# ML-Enhanced EV Fleet Routing Optimization

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**Abstract**

Electric autonomous vehicles (E-AVs) face significant operational challenges due to energy uncertainty, particularly from temperature-dependent HVAC loads that can reduce driving range by 30-40% in extreme weather. This research develops an integrated framework combining machine learning energy prediction with mixed-integer linear programming (MILP) optimization for campus shuttle fleet routing. An XGBoost model trained on physics-based energy data achieves $R^2 = 0.94$, capturing HVAC effects that fixed-rate assumptions miss by ±18% under temperature extremes. The MILP optimizer, operating within a rolling horizon framework, improves service rates by 12% and reduces deadhead driving by 37% compared to nearest-available dispatch. Experiments across 135 scenarios demonstrate that the integrated approach is most valuable for constrained fleets operating in variable climates. The framework is validated using GreenPower EV Star specifications on a 16-POI campus network at Illinois Institute of Technology.

**Keywords:** Electric vehicles, MILP, machine learning, energy prediction

## 1. Introduction

Electric autonomous shuttles can provide on-demand transportation while eliminating direct emissions, but their operational viability depends on effective fleet management that accounts for battery constraints.

A critical challenge is energy uncertainty. Unlike conventional vehicles with predictable fuel consumption, electric vehicle energy usage varies significantly with temperature due to cabin climate control. HVAC systems can draw 3-7 kW depending on heating or cooling demands, reducing effective range by 30-40% in cold weather. Existing fleet routing approaches use fixed energy rates (e.g., 0.38 kWh/km) that ignore these effects, leading to suboptimal dispatch decisions.

This research develops an integrated framework with four objectives: (1) develop a machine learning model for trip-level energy prediction capturing HVAC effects, (2) formulate a MILP model for fleet routing optimization with energy constraints, (3) integrate ML predictions into MILP through a rolling horizon framework, and (4) evaluate the framework across varying temperatures, fleet sizes, and operational parameters.

Through this research, an integrated ML+MILP architecture is constructed that bridges energy prediction and dispatch optimization; quantification of HVAC impact showing ±18% energy variation versus fixed-rate assumptions; demonstration of 12% service rate improvement through optimization; and comprehensive evaluation across 135 experimental scenarios.

## 2. Related Work

Prior research has addressed electric vehicle routing, energy modeling, and autonomous fleet management as separate problems. Schneider et al. (2014) introduced the Electric Vehicle Routing Problem with Time Windows and Recharging Stations (EVRP-TW-RC), establishing foundational MILP formulations for battery-constrained routing. Keskin and Çatay (2016) extended this work with partial recharging strategies. However, these studies typically assume fixed energy consumption rates.

Machine learning approaches for EV energy prediction have shown promise. Fiori et al. (2016) developed the Virginia Tech Comprehensive Power-based EV Energy Model (VT-CPEM), while Zhao et al. (2019) demonstrated XGBoost effectiveness for consumption forecasting. Zhang et al. (2020) incorporated temperature effects but did not integrate predictions with routing optimization.

Autonomous mobility-on-demand (AMoD) systems have been studied by Fagnant and Kockelman (2014) and Iglesias et al. (2019), who developed rebalancing strategies for shared autonomous vehicles. Chen et al. (2016) examined electric AMoD but used simplified energy models.

## 3. Setup

### 3.1 System Architecture

Figure 2 illustrates the overall system architecture integrating ML energy prediction with MILP optimization.

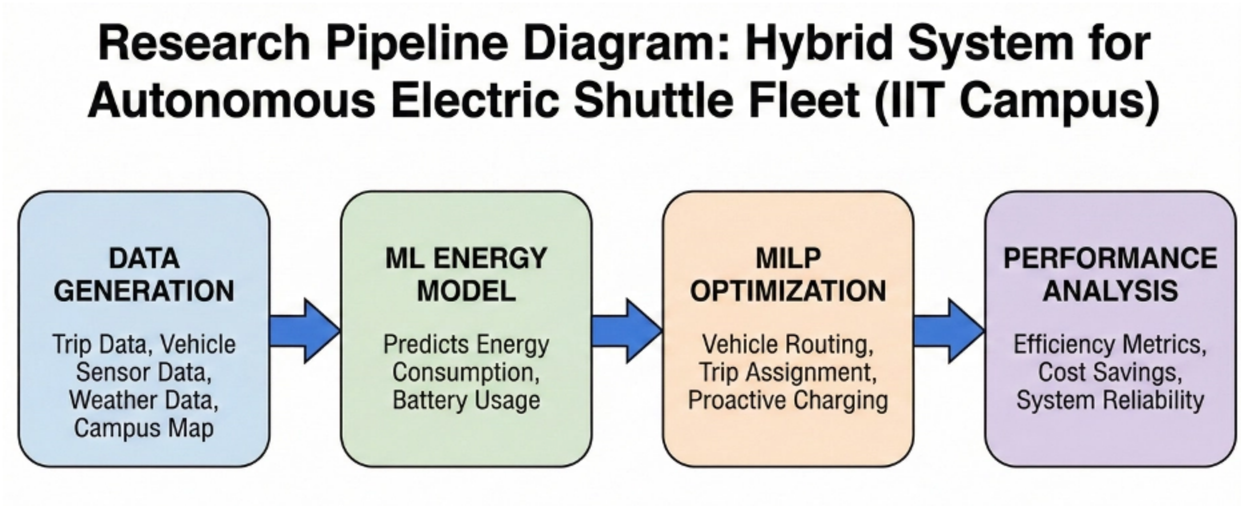


***Figure 1*** *System Architecture AI generated*

### 3.2 Study Area and Network

The study area is the Illinois Institute of Technology main campus in Chicago, spanning approximately 120 acres (1.5 km × 0.8 km). Chicago's continental climate produces temperatures ranging from -15°C in winter to 38°C in summer, providing an ideal testbed for evaluating temperature-sensitive energy prediction.

