Electrifying Airport GSE: Monte Carlo Grid Impacts

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Abstract*— Airports globally are shifting from ICE-powered to electric Ground Support Equipment (eGSE) to enhance efficiency, reduce operational costs, and improve operator health. Leveraging predictable routes, flat terrain, and low operational speeds, airports provide ideal conditions for electrification. This study evaluates freight GSE electrification at Dallas-Fort Worth International Airport (DFW), USA, using the Agile@ platform, which integrates three analytical methods: Freight Facility Model (FFM), Activity-Structure-Intensity-Fuel (ASIF), and Monte Carlo simulations. Results from 10,000 simulations indicate modest but critical increases in electricity demand and significant variability in GSE energy consumption. These insights emphasize the importance of data-driven scheduling, targeted maintenance, and strategic infrastructure planning. For high-uncertainty scenarios, airports are advised to deploy buffer energy storage systems (battery banks), implement demand-response charging strategies, schedule flexible workforce shifts, and prioritize proactive maintenance—particularly for equipment with higher operational uncertainty, such as tug tractors with trailers. Agile@ thus offers a robust, scalable, and data-driven framework to optimize long-term GSE planning and enhance reliability across diverse airport environments.

***Keywords*—airport freight, ground support equipment, data, analysis, tool, electricity demand, grid impact.**

I. Introduction

Airports globally are increasingly transitioning from internal combustion engine (ICE)-powered Ground Support Equipment (GSE) to electric alternatives (eGSE), driven by operational efficiency improvements, reduced operational costs, and improved working conditions for GSE operators. Airports provide an ideal operating environment for eGSE due to their predictable, short-distance logistics routes, consistently flat terrain, and operational characteristics characterized by frequent stop-and-go cycles. These features inherently favor electric powertrains, enabling significant performance improvements in cargo handling efficiency and equipment reliability [1, 2].

Over the past two decades, airports have progressively integrated electric equipment within ground operations. Major North American airports, including Seattle-Tacoma, Philadelphia, and Dallas-Fort Worth International Airport (DFW), have pioneered large-scale adoption of electric ground equipment, motivated by efficiency gains and reduced lifecycle costs [2, 3]. For instance, by 2016, major airlines such as Delta had already transitioned over 15% of their GSE fleets to electric vehicles, highlighting sustained industry momentum towards electrification [3]. Additionally, recent advances in Internet of Things (IoT) technologies and automation have allowed airports to further capitalize on operational reliability and decreased turnaround times by optimizing ground equipment use patterns within the highly structured airport environment [4].

Building upon this momentum, the U.S. Department of Energy's Vehicle Technologies Office initiated the Athena Zero Emission Vehicle (ZEV) project at DFW Airport in August 2023, focused on systematically planning and deploying electrified airport logistics equipment [5]. In support of this initiative, Oak Ridge National Laboratory (ORNL) developed a novel analytical platform: the Airport GSE Infrastructure & Logistics Electrification Assessment Tool, known as Agile@. This research introduces Agile@ as an integrated, flexible, data-driven simulation tool explicitly designed to guide airport stakeholders in operational planning, infrastructure sizing, and strategic decision-making for freight handling electrification.

The core novelty of Agile@ lies in its unique methodological synthesis, integrating three previously independent analytical approaches—Freight Facility Modeling (FFM), Activity-Structure-Intensity-Fuel (ASIF) frameworks, and Monte Carlo probabilistic simulation methods—into a singular cohesive platform. While existing tools typically address operational logistics modeling and energy consumption analysis separately, Agile@ innovatively merges detailed operational data simulation through the event-driven FFM, structured energy analysis via the ASIF framework, and robust uncertainty quantification using Monte Carlo techniques. This integration provides decision-makers with comprehensive and actionable insights regarding infrastructure demands, equipment utilization rates, and robust planning scenarios that effectively capture operational variability and future uncertainty.

