Next Stop Station – Smart Bus Fleet Management System

Problem Statement

Based on our research with TTC buses, Electric bus fleets suffer from unpredictable battery/powertrain failures, unreliable state-of-charge telemetry, and weather/route-driven range swings, leading to unplanned road calls, low availability, and high maintenance/spare costs. Winter HVAC loads and charger/cable faults further erode usable range and depot readiness, while inconsistent diagnostics across vendors complicate dispatch and repairs.

Fleets lack a unified, real-time view of asset health and remaining range to turn emerging faults into scheduled interventions.

Solution:
A data-driven digital twin with AI forecasting is needed to surface incipient failures, standardize health signals, and enable proactive, low-cost maintenance and reliable service

Cost-Benefit Analysis

1. Mock Data Simulation (Data csv files in folder). Green: based on real world data, yellow: AI assumptions

Mock Data Assumptions:
- Fleet: 100 e-buses, one year (2025). (TTC currently has 400)
- Reactive world: ~2 roadside breakdowns/bus-year (≈200 potential events).
- Digital twin world: 55% of potential failures become planned interventions.
- Program cost (sensors + connectivity + cloud + ML/agent): $700 per bus-year ($70,000/yr fleet).
- Target per-event costs used to generate data:
- Baseline failure ≈ $7.5k; Twin remaining unplanned ≈ $4.5k; Planned ≈ $0.6k.

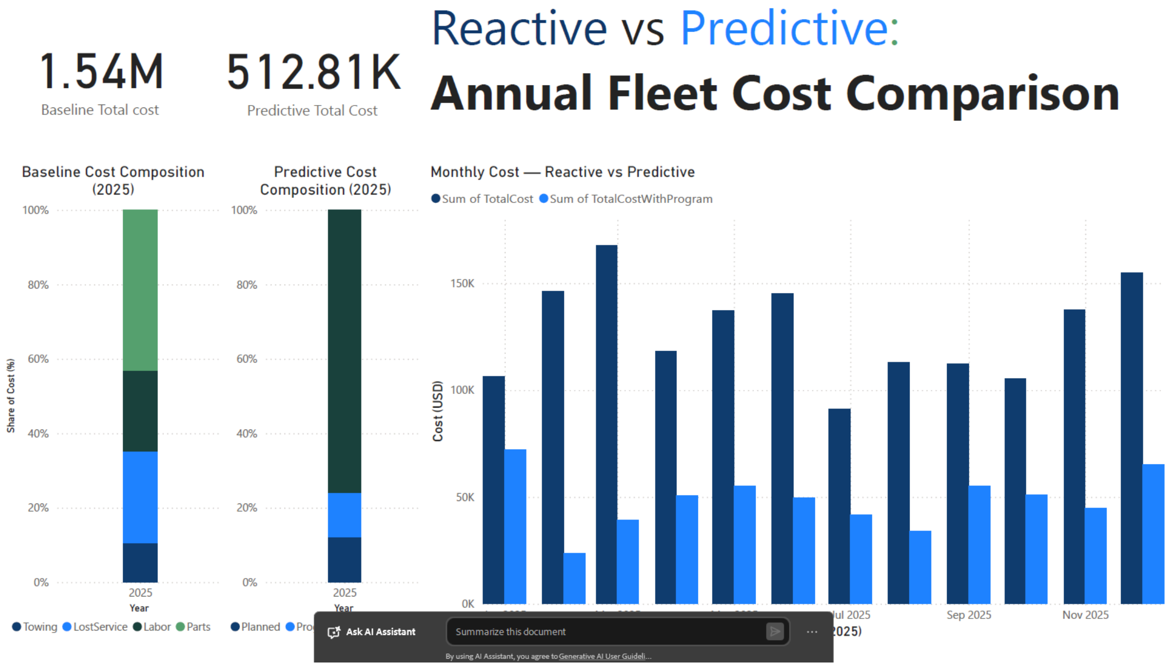
Results – Baseline (reactive, current)
- Events: 201 roadside breakdowns (≈2/bus-year).
- Total cost: $1,535,565.
- Avg cost per failure: $7,640.
- Total downtime: 1,144 hours → ~5.7 hrs/event.