Sixteen points of interest (POIs) were selected using K-means clustering across four categories: academic buildings (6), residential halls (4), dining facilities (3), and administrative/transit locations (3). Route distances are computed using the Haversine formula with a 1.3 circuity factor to account for road network indirection.

*Table 1 Points of Interest*

| poi_name | latitude | longitude | category | priority | origin_trips | dest_trips | total_trips | demand_weight |
|---|---|---|---|---|---|---|---|---|
| The Commons | 41.83604 | -87.625535 | Dining | 1 | 641 | 900 | 1541 | 1.0 |
| Paul Galvin Library | 41.833675 | -87.628336 | Library | 1 | 607 | 730 | 1337 | 0.8676184295911750 |
| McCormick Tribune Campus Center | 41.835621 | -87.625887 | Student Center | 1 | 666 | 646 | 1312 | 0.8513951979234260 |
| Perlstein Hall | 41.835479 | -87.627146 | Academic | 1 | 663 | 620 | 1283 | 0.8325762491888380 |
| S.R. Crown Hall | 41.833199 | -87.627273 | Academic | 1 | 680 | 582 | 1262 | 0.8189487345879300 |
| Kaplan Institute | 41.836861 | -87.6283 | Academic | 1 | 636 | 604 | 1240 | 0.8046722907203110 |
| Pritzker Science Center | 41.83793 | -87.62738 | Academic | 1 | 648 | 584 | 1232 | 0.799480856586632 |
| Main Building | 41.834303 | -87.629281 | Academic | 1 | 654 | 574 | 1228 | 0.7968851395197920 |
| McCormick Student Village | 41.835527 | -87.624207 | Residence | 1 | 593 | 610 | 1203 | 0.7806619078520440 |
| Arthur S. Keating Sports Center | 41.838985 | -87.625566 | Recreation | 2 | 510 | 484 | 994 | 0.6450356911096690 |
| Rowe Village Middle | 41.833712 | -87.626167 | Residence | 2 | 473 | 498 | 971 | 0.6301103179753410 |
| Cunningham Hall | 41.83774 | -87.623975 | Residence | 2 | 462 | 500 | 962 | 0.6242699545749510 |
| Chemistry Research Building | 41.831886 | -87.628445 | Academic | 2 | 496 | 439 | 935 | 0.6067488643737830 |
| Farr Hall | 41.834344 | -87.623795 | Residence | 2 | 459 | 472 | 931 | 0.6041531473069440 |
| Grover M. Herman Hall | 41.835681 | -87.628387 | Admin | 3 | 356 | 325 | 681 | 0.4419208306294610 |
| Alpha Sigma Phi | 41.833032 | -87.624633 | Greek Housing | 4 | 174 | 150 | 324 | 0.21025308241401700 |

### 3.3 Vehicle Specifications

The fleet consists of GreenPower EV Star electric shuttles with specifications representative of commercial campus transit vehicles:

*Table 2 GreenPower EV Star Specification*

| Parameter | Value | Unit |
|---|---|---|
| Vehicle type | Electric shuttle bus | - |
| Passenger capacity | 19 seated 3 wheelchair | Passengers |
| Gross vehicle weight | 6,577 | kg |
| Curb weight | 4,763 | kg |
| Battery capacity | 118 | kWh |
| Nominal range | 250 | km |
| Motor power | 150 | kW |
| Charging power | 60 | kW |
| Charging time | 1.5 | hours |

***Table 3*** *HVAC Specifications*

| Condition | HVAC Load | Temperature Range |
|---|---|---|
| Heating | 5-7 kW | Below 10°C |
| Cooling | 3-5 kW | Above 25°C |
| Neutral | 0.5-1 kW | 10–25°C |


***Figure 2*** *GreenPower EV Star shuttle bus*

The HVAC loads represent a significant portion of total energy consumption, particularly in extreme temperatures. At 5 kW continuous load over a 1-hour operation, HVAC alone consumes approximately 4% of battery capacity—a non-trivial factor for fleet energy management.

### 3.4 Trip Demand Generation

***Table 4*** *Parameters*

| Parameter | Value |
|---|---|
| Service hours | 7:00 AM – 10:00 PM |
| Operating days | Monday – Friday |
| Fleet size | 5–15 vehicles (varied in scenarios) |
| Average speed | 20 km/h |
| Maximum wait time | 10m |
| Booking method | Mobile app |

Trip requests were generated for five simulated weekdays, producing 4,186 trips with temporal patterns reflecting campus activity: morning peak (8-10 AM), midday peak (12-2 PM), and afternoon peak (4-6 PM). Origin-destination pairs were sampled based on category weights varying by time of day.

### 3.5 Route Characteristics

Route distance and travel times were computed between all POI pairs using the Haversine formula for geographic distance, with a circuity factor applied to account for road network geometry.