In this study, we showcase the Agile@ platform's effectiveness by analyzing freight operations at DFW. We simulate various electrification scenarios for key Ground Support Equipment (GSE) types, including forklifts, loaders, pushback tractors, and tug tractors. By quantifying energy usage patterns, infrastructure requirements, and operational characteristics, our findings aim to guide stakeholders in optimal equipment deployment and targeted investments to manage the increased electricity demands of large-scale GSE electrification. Although this demonstration focuses on a major international cargo airport, Agile@'s adaptable structure and flexible inputs make it a practical analytical resource for airports of varying sizes, regional cargo hubs, and logistics facilities beyond the aviation sector.

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II. FRAMEWORK FOR ANALYSIS

The Agile@ Platform integrates three analytical methods—the Freight Facility Model (FFM), the Activity-Structure-Intensity-Fuel (ASIF) framework, and Monte Carlo simulations—to systematically estimate freight demand and evaluate the impacts of electrifying ground support equipment (GSE) at DFW airport, as depicted in Figure 1.

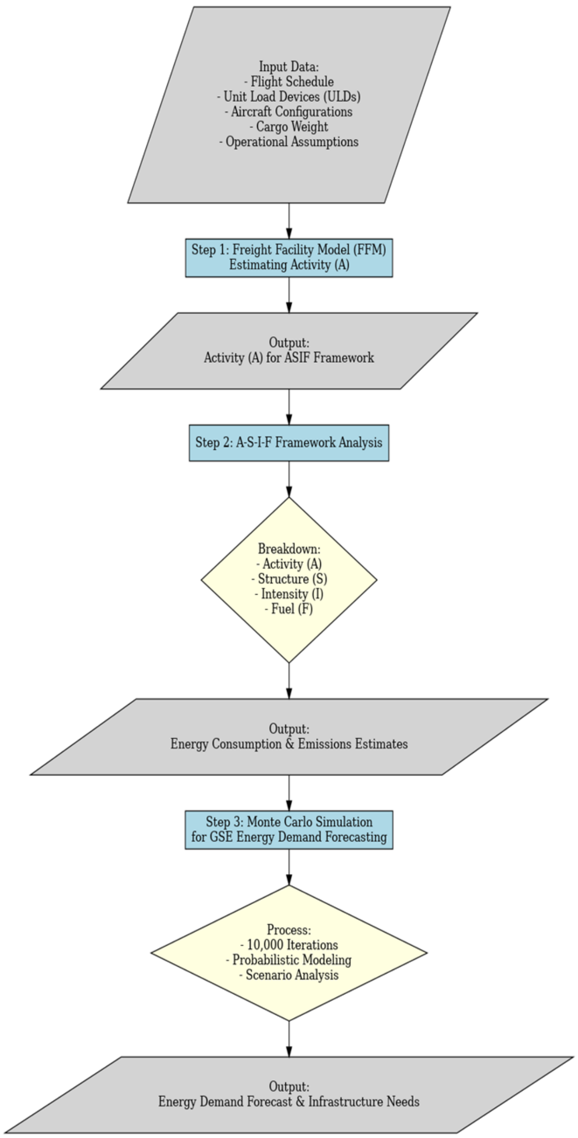

FIGURE 1. Flowchart of the Agile@ Platform

A. Freight Facility Model (FFM) – Estimating Activity (A)

Step 1 involves the Freight Facility Model (FFM), an event-based simulation tool developed in C# with a SQL database, designed to simulate cargo operations between aircraft and cargo terminals. FFM processes cargo flight schedules provided by cargo operators or airport authorities, calculates Unit Load Device (ULD) requirements based on aircraft configurations, and integrates cargo weight data using historical monthly tonnage levels. Operational assumptions incorporated into the model include a 60-minute aircraft refueling period, a maximum of five dollies per tug tractor, a 200-foot aircraft pushback lasting approximately 10 minutes, and a standardized cargo density of 10 lb/ft^3. Additionally, GSE charging protocols are established, triggering recharging when battery levels drop below 20% and continuing until they reach 80%. The FFM provides Excel-based outputs detailing operational metrics such as equipment utilization, freight capacity utilization per aircraft, and estimated energy consumption.