Results – With Digital Twin (predictive)
- Events: 90 remaining unplanned + 110 planned interventions = 200 total handled.
- Unplanned cost: $442,562 (avg $4,917/event).
- Planned cost: $70,252 (avg $639/event).
- Program cost: $70,000 (spread across months).
- Total cost (incl. program): $582,814.

Impact
- Annual savings: $952,751 (= $1,535,565 − $582,814).
- Savings rate: ~62% reduction vs baseline.
- Program ROI: ~13.6× (= $952,751 / $70,000). (return on investments)

- Operational shift: 201 unplanned road calls → only 90 unplanned, 110 handled as planned shop work (cheaper, shorter, schedulable).

Visualizations (can add more)



User Story

In this project, the User Stories are divided into three primary roles: Operations Manager, Maintenance Engineer, and Digital Twin Operator. These roles represent the main stakeholders involved in electric bus management and decision-making.
Additionally, the Driver is defined as a supportive user, who directly interacts with the AI system through real-time feedback and dashboard interfaces during vehicle operation. While the Driver does not make operational or maintenance decisions, this role demonstrates how the AI model impacts the user experience in real-world settings.

1. Operations Manager
As an Operations Manager, I want to predict potential battery failures 2~3 weeks in advance so that I can schedule maintenance and prevent service disruptions.

Goal : To schedule maintenance proactively by predicting potential battery failures in advance.

Problem : Unexpected battery-related breakdowns disrupt bus schedules and increase emergency maintenance costs. Current monitoring systems only show basic data such as speed or location without predictive insights into battery degradation.

AI / Digital Twin Application :

- AI models detect abnormal temperature, voltage, or charge patterns that indicate early-stage degradation.

- Digital Twin simulates operating conditions such as season, route type, passenger load, and driving habits to forecast remaining battery life.
- Predictive alerts notify the manager before failures occur.

Expected Impact :
- 20% reduction in maintenance costs
- Zero mid-route breakdowns
- 15% improvement in scheduling accuracy

2. Maintenance Engineer
As a Maintenance Engineer, I want to monitor real-time battery health and receive alerts for abnormal degradation so that I can prioritize maintenance and minimize unplanned downtime.

Goal : To detect degradation trends early, prioritize maintenance tasks, and prepare replacement parts in advance.

Problem : Battery issues are often discovered only after failure. Engineers rely on manual inspections and reports, causing delays and increasing downtime.

AI / Digital Twin Application :
- AI analyzes temperature, voltage, and charge cycle data to detect abnormal wear patterns.
- Digital Twin creates a virtual replica of each battery to simulate maintenance scenarios.
- Engineers receive prioritized alerts for components nearing critical thresholds

Expected Impact :
- 25% reduction in repair time
- Fewer unplanned repairs
- Improved spare-part inventory management

3. Digital Twin Operator
As a Digital Twin Operator, I want to continuously synchronize virtual battery models with real-world data so that prediction accuracy improves over time.

Goal : To continuously synchronize and refine virtual battery models based on operational data.

Problem : There is no unified platform to visualize both real-time and simulated battery performance. Predictive models lose accuracy without regular updates.

AI / Digital Twin Application :
- Digital Twin mirrors each battery’s structure, temperature, and degradation behavior.
- AI retrains prediction models as seasonal and operational data accumulate.
- Operators compare simulated versus actual results to improve long-term accuracy.

Expected Impact :

- Improved model accuracy over time
- Adaptation to seasonal and route variations
- Data-driven strategies for extending battery life

4. Driver(Secondary User)

As a Driver, I want to receive real-time feedback on remaining range and battery condition so that I can drive safely and avoid mid-route breakdowns.

Goal : To receive accurate real-time feedback about range and battery condition during operation.