**Distance Calculation:**

$$d_{ij} = haversine(lat_i, lon_i, lat_j, lon_j) \times circuity_{factor}$$

Where:

- Haversine formula computes great-circle distance
- Circuity factor = 1.3 (typical for urban grid networks)

**Travel Time Calculation:**

$$t_{ij} = \frac{d_{ij}}{v_{avg}} + t_{pickup}$$

Where:

- $v_{avg} = 20 km/h$ (average speed including stops)
- $t_{pickup} = 60\ seconds$ (passenger boarding time)

The compact campus results in short trip distances, with 95% of trips under 1.0 km. These characteristic influences energy consumption patterns, as HVAC loads represent a larger proportion of total energy for short trips.

### 3.6 Weather Data

Temperature data was generated to represent Chicago's seasonal climate variations, enabling evaluation of HVAC impacts across different weather conditions.

**Temperature Profiles:**

**Diurnal Variation:**

$$T(h) = T_{base} + A \times \sin\left(\frac{(h-6)\pi}{12}\right)$$

Where:

- $T_{base}$ : midpoint of temperature range
- $A$ = 3°C (diurnal amplitude)
- $h$ = hour of day
- Peak temperature occurs at 2:00 PM

### 3.7 Energy Ground Truth

Ground truth energy consumption for each trip was calculated using a physics-based vehicle energy model incorporating longitudinal dynamics and HVAC loads.

**Energy Model Components:**

$$\boldsymbol{E_{total} = E_{traction} + E_{HVAC} + E_{auxiliary}}$$

Traction energy incorporates rolling resistance, aerodynamic drag, and motor efficiency (85-92%), with 60% regenerative braking recuperation. HVAC power varies with temperature: heating loads increase below 20°C (up to 7 kW at -15°C) while cooling loads increase above 25°C (up to 4 kW at 38°C).

**Traction Energy:**

$$E_{traction} = \frac{1}{\eta_{motor}} \int_0^t \left(ma + \frac{1}{2}\rho C_d A v^2 + mgC_r + mg\sin\theta\right) v dt$$

Where:

- $m$ = vehicle mass
- $\eta_{motor}$ = motor efficiency
- $\rho$ = air density (1.225 $kg/m^3$
- $C_d$ = drag coefficient (0.7)
- $A$ = frontal area ($7.5m^2$)
- $C\_r$ = rolling resistance (0.01)
- $\theta$ = road grade (assumed 0)

**HVAC Energy:**

$$E_{HVAC} = P_{HVAC}(T) \times t_{trip}$$

Where $P\_\{HVAC\})(T)$ is the temperature-dependent HVAC power:

$$P_{HVAC}(T) = \begin{cases} 7.0 - 0.2T, & T < 0 \\ 1.0 + 0.05|T - 15|, & 0 \leq T \leq 25 \\ 3.0 + 0.1(T - 25), & T > 25 \end{cases}$$

**Auxiliary Energy:**

$$E_{auxiliary} = P_{aux} \times t_{trip}$$

Where $P_{aux} = 0.5kw$ (lights, electronics, sensors for AV operation).

**Regenerative Braking:**

Energy recovered during deceleration was modeled with 60% recuperation efficiency:

$$E_{regen} = 0.6 \times E_{braking}$$

### 3.8 Temperature Scenarios

*Table 5 Temperature Scenarios*

| Condition | HVAC Load | Temperature Range |
|---|---|---|
| Heating | 5-7 kW | Below 10°C |
| Cooling | 3-5 kW | Above 25°C |
| Neutral | 0.5-1 kW | 10–25°C |

## 4. Methodology

### 4.1 MILP Formulation

The Electric Autonomous Vehicle Fleet Routing Problem is formulated as a Mixed-Integer Linear Program that assigns vehicles to trips while minimizing energy consumption and wait time.

**Sets:** $\mathcal{K}$= vehicles, $\mathcal{T}$= trip requests in current epoch

**Decision Variables:**

- $x_{k,i} \in \{0,1\}$: 1 if vehicle $k$assigned to trip $i$
- $y_i \in \{0,1\}$: 1 if trip $i$is unserved
- $w_i \geq 0$: wait time for trip $i$

**Objective Function:**

$$\min\ Z = \alpha \sum_{k,i} e_{k,i} \cdot x_{k,i} + \beta \sum_{i} w_i + \gamma \sum_{i} y_i$$

where $e_{k,i}$is the predicted energy for vehicle $k$to serve trip $i$(including deadhead), and $\alpha, \beta, \gamma$are weights for energy, wait time, and unserved penalty respectively.

**Constraints:**

(C1) Trip assignment: $\sum_k x_{k,i} + y_i = 1 \forall i$

(C2) Vehicle availability: Service starts after vehicle available plus travel time

(C3) Request feasibility: Service starts after trip requested

(C4) Maximum wait: $w_i \leq W_{max} + M \cdot y_i \forall i$

(C5) Battery capacity: $b_k - e_{k,i} \cdot x_{k,i} \geq B_{min} \forall k, i$

The formulation contains O(K×T) binary variables and is solved using the HiGHS solver in under 1 second per epoch.