B. ASIF Framework – Estimating Energy Demand

Step 2 utilizes the ASIF framework, which breaks down energy demand and environmental emissions into four interrelated components: Activity (A), Structure (S), Intensity (I), and Fuel (F). Activity encompasses operational data derived from FFM outputs, including metrics such as daily distances, operational hours, and ton-kilometers. Structure evaluates fleet composition, categorizing GSE by type and operational share percentages. Intensity calculates energy consumption per unit of operation, expressed in kWh/km or kWh/ton-km, while Fuel assesses emissions based on fuel types, measured in grams of pollutants per liter. The ASIF framework first estimates electricity consumption from ICE-powered GSE operations and then total exhaust emissions (G) through Equation 1 [6].

$$G = \sum_{k,f}(A \times S \times I \times F) \tag{1}$$

In Equation 1, *G* represents the exhaust emissions from cargo handling using GSEs, measured in tons of emissions. *A* denotes the total freight movement by GSE, expressed in ton-kilometers (tkm), as derived from the Freight Facility Model (FFM). *S* corresponds to the modal share of GSE composition, given as a percentage. *I* signifies the energy intensity of GSE by type, measured in kWh/km for GSEs moving laterally such as tugs and kWh/ton for GSEs used in lifting load such as loaders. *F* accounts for the fuel mix and emission characteristics, defined in grams of pollutant per liter. The indices k and f represent the fuel type and GSE mode type, respectively. In this study we only considered the first three variables in Equation 1 to estimate energy demand from ICE-powered GSEs and assess the impact of ICE-powered GSE operations transition to eGSEs.

C. Monte Carlo Simulation – GSE Energy Use

Step 3 involves Monte Carlo simulations, a probabilistic method used to quantify uncertainties in future GSE operations and energy demand. The Monte Carlo simulation models were developed in Python. For each scenario, 10,000 simulations were conducted, systematically varying critical parameters to reflect realistic operational conditions and variability [7].

Key assumptions include an annual freight growth rate of 1.25%–1.5% based on historical cargo activity at DFW Airport, and a GSE fleet expansion rate of 3.9% derived from historical fleet trends observed at the same airport. Battery capacities for electric GSE ranged from 50–350 kWh, reflecting commercially available models currently deployed at major airports. Equipment-specific energy consumption rates were set between 0.5 and 2.5 kWh/km based on physics-based calculations considering equipment mass, operational speeds, and task profiles.

The simulations provide hourly, daily, and weekly probabilistic energy demand profiles, informing infrastructure sizing, transformer capacity, and grid management strategies. The probabilistic outputs enable stakeholders to plan proactively for operational variability, implementing targeted contingency measures like energy storage and demand-response strategies to mitigate potential high-demand impacts.

TABLE 1
Energy Consumption Pattern of GSEs

GSE Type	Pushback Tractor (kWh/pushback)	Loader (kWh/kg/hour)	Tug (kWh/km/kg)	Forklift (kWh/kg)
Min	7	0.0003	0.001	0.002
Max	10	0.0005	0.003	0.003

Monte Carlo simulation outputs generate probabilistic hourly energy demand profiles, comprehensive daily and weekly energy consumption distributions, and robust infrastructure demand forecasts under various electrification and growth scenarios.

III. FFM RUN AND SIMULATION RESULTS

The FFM simulates aircraft scheduling by integrating arrival times, cargo volumes, and GSE usage. It estimates the number of unit load devices (ULDs) enplaned and deplaned based on monthly cargo tonnage while assigning aircraft configurations to determine available cargo capacity. Using cargo density factors, the model ensures realistic load estimates by calculating the proportion of ULDs loaded per turnaround, aligning with volume constraints. The following illustrative example provides a clearer understanding of aircraft cargo loading calculations.

A. Illustrative Example: Aircraft Cargo Loading Calculation

To determine cargo distribution, the model selects an aircraft configuration and applies a standard air cargo density factor (10 lbs per cubic foot). Since cargo aircraft typically reach volume limits before weight limits, the model ensures feasible capacity estimates. For example, if the simulation horizon is from 16 January to 15 February, the amount of cargo loaded is (16/31) of the January cargo enplaned plus (15/28) of the February cargo enplaned. In this example, we calculate the total enplaned tonnage and the capacity utilization for aircraft based on cargo enplaned using the following steps:

Step 1: Enplaned Tonnage Calculation:

- The carrier enplaned 10,305 tons in January and 9,111 tons in February, resulting in a calculated enplaned tonnage of 9,867 tons for the simulation period from January 16 to February 15, based on prorated daily averages. The enplaned tonnage = (16/31) × 10,305 + (15/28) × 9,111 = 9,867 tons

Step 2: Available ULD Volume:

- The total available ULD volume is 4,611,074 cubic feet.