Problem : Drivers often worry about running out of charge mid-route, especially during cold weather or heavy load conditions. They have limited visibility into the actual remaining range.

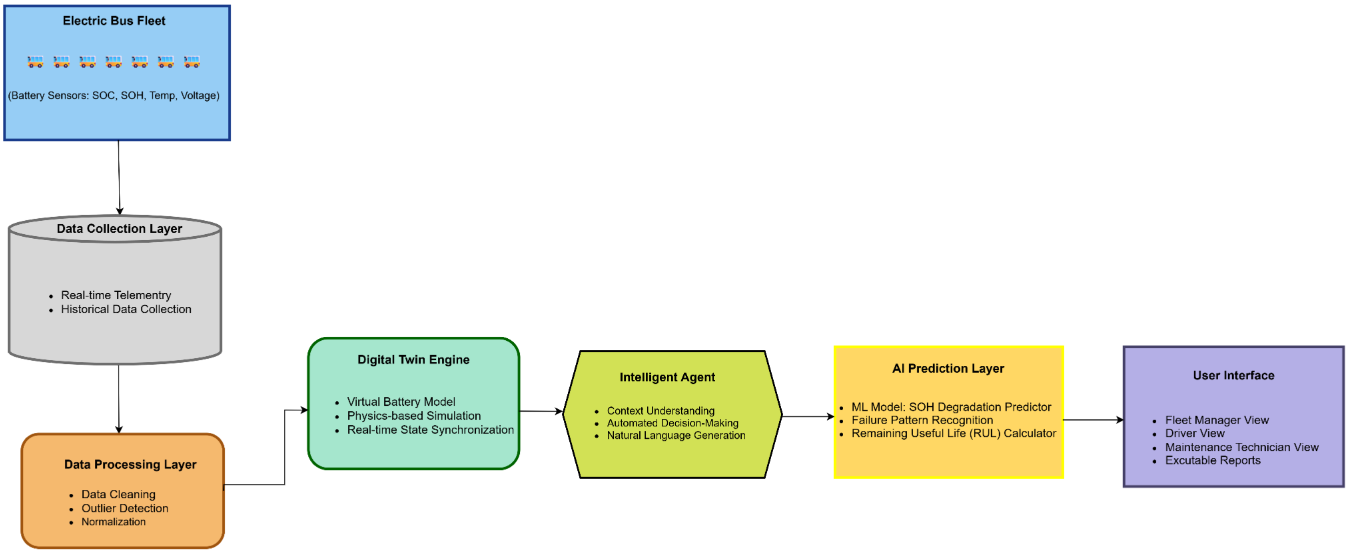
AI / Digital Twin Application :

- Digital Twin calculates dynamic range based on charge level, temperature, and passenger load.
- AI adjusts range prediction in real time considering road slope and heating, ventilation, and air conditioning usage.
- Dashboard displays alerts such as ‘safe to continue’ or ‘charge soon.’

Expected Impact :

- Increased driver confidence
- Fewer mid-route stoppages
- Improved passenger safety and reliability

System Architectural Diagram



Component Roles and Functions

1. Electric Bus Fleet

Role**:** Physical data source

Function:

- Monitors battery health via sensors (voltage, current, temperature, SOC, SOH)
- Transmits real-time data every 10-30 seconds via CAN Bus and cellular network
- Provides continuous telemetry from all fleet vehicles

Key Output**:** Raw sensor data stream

2. Data Collection Layer

Role: Data ingestion and storage

Function:

- Receives incoming sensor data from all buses via API
- Validates data format and integrity
- Stores time-series data in database for historical analysis
- Routes real-time data to processing layer

Key Output: Stored and streamed sensor data

3. Data Processing Layer

Role: Data preparation and quality control

Function:

- Cleans raw data (removes errors, handles missing values)
- Detects and corrects outliers
- Engineers features for analysis (power calculations, degradation rates)
- Normalizes data for AI/ML models
- Enriches with contextual information (weather, route data)