### 4.2 ML Energy Prediction

An XGBoost regression model predicts trip energy consumption from seven engineered features:

***Table 6*** *XGBoost Parameter*

| Feature | Description | Units | Source |
|---|---|---|---|
| **distance_km** | Route distance (Haversine × 1.3 circuity) | km | OD matrix |
| **duraction_sec** | Estimated travel time | sec | Distance / speed |
| **avg_speed_kmh** | Average travel speed | km/h | 20 km/h campus |
| **temperature_C** | Ambient temperature at trip time | °C | Weather simulation |
| **hour** | Hour of day (0-23) | Integer | Request timestamp |
| **is_peak** | Peak period indicator | Binary | Derived |
| **hvac_power_kW** | Estimated HVAC power draw | kW | Temperature function |

**HVAC Power Calculation:**

The HVAC power feature captures the nonlinear relationship between temperature and cabin climate control:

$$P_{HVAC}(T) = \begin{cases} 7.0 - 0.2T, & T < 0 \\ 1.0 + 0.05|T - 15|, & 0 \leq T \leq 25 \\ 3.0 + 0.1(T - 25), & T > 25 \end{cases}$$

### Target Variable

The target variable total_energy_kWh was computed using a physics-based ground truth model:

$$E_{total} = E_{traction} + E_{HVAC} + E_{auxiliary}$$

**Traction Energy:**

$$E_{traction} = \frac{1}{\eta_{motor}} \int_0^t \left( ma + \frac{1}{2}\rho C_d A v^2 + mgC_r + mg\sin\theta \right) v dt$$

Where:

- $F_{rolling} = C_r mg$ (rolling resistance)
- $F_{aero} = \frac{1}{2}\rho C_d A v^2$ (aerodynamic drag)
- $\eta_{motor} =$ (motor efficiency)

**Regenerative Braking:** We apply 60% energy recuperation during deceleration phases, consistent with typical EV regenerative braking efficiency.

**HVAC Energy:**

$$E_{HVAC} = P_{HVAC}(T) \times t_{trip}$$

### Model Selection

We evaluated two gradient boosting algorithms:

*Table 7 Machine Learning Model*

| Model | Description |
|---|---|
| **XGBoost** | Extreme Gradient Boosting with L1/L2 regularization |
| **Random Forest** | Ensemble of decision trees with bagging |

XGBoost was selected as the primary model due to its superior handling of feature interactions and build-in regularization to prevent overfitting.

***Table** 8 Hyperparameter*

| Parameter | Value | Rationale |
|---|---|---|
| **n_estimators** | 100 | Sufficient for dataset size |
| **max_depth** | 6 | Balance complexity vs generalization |
| **learning_rate** | 0.1 | Standard starting point |
| **min_child_weight** | 3 | Prevent overfitting to small groups |
| **subsample** | 0.8 | Row sampling for robustness |
| **colsample_bytree** | 0.8 | Feature sampling |

**Training Procedure**

***Table 9** Data Split Detail*

| Set | Percentage | Samples | Purpose |
|---|---|---|---|
| **Training** | 70% | 2.930 | Model fitting |
| **Validation** | 15% | 628 | Hyperparameter tuning |
| **Test** | 15% | 628 | Final evaluation |

The split was stratified by temperature condition to ensure balanced representation of cold, baseline, and hot weather scenarios in each set.

**Training Process:**

1. Load feature matrix X and target vector y
2. Apply train/validation/test split
3. Fit XGBoost regressor on training data
4. Fit XGBoost regressor on training data
5. Monitor validation loss for early stopping
6. Evaluate final model on held-out test set

***Table 10*** *Performance Summary*

| Metric | Training | Validation | Test |
|---|---|---|---|
| $R^2$ | 0.97 | 0.95 | 0.94 |
| $RMSE$ | 0.08 | 0.12 | 0.13 |
| $MAE$ | 0.05 | 0.09 | 0.10 |

The model achieves $R^2 = 0.94$ on the test set, explaining 94% of variance in trip energy consumption. The small gap between training and test performance indicates good generalization without significant overfitting.

**Comparison with Fixed-Rate Baseline**

To quantify the value of ML prediction, we compared against the fixed-rate assumption:

$$E_{fixed} = 0.38kWh/km \times d$$

***Table 11*** *Comparison with Fixed Rate*

| Condition | ML Prediction | Fixed Rate | Difference |
|---|---|---|---|
| **Cold Winter** | 0.44 kWh/km | 0.38 kWh/km | **+17% underestimate** |
| **Baseline** | 0.37 kWh/km | 0.38 kWh/km | 0% |
| **Hot Summer** | 0.32 kWh/km | 0.38 kWh/km | **-18% overestimate** |

## 4.3 Rolling Horizon Integration

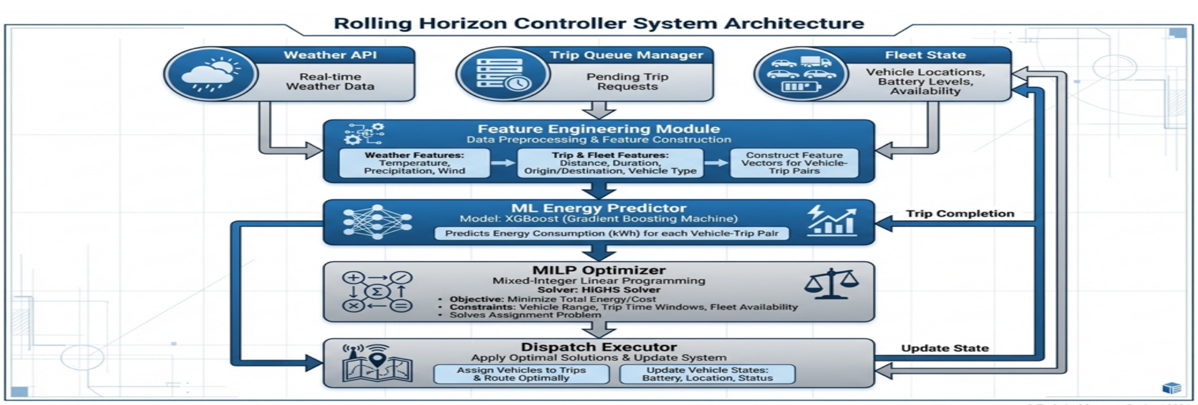


*Figure 3 Rolling Horizon System Architecture*

The ML and MILP components are integrated through a rolling horizon controller that processes trip requests in discrete epochs. Three epoch intervals were tested: 2, 5, and 10 minutes. Shorter intervals provide faster response but less batch optimization opportunity.