Step 3: Using Cargo Density:

- Using a standard air cargo density of 10 lbs per cubic foot, and 1 lb = 0.0005 US ton, the total capacity = 23,055 tons.

Step 4: Capacity Utilization:

- The capacity utilized by the enplaned cargo is:

(9,867/23,055) ×100=42.8%

Step 5: Aircraft Loading:

- Each aircraft loads 42.8% of its maximum ULD capacity.

The same logic applies to unloading ULDs, ensuring accurate tracking of cargo movement within the simulation framework.

B. FFM Outputs

The FFM generates outputs that inform analysts about simulated operations and compiles them into a Microsoft Excel workbook as given in Table 2. Worksheet details hourly equipment usage and key parameters for energy calculations. Agile@ utilizes these data to predict GSE energy demand. The FFM generated table is used as an input for Agile@. The values from the activity to weight columns in table 2 are used to calculate the energy consumption for each activity. Prior to using the values from the table, all the values are converted to Metric system within Agile@.

TABLE 2
Model Outputs – Sample Worksheet

equipment	date	hour	activity	dollies (loaded)	dollies (empty)	distance (miles)	weight (pounds)	time (hours)
loader	1/1/2025	2	travelling to plane			0.095		0.093
tug tractor	1/1/2025	2	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	2	unloading				8585	0.285
tug tractor	1/1/2025	3	travelling to facility	5		0.095	11085	0.090
tug tractor	1/1/2025	3	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	3	unloading				8585	0.251
tug tractor	1/1/2025	3	travelling to facility	5		0.095	11085	0.090
tug tractor	1/1/2025	3	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	4	unloading				8585	0.310
loader	1/1/2025	4	travelling to plane			0.095		0.093
tug tractor	1/1/2025	4	travelling to facility	5		0.095	11085	0.090
tug tractor	1/1/2025	4	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	4	unloading				22686	0.313
tug tractor	1/1/2025	4	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	4	unloading				23543	0.253
tug tractor	1/1/2025	4	travelling to facility	5		0.095	25186	0.090
tug tractor	1/1/2025	4	travelling to facility	5		0.095	26043	0.090
tug tractor	1/1/2025	5	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	5	unloading				27890	0.341
tug tractor	1/1/2025	5	travelling to plane		5	0.095	2500	0.090
loader	1/1/2025	5	unloading				33515	0.299

IV. RESULTS AND DISCUSSION

This section uses Monte Carlo simulations to analyze energy use by cargo loaders, tug tractors, forklifts, and pushback tractors, revealing trends to guide operators, planners, and policymakers on infrastructure and demand.

A. Aggregate Energy Consumption Patterns

Hourly Patterns: Energy demand peaks in the morning (07:00–09:00) and late afternoon (16:00–18:00), reaching 45–50 kWh, while overnight consumption remains low (below 20 kWh) as shown in Figure 2.

Daily Patterns: Median daily energy usage is ~0.45 MWh, with extremes reaching 1.4–1.8 MWh due to wide-body arrivals or cargo surges. These variations guide staffing, equipment rotation, and contingency planning as shown in Figure 3.

Weekly Patterns: Cumulative weekly energy consumption typically ranges from 2.5–5 MWh, exceeding 5 MWh on peak weeks. Surges necessitate robust transformer capacity, on-site storage, and flexible grid connections as shown in Figure 4.

