$$N_{X,\text{avail}}(t) < N_{X,\text{required}}(t) \tag{9}$$

the number of gas vehicles $N_{X,gas}$ is

$$N_{X,\text{gas}}(t) = N_{X,\text{required}}(t) - N_{X,\text{avail}}(t) \tag{10}$$

where L is defined as the electrical load of the airport, C is the total cost of the system and is a function of the amount of vehicles in each class and $N_X(t)$ is the number of vehicles at a given time step.

Equation (7) requires that the system only use up to the max power. This forces the system to charge more vehicles during off periods of the day while at the same time, avoiding excessive power spikes when the load is high.

Equation (8) defines the design goal of minimizing the cost of the system in the form of the number of vehicles purchased. It is supported by equations (9) and (10), which state that when there are not enough electric vehicles to fulfill the required duties, gas vehicles would be used in their place. From this, the amount of gas used per simulation and revolving set of parameters is calculated.

As previously mentioned, the Monte Carlo simulation is run with a range of parameters. As the simulation is running, the amount of gas is calculated by

$$G = \sum_{A,B,C} \frac{N_{X,\text{gas}} \cdot SOC_{\text{used}} \cdot \text{Capacity}_X \cdot 3.6}{E_{\text{spec}} \cdot 3.7854} \tag{11}$$

where G is defined as gallons of gas, $N_{X,\text{gas}}$ is the number of gas vehicles of class X, SOC_{used} is the amount of electrical energy required to complete the task, and E_{spec} is the specific energy per liter of automotive gas. The constant 3.6 converts from kW-hr to MJ and 3.7854 converts from liters to gallons.

In addition, Class A vehicles are set at \$60,000, Class B vehicles are set at \$40,000, and Class C vehicles are set at \$20,000. These prices reflect the average price of a small to medium size vehicle in each class [10], [11]. The total cost is calculated by

$$C = \sum_{A,B,C} N_X \cdot c_X \tag{12}$$

where C is the total cost of the vehicles, N_X is the number of vehicles in each class and c_X is the cost of a single vehicle in a given class.

A sample case study is proposed using the parameters shown in Table II. Each parameter is set to have a range of values. All parameters begin at the initial value and increment up by delta until it reaches the max. Every unique combination of the various parameters is tested which allows for the most ideal solution within the set ranges to be seen.

Figure 3 shows the total amount of gas used versus the cost for the vehicles required. Within this plot, one can see the Pareto front in red. A clear example of a segment of this front is the set of data close to the point where less gas cannot be used without additional cost. This curve forms nearest to the point (0,0).

TABLE II
PARAMETERS USED FOR VEHICLE CHARGING SIMULATION

Parameter	Initial	Delta	Final
Class A Vehicles	10	5	35
Class B Vehicles	2	2	10
Class C Vehicles	15	5	35
Chargers	25	5	45
SOC Weight	1	2	9
Availability Weight	1	2	9

Multidimensional graphs can be created to show and optimize how many vehicles are being used. Figure 4 shows a plot of the same data presented previously coupled with the number of Class A vehicles. From this plot, the minimum number of Class A vehicles required to achieve zero gas usage can be found. For each number of Class A vehicles within its range, every other combination of parameters has been tested with it. Thus, if no points on a level reach the y-axis (0 gallons of gas used), there is no solution that uses that number of Class A vehicles within the bounds of the parameters set. This process is then repeated for each other class of vehicle as well as the number of chargers to ensure that every optimal solution along the entire Pareto Front is found. Using this method, the minimum number of class A vehicles to achieve no usage of gas is within the range of 25 and 30 vehicles.

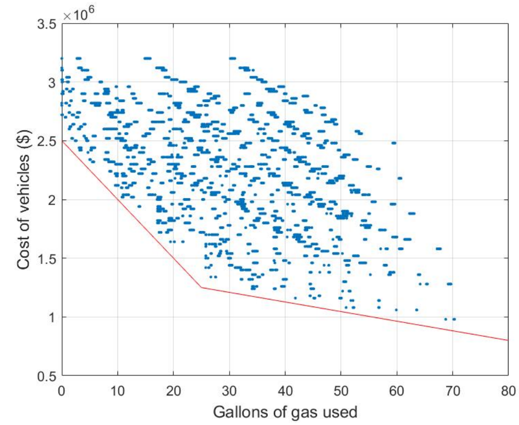

Fig. 3. Total cost of vehicles versus gallons of gas used for parameters set in Table 1. The Pareto Front is shown in red.

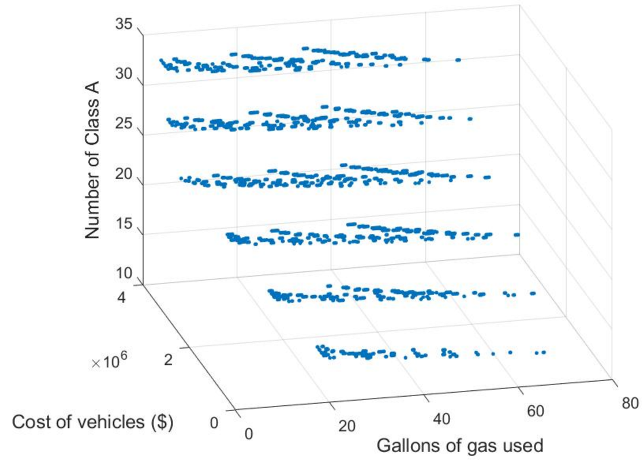

Fig. 4. Total cost of vehicles versus gallons of gas used versus number of Class A vehicles for the parameters set in Table II.