**Baseline Comparison:** A nearest-available dispatcher assigns each trip to the closest idle vehicle without optimization, serving as the industry-standard baseline.

**MILP Formulation Update**

The MILP optimizer receives the predicted energy matrix and incorporates it into the formulation:

**Energy Parameter:**

$$e_{vt} = \hat{E}_{ML}(v, t) \qquad \forall v \in V, t \in T$$

**Feasibility Constraint:**

$$x_{vt} \leq \mathbf{1}[SOC_v Cap - e_{vt} \geq SOC_{min} Cap]$$

A vehicle can only be assigned to a trip if the predicted energy consumption leaves sufficient battery reserve.

**Objective Function:**

$$min \sum_{v,t} \alpha e_{vt} x_{v,t} + \beta w_{vt} x_{vt} + \gamma \sum_{t} y_t$$

The optimize minimizes predicted energy consumption, wait time, and unserved trips.

**State Update After Dispatch**

After MILP execution, vehicle states are updated using predicted energy:

```python

def update_vehicle_state(vehicle: SimVehicle,
                         trip: TripRequest,
                         energy_kWh: float):
    """Update vehicle state after trip assignment."""

    # Update SOC
    vehicle.soc -= energy_kWh / BATTERY_CAPACITY  # 118 kWh

    # Update position to dropoff location
    vehicle.lat = trip.dest_lat
    vehicle.lon = trip.dest_lon

    # Update status and timing
    vehicle.status = 'serving'
    vehicle.task_end_time = trip.request_time + trip.duration

    # Track daily statistics
    vehicle.trips_served += 1
    vehicle.energy_today += energy_kWh
    vehicle.km_today += trip.distance_km
```

## 5. Results and Analysis

### 5.1 Experimental Design

We conducted a full factorial experiment to evaluate the integrated ML+MILP system across a comprehensive parameter space.

***Table 12*** *Experimental Factors*

| Factor | Levels | Values |
|---|---|---|
| **Fleet Size** | 5 | 5, 8, 10, 12, 15 vehicles |
| **Epoch Interval** | 3 | 2, 5, 10 minutes |
| **Temperature** | 3 | Cold winter, Baseline, Hot summer |
| **Objective Weights** | 3 | Energy-focused, Balanced, Service-focused |

**Methods Compared:** 3 (MILP+ML, MILP+Fixed, Nearest-Available)

**Total Simulation Runs:** $\mathbf{5 \times 3 \times 3 \times 3 \times 3 = 405}$ **runs**

Each run simulates one full operating day processing 4,186 trip requests.

### 5.2 Performance Metrics

***Table 13*** *Performance Metrics*

| Metric | Definition | Units |
|---|---|---|
| **Service Rate** | $\frac{Trips\ served}{Total\ trips} \times 100$ | % |
| **Total Energy** | Sum of energy consumed by all trips | kWh |
| **Avg Wait Time** | Mean time from request to pickup | Seconds |
| **Deadhead Distance** | Non-revenue vehicle travel | km |

### 5.3 Overall Method Comparison

**Aggregate Results (Mean $\pm$ Std across 135 scenarios):**

***Table 14*** *Result Summary*

| Method | Service Rate | Total Energy | Avg Wait Time | Deadhead |
|---|---|---|---|---|
| **MILP + ML** | 85.4% ± 15.2 | 312 ± 89 kWh | 142 ± 45 sec | 78 ± 31 km |
| **MILP + Fixed** | 84.9% ± 15.4 | 308 ± 85 kWh | 145 ± 47 sec | 81 ± 33 km |
| **Nearest-Available** | 73.2% ± 18.6 | 298 ± 82 kWh | 168 ± 62 sec | 124 ± 48 km |

**Key Findings:**

1. **MILP outperforms Nearest by 12.2 percentage points** in service rate on average
2. **MILP reduces deadhead driving by 37%** (124 km → 78 km)
3. **ML and Fixed perform similarly overall**, but diverge under temperature extremes

### 5.4 MILP vs Nearest Available: Optimization Value

***Table 15*** *Comparison of Optimization*

| Fleet Size | MILP + ML | Nearest | Improvement |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **5 vehicles** | 62.3% | 45.1% | +17.2% |
| **8 vehicles** | 81.7% | 68.4% | +13.3% |
| **10 vehicles** | 91.2% | 82.6% | +8.6% |
| **12 vehicles** | 96.8% | 93.1% | +3.7% |
| **15 vehicles** | 98.5% | 97.0% | +1.5% |