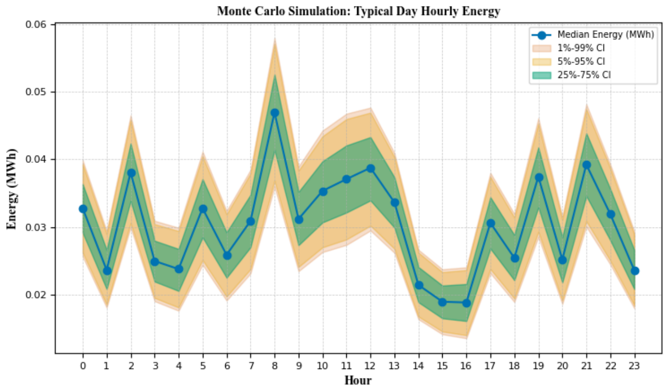

FIGURE 2. Hourly GSE Energy Consumption Over a Day

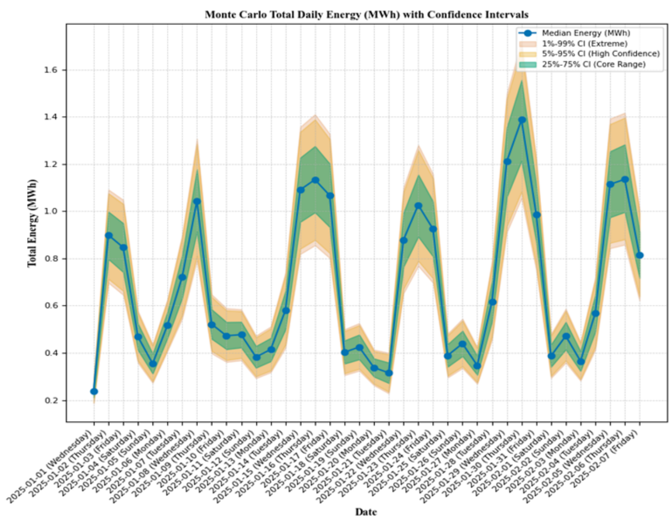

FIGURE 3. Daily GSE Energy Consumption Over a Month

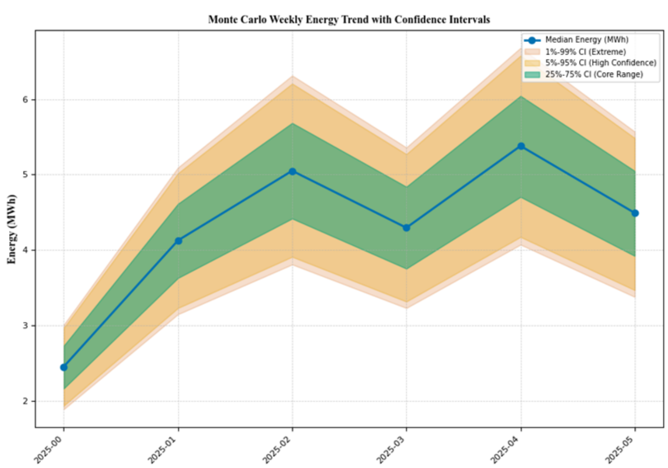

FIGURE 4. Weekly GSE Energy Consumption

B. Energy Consumption by GSE Type

Hourly patterns: Figure 5 illustrates 24-hour energy use of forklifts, loaders, pushback tractors, and tug tractors, with Monte Carlo-derived confidence intervals (e.g., 1–99%, 5–95%, 25–75%) shown as variable color shades. Tug tractors peak above 0.02–0.03 MWh/hour due to heavy cargo operations, while loaders and pushbacks show moderate use (0.01–0.02 MWh/hour), and forklifts stay below 0.01 MWh/hour. Morning and evening surges align with flight activity; overnight lows enable fueling, charging, and maintenance. Simulations show peak hourly demands of 30–40 kWh for tugs, 10–20 kWh for loaders and pushbacks, and under 10 kWh for forklifts."