Key Output: Clean, validated, feature-rich data

4. Digital Twin Engine

Role: Physics-based simulation

Function:

- Creates virtual battery model using electrochemical and thermal equations
- Synchronizes with real battery state in real-time
- Simulates future battery behavior based on physics
- Tests "what-if" scenarios without risking physical assets
- Provides explainable predictions based on scientific laws

Key Output: Physics-based predictions, optimal operating conditions

5. AI Prediction Layer

Role: Pattern-based intelligence

Function:

- Learns from historical failure patterns across fleet
- Detects anomalies and manufacturing defects
- Refines predictions using machine learning models
- Calculates failure probability and risk scores
- Improves accuracy over time through continuous learning

Key Output: AI-enhanced predictions, risk assessment, remaining useful life

6. User Interface(Dashboard)

Role: Visualization and action center

Function:

- Displays fleet health status and individual bus details
- Presents predictive alerts with actionable recommendations
- Provides ROI calculator and financial impact analysis

- Enables maintenance scheduling and reporting
- Delivers real-time updates via web and mobile

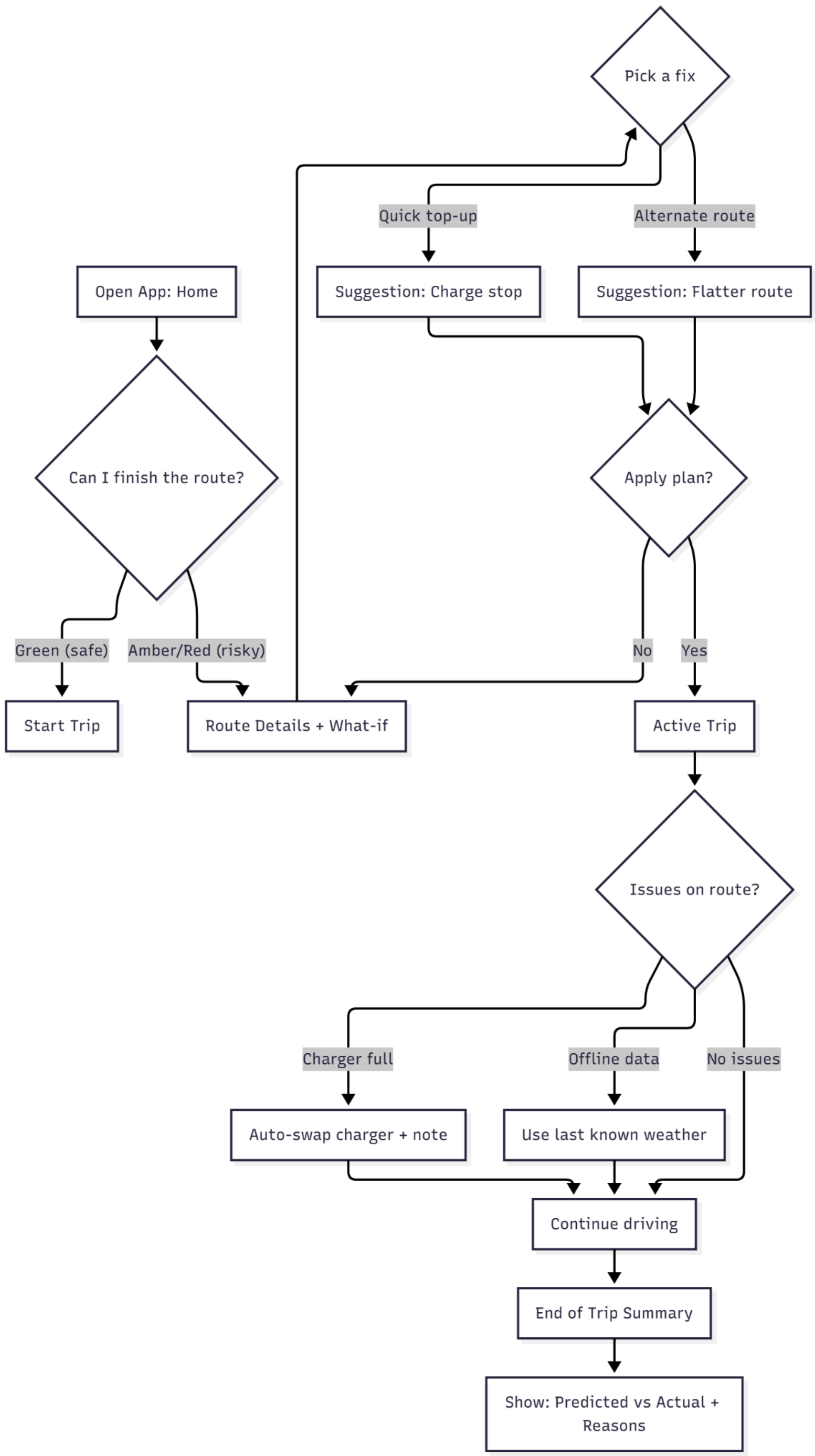
Key Output: Insights, alerts, reports, maintenance schedules