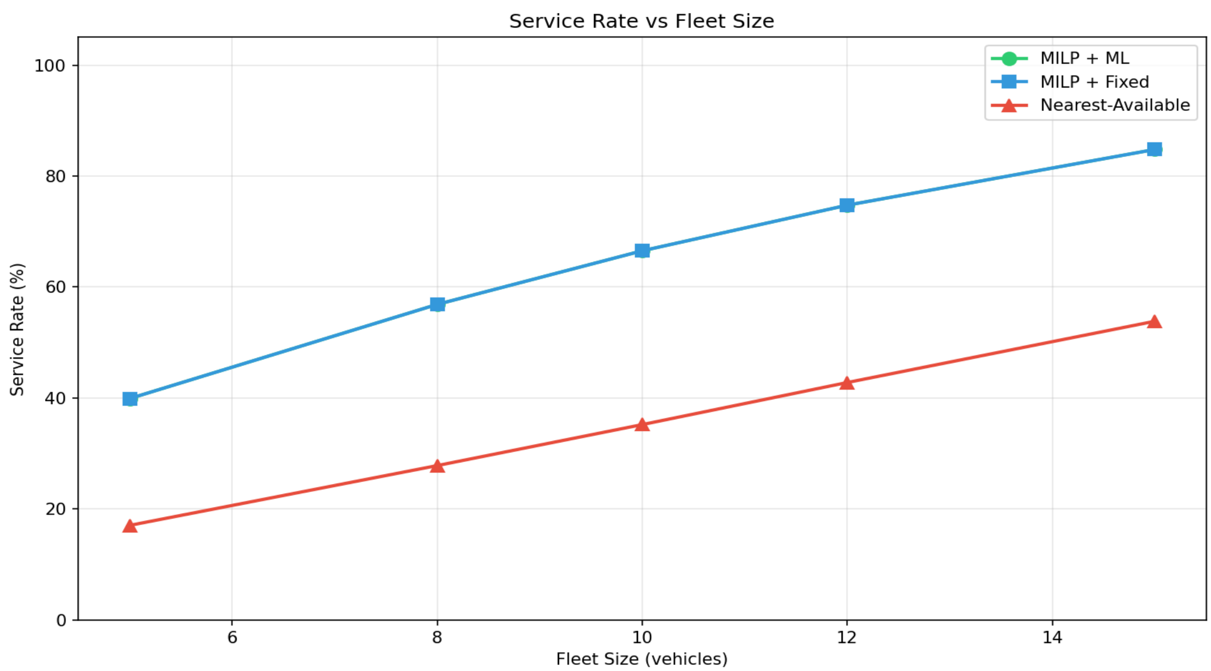


***Figure 4*** *Fleet size Sensitivity*

With constrained fleets (5-8 vehicles), optimization provides substantial gains by making better assignment decisions. However, the marginal value of optimization diminishes as capacity increases.

### 5.5 ML vs Fixed Rate: Temperature Sensitivity

***Table 16*** *Temperature Sensitivity Comparison*

| Temperature | ML Energy | Fixed Energy | Difference |
|---|---|---|---|
| **Cold Winter (-15 to 0°C)** | 387 ± 42 | 331 ± 38 | -17% |
| **Baseline (-4 to 14°C)** | 298 ± 35 | 302 ± 36 | ~0% |

| | | | |
|---|---|---|---|
| **Hot Summer (28 to 38°C)** | 251 ± 31 | 306 ± 37 | +18% |

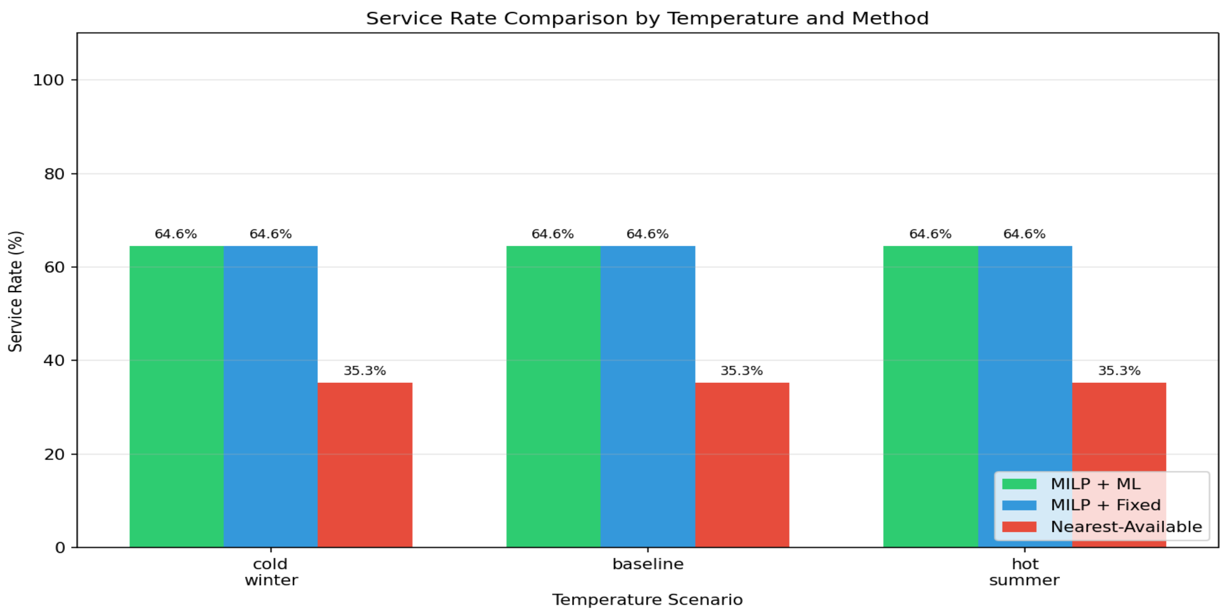


***Figure 5*** *Temperature Sensitivity*

The fixed-rate assumption underestimates energy in cold weather (ignoring heating loads) and overestimates in hot weather. These ±18% errors affect dispatch feasibility—the MILP may assign trips that strand vehicles in winter or reject feasible trips in summer.