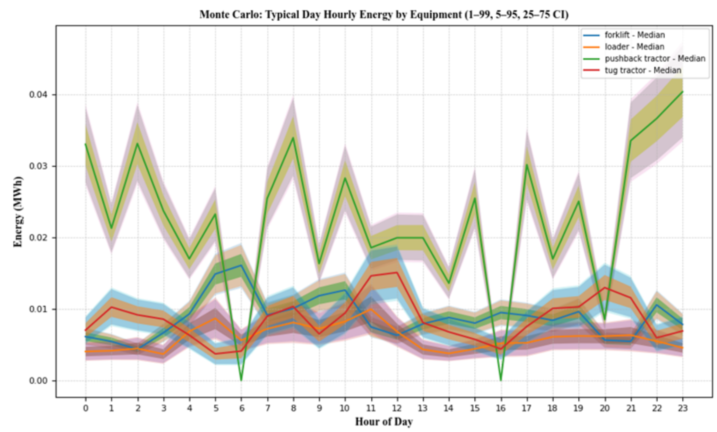

FIGURE 5. Hourly Energy Use Profile of GSEs by type

Daily patterns: Figure 6 presents daily energy use by GSE type, showing tug tractors as the highest consumers, peaking at 0.4–0.5 MWh on busy days. Loaders and pushbacks range from 0.1–0.3 MWh/day, and forklifts stay below 0.1 MWh/day. Tug tractor spikes align with heavy cargo flights and extended towing, dropping to ~0.2 MWh on lighter days. Monte Carlo simulations confirm ranges: 200–500 kWh for tugs, 100–300 kWh for loaders and pushbacks, and under 100 kWh for forklifts. Spikes reflect high-activity periods and underscore the need to forecast demand and adjust staffing, fueling, and equipment accordingly.

Weekly patterns: Figure 7 aggregates weekly GSE energy use, showing how daily fluctuations build over seven days. Tug tractors often exceed 2.0 MWh/week, with some weeks showing significant increases, surpassing 2.5 MWh during high-activity periods. Loaders and pushbacks reach 1.0–1.5 MWh, while forklifts stay under 1.0 MWh. Monte Carlo simulations show typical weeks at 300–400 kWh, with peaks over 420 kWh driven by tug usage. Planners can leverage this data to assess infrastructure capacity and schedule major maintenance during low-demand weeks.

Figures 5, 6 and 7 confirm that tug tractors exhibit the highest variability and peaks, while loaders and pushback tractors show moderate swings tied to flight traffic and forklift remains stable. By understanding these consumption patterns, ground operations managers can optimize task distribution, resource planning, and prevent GSE capacity or airport infrastructure overload.

In Figure 5, the hourly energy for tug tractors happens to be relatively low because it captures a worm's-eye (hour-by-hour) snapshot on a day or set of hours when tug use was not at its peak. Tug tractors typically move large amounts of cargo and can tow multiple dollies, but their exact usage depends on factors like flight schedules, cargo loads, and operational timing. If those factors happen to be modest in the particular hours shown in Figure 5, the tug tractor's energy curve appears low relative to other equipment.

By contrast, Figures 6 and 7 aggregate daily and weekly usage, respectively. Over these broader time spans, tug tractors usually emerge as the largest total consumers of energy because their overall workload accumulates to higher levels. In other words, the bird's-eye perspective in Figures 6 and 7 shows tug tractors dominating due to repeated heavy-duty hauling across multiple days, whereas the worm's-eye perspective in Figure 5 caught a period in which tug operations were comparatively lighter. These different levels of detail—hourly versus daily or weekly—naturally highlight different peaks and patterns for each GSE type, reflecting real-world variability in cargo arrivals, distances traveled, and the number of loaded dollies.