The number of chargers has a significant effect on how the system operates. Figure 5 shows how the number of chargers affects the performance of the system. One can see that having the correct number of chargers is vital for the system to function as efficiently as possible. There are many cases where the system has an excessive number of vehicles but because there is a shortage of chargers, a system with fewer vehicles but more chargers is able to outperform it.

For example, looking up at the data above the point within the right most circle, there is a range of colors. This represents the cases where more vehicles may be purchased but because there are not enough chargers, the overall system does not function as efficiently. There is also a significant gradient of colors in the horizontal direction. Typically systems that perform worse with respect to amount of gas used have less chargers in their system.

Figure 5 highlights two points which represent the two optimal solutions. Test point one located on the y-axis shows the case that optimizes the system to use fully electric vehicles while reducing the cost as much as possible. This test point has multiple possible solutions to get the indicated result. Each one includes 30 class A vehicles, 8 class B vehicles, 30 class C vehicles, and 45 chargers. This result is expensive but due to the large amount of vehicles, it can always meet the job requirements. The second highlighted point shows test point two, which indicates where the slope of the Pareto front shown in Figure 3 changes. This point represents the case where the rate of reduction in fuel use begins to decrease with respect to the cost. This test point has a number of combinations of parameters that achieve the same result. Each case has 10 class A vehicles, 6 class B vehicles, 25 class C vehicles and a range of chargers including 35, 40, and 45. This simulation point minimizes the number of expensive class A vehicles while reserving the chargers for the class B and C vehicles which are cheaper and faster charging in terms of SOC.

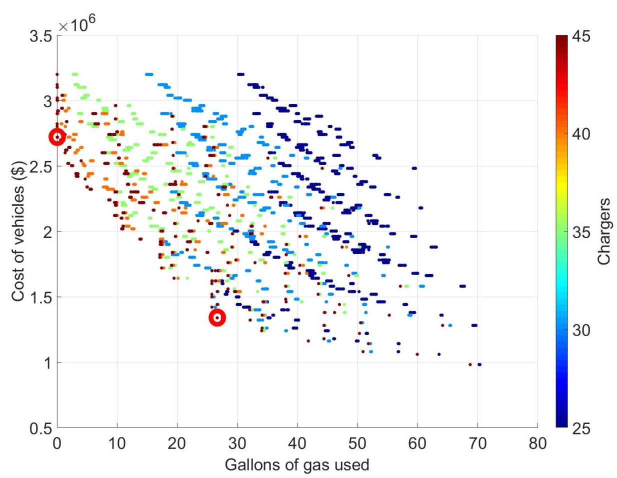

Fig. 5. Total cost of vehicles vs. gallons of gas used vs. number of chargers for the parameters set in Table II.

Two parameters that did not seem to influence the results of the simulation were the availability and SOC weights used to determine the charging order despite having a wide range. Figure 6 shows how neither variable affects the final solution in a quantifiable way. There is no pattern in the color scheme which represents the availability weights and no discernible change between each layer which is representing the SOC weights. One potential cause of this is due to both of these variables being a function of SOC. SOC is a function of only one vehicle while availability is calculated between all the vehicles within one class.

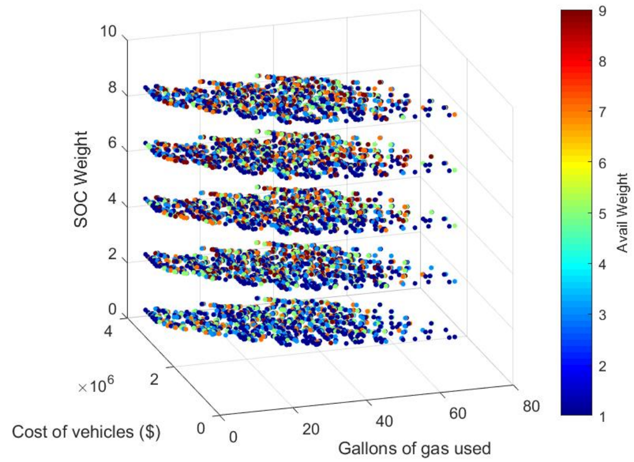

Fig. 6. Total cost of vehicles versus gallons of gas used versus SOC weight and color coded by Availability weights

Overall, it is clear that using a charging algorithm improves the performance of the system. By implementing the same constraints on an identical system that does not use a charging algorithm but allows for random charging, a decrease in performance of 5-8% is found for test point two, while test point one uses a small amount of gasoline and no longer can fully operate on electric vehicles alone. This comparison with a “naive” charging model shows how important it is to intelligently charge a fleet of vehicles within a system such as an electrified airport. Even the most basic of charging algorithms can increase performance and reduce the cost of both vehicles and electricity.

V. Conclusion

This paper models how a futuristic airport with electrified ground support vehicles can be constructed within the specific set of constraints given. It also illustrates how a Monte Carlo simulation can then be implemented and the concept of the Pareto Front can be used to find multiple optimal points for the system with a given specific set of constraints. This method of optimization is recommended with similar systems of unknown behavior that contain a large number of tunable parameters.

Because of the broad nature and limited number of works regarding electrified airports, there are a number of areas that could be delved further into as future work. The efficiency of the system including the vehicles, chargers, and overall distribution within the airport could be modeled with a higher level of detail. The cases tested are also quite coarse due to the large matrices that are created which cause significant delay in simulation run time. One way to get alleviate this issue would be to use a computer cluster or other high powered simulation hardware that can handle the large amount of data. Parallel computing is also an option to help speed up the simulation. The process of battery charging could also be explored which could change how the system operates in regards to how quickly vehicles reach full charge. Some factors such as the amount of energy used by a vehicle and daily energy consumption of the airport would need to be found experimentally over a period of time and then properly aggregated.

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