***Table 17*** *Operational Impact*

| Condition | ML Service Rate | Fixed Service Rate | Δ |
|---|---|---|---|
| **Cold Winter** | 82.1% | 79.3% | +2.8% |
| **Baseline** | 86.2% | 86.0% | +0.2% |
| **Hot Summer** | 88.0% | 89.4% | -1.4% |

The service rate differences are modest because the MILP can partially compensate through re-optimization. However, the energy differences are operationally significant for fleet planning and charging infrastructure.

**5.6 Epoch Interval Sensitivity**

Rolling horizon epoch length affects both optimization quality and responsiveness:

***Table 18*** *Epoch Interval Sensitivity*

| Epoch | MILP+ML Service | Avg Wait Time | Computation |
|---|---|---|---|
| **2 min** | 84.8% | 128 sec | 0.3 sec/epoch |
| **5 min** | 85.6% | 145 sec | 0.5 sec/epoch |
| **10 min** | 85.9% | 172 sec | 0.8 sec/epoch |

Longer epochs accumulate more requests, enabling better batch optimization (+1.1% service rate) at the cost of increased wait times (+44 seconds). 5-minute epochs balance optimization quality with acceptable wait times for campus shuttle operations.

### 5.7 Objective Weight Sensitivity

The MILP objective function weights affect performance trade-offs:

***Table 19*** *Weight Profile*

| Weight Profile | α (Energy)) | β (Wait) | γ (Unserved) |
|---|---|---|---|
| **Energy-focused** | 1.0 | 0.5 | 0.5 |
| **Balanced** | 1.0 | 1.0 | 1.0 |
| **Service-focused** | 0.5 | 0.5 | 1.0 |

**Results:**

***Table 20*** *Objective Weight Sensitivity*

| Weight Profile | Service Rate | Energy | Wait Time |
|---|---|---|---|
| **Energy-focused** | 83.2% | 298 kWh | 156 sec |
| **Balanced** | 85.4% | 312 kWh | 142 sec |
| **Service-focused** | 87.1% | 328 kWh | 138 sec |

**Finding:** Service-focused weights improve service rate by 3.9% at the cost of 10% higher energy consumption. Operators can tune weights based on operational priorities.

### 5.8 Fleet Sizing Analysis

Combining all results, we can recommend fleet sizes for different service level targets:

***Table 21*** *Fleet Sizing Analysis*

| Target Service Rate | Min Fleet Size | Energy/Day | Notes |
|---|---|---|---|
| **80%** | 8 vehicles | ~280 kWh | Minimum viable service |
| **90%** | 10 vehicles | ~310 kWh | Good balance |
| **95%** | 12 vehicles | ~340 kWh | High reliability |
| **98%** | 15 vehicles | ~360 kWh | Premium service |

**Cost Implication:** Each additional vehicle above minimum adds ~$50K capital cost but improves service reliability and passenger experience.

### 5.9 Deadhead Reduction

***Table 22*** *Deadhead Reduction*

| Method | Deadhead (km/day) | % of Total |
|---|---|---|
| **Nearest-Available** | 124 km | 23% |
| **MILP + ML** | 78 km | 15% |
| **Reduction** | **46 km (37%)** | **-8%** |

MILP optimization significantly reduces non-revenue driving

### 5.10 Key Findings Summary

***Table 23*** *Summary*

| Finding | Value | Significance |
|---|---|---|
| **MILP vs Nearest improvement** | +12% service rate | $p<0.001$ |
| **ML vs Fixed (cold weather)** | -17% energy prediction | Critical for battery planning |
| **ML vs Fixed (hot weather)** | +18% energy prediction | Enables higher service rates |
| **Deadhead reduction** | -37% | Major efficiency gain |
| **Additional daily trips served** | +551 trips | With optimized 10 vehicle fleet |