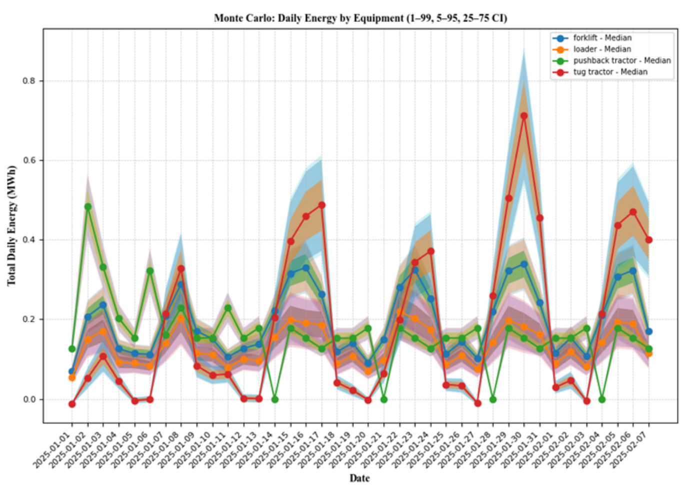

FIGURE 6. Daily Energy Use Profile of GSEs by type

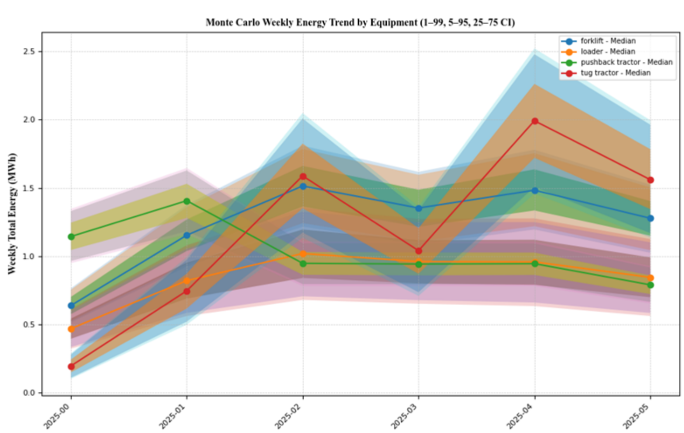

FIGURE 7. Weekly Energy Use of GSE by type

C. *Heatmaps and Eqipment -Specific Highlights*

Figures 8–10 expand the Monte Carlo framework by dissecting energy use patterns across time scales and equipment types, enabling more granular planning and operational decisions.

Visualize Load Peaks: Figure 8 presents a typical day heatmap, charting hour-by-hour energy usage over several days. Darker cells denote higher loads, revealing peak periods—typically mid-morning and late afternoon—driven by overlapping flight operations. This view supports real-time load shifting, such as rescheduling forklift usage during low-demand windows.

Pinpoint Temporal Surges: Figure 9 maps day-of-week vs. week-by-week variations, exposing recurring high-demand periods (e.g., repeated Wednesday spikes >1 MWh). It enables planners to target low-usage days, like Sundays (20–30% lower), for GSE overhauls or battery replacements, and to identify consistent high-demand days (e.g., Tuesdays or Thursdays) across weeks for strategic resource alignment.