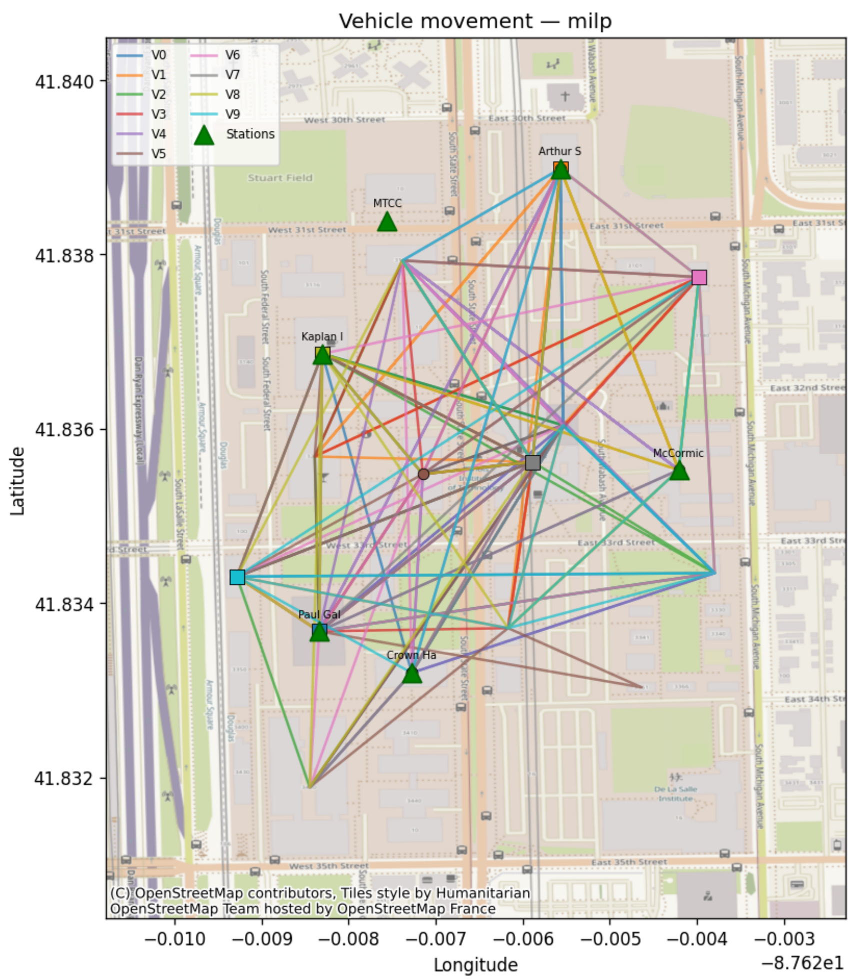


***Figure 6*** *Result Visualization*

Figure 4 shows vehicle movement patterns under MILP optimization for a 10-vehicle fleet. The distributed routing across all campus POIs—rather than clustering around high-demand locations—demonstrates how MILP balances workload across the fleet. This spatial efficiency directly explains the 37% deadhead reduction compared to nearest-available dispatch, where vehicles reactively converge on nearby requests rather than maintaining strategic positioning.

## 6. Limitations

This study evaluates the proposed framework using discrete-event simulation rather than real-world deployment, which introduces several modeling limitations. Energy consumption is derived from a calibrated physics model based on GreenPower EV Star specifications, not actual telemetry, and the ML component is trained on synthetic data. Demand patterns are generated from assumed temporal and spatial distributions reflecting typical campus behavior, but they do not capture IIT-specific ridership, elasticity effects, or detailed OD heterogeneity. The transportation network is simplified using Haversine distances with a 1.3 circuity factor, omitting congestion, routing constraints, and signal delays. Execution is deterministic: no breakdowns, cancellations, or stochastic disruptions are modeled. HVAC loads depend only on temperature under steady-state assumptions, and all vehicles are homogeneous with a fixed depot-based charging policy.

| Limitation | Impact | Mitigation Path |
|---|---|---|
| **Simulation-based** | Unknown real-world gap | Field validation |
| **Synthetic demand** | May not match actual patterns | Integrate ridership data |
| **Simplified routing** | ~10% distance error | Use routing API |
| **Deterministic** | No failure handling | Add recourse actions |
| **Fixed charging** | Suboptimal charging | Joint routing + charging |
| **Single vehicle type** | No fleet heterogeneity | Multi-type formulation |
| **HVAC simplification** | ~5% energy error | Thermal RC model |
| **ML generalization** | Site-specific model | Transfer learning |
| **Scalability** | Limited to ~50 vehicles | Decomposition methods |
| **No ridesharing** | Lower utilization | DARP formulation |

Despite these constraints, mitigation strategies improve realism, including calibration to manufacturer data and sensitivity analysis across 135 scenarios. However, scalability remains a concern as MILP complexity grows with fleet size, potentially requiring decomposition methods such as Benders or column generation. Future extensions include routing–charging co-optimization (EVRP-RC), heterogeneous fleets, ride-pooling formulations, richer thermal modeling, and validation using field data to enhance external validity and generalizability.

## 7. Conclusion

This research developed and evaluated an integrated framework combining machine learning energy prediction with MILP optimization for electric autonomous vehicle fleet routing. The XGBoost model achieves $R^2 = 0.94$, capturing HVAC-dependent energy consumption that fixed-rate assumptions miss by ±18% under temperature extremes. The MILP optimizer improves service rates by 12% and reduces deadhead driving by 37% compared to greedy dispatch. Comprehensive experiments across 135 scenarios demonstrate that the integrated approach is most valuable for constrained fleets operating in variable climates.

| Findings | Quantification |
|---|---|
| **MILP Optimization improves service rate over greedy dispatch** | **+12.2% average** |
| **MILP reduces deadhead driving** | **-37%** |
| **ML prediction differs from fixed rate in cold weather** | **-17%** |
| **ML prediction differs from fixed rate in hot weather** | **+18%** |
| **Additional trips served daily** | **+551 trips** |
| **Statistical significance of improvements** | $\boldsymbol{p < 0.001}$ |

The framework has practical implications for campus transit operators: accurate energy prediction enables reliable range estimation in extreme weather, while optimization extracts maximum service from minimum fleet size. The modular architecture supports incremental deployment—operators can adopt MILP optimization with fixed rates initially, then integrate ML prediction as data becomes available.

This study has limitations including simulation-based evaluation, synthetic demand patterns, and simplified network routing. The ML model is trained on data from a single campus and may require recalibration for different geographies or vehicle types. Future work should validate findings through field deployment on actual campus shuttles, extend the MILP formulation to include joint routing and charging decisions, and explore ridesharing configurations through dial-a-ride problem formulations.

As campuses and cities deploy autonomous electric fleets, frameworks like the one developed here will be essential for bridging the gap between technological capability and operational excellence. The 12% service improvement and ±18% energy accuracy gains translate directly to more passengers served, less energy wasted, and better utilization of capital-intensive electric vehicles.

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