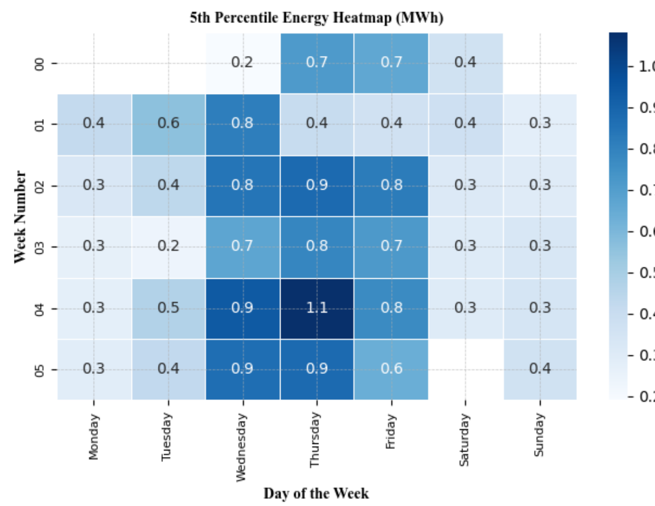

FIGURE 8. Day-of-Week vs. Hour-of-Day Heatmap

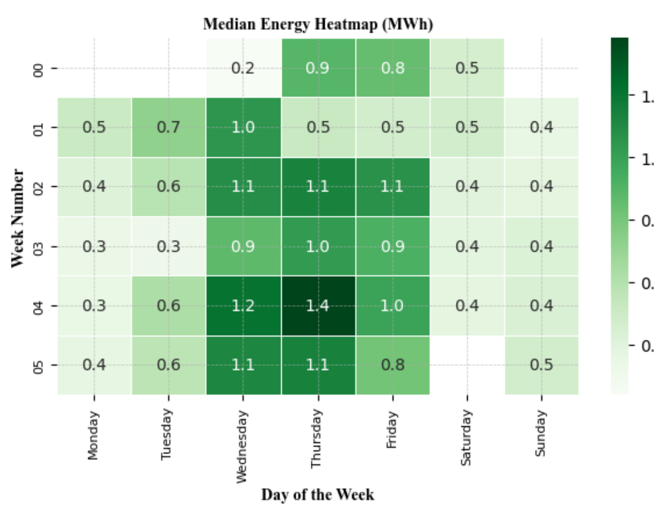

FIGURE 9. Week-by-Week vs. Hour-of-Day Heatmap

Differentiate Equipment Variability: Figure 10 details equipment-segregated Monte Carlo results, separating energy usage by GSE type. It identifies high-variability assets (e.g., tugs with dollies) versus predictable loads (e.g., pushback tractors), allowing operators to allocate buffer capacity where uncertainty is highest and optimize maintenance for stable equipment.

Together, Figures 8-10 reveal interlocking temporal and equipment-level patterns, reinforcing the need for precision scheduling, targeted maintenance, and policy-driven interventions to manage demand variability and prevent energy spikes

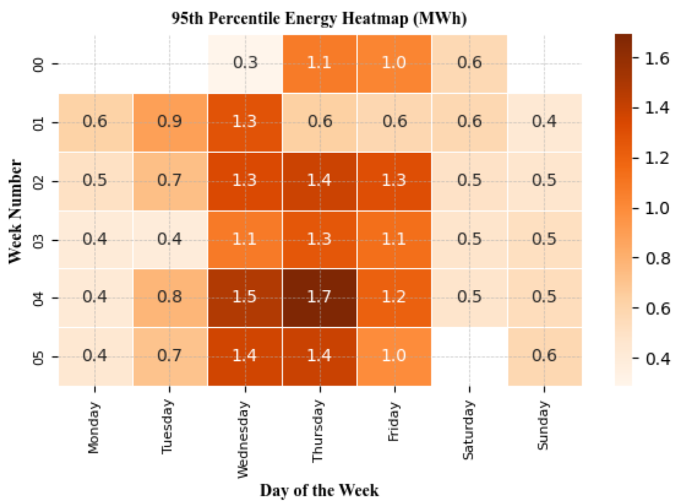

FIGURE 10. Equipment-Specific Monte Carlo Distributions

D. Key Takeaways

The analysis reveals significant fluctuations in GSE energy demand, highlighting the importance of data-driven scheduling, targeted maintenance, and infrastructure planning to mitigate peak loads and optimize airport operations. The significant variability observed in the Monte Carlo-derived energy consumption forecasts underscores the necessity of contingency planning. For high-uncertainty scenarios, airports should consider measures such as establishing buffer energy storage systems (battery banks) capable of handling unexpected demand peaks, implementing demand-response charging strategies to mitigate grid stress, and scheduling flexible workforce shifts to respond dynamically to operational variations. Additionally, equipment with consistently high uncertainty (such as tug tractors with trailers) should be prioritized for increased redundancy and proactive maintenance schedules to ensure service reliability during demand surges.

V. CONCLUSION

Electrification of GSE at airports offer cost savings, improved reliability, and operational efficiency. Their structured operations—short routes, low speeds, and centralized maintenance—enable a seamless transition. As cost pressures and regulations increase, electrifying GSE presents a strategic opportunity to reduce fuel costs and emissions while optimizing workflows.

This study simulated GSE energy consumption at Dallas-Fort Worth International Airport (DFW) to evaluate electrification's impact on energy demand. Results show that while GSE electricity consumption remains a small fraction of the airport's total use, accurate estimates are crucial for infrastructure planning. Understanding peak and average load profiles helps optimize charging strategies, reducing strain on local grids and minimizing costs.

The approach used in this study is scalable and adaptable, allowing similar energy demand assessments across airports of varying sizes and cargo profiles. Although initially demonstrated at DFW, the Agile@ platform is readily adaptable for use across diverse airport scales and logistics environments. Its modular design—where operational schedules, fleet configurations, energy intensities, and growth parameters are defined as user-input variables—enables application at regional airports, large cargo hubs, or even intermodal logistics facilities beyond the aviation sector. By adjusting inputs reflective of local operational characteristics and market conditions, stakeholders can leverage Agile@ to conduct detailed scenario analyses and infrastructure assessments at virtually any site managing electrified logistics equipment.

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