QUICK REFERENCE TABLE

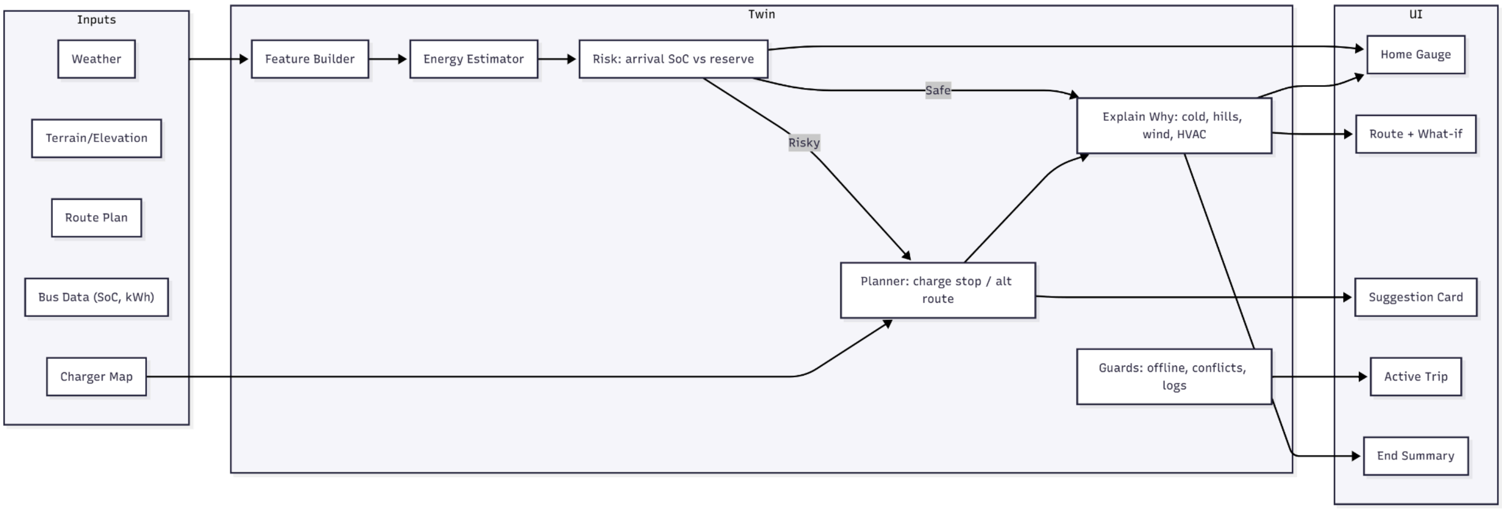
Component	Role	Key Function	Output
Bus Fleet	Data Source	Collect sensor data	Raw telemetry
Data Collection	Ingestion	Receive & store data	Stored streams
Data Processing	Preparation	Clean & enrich data	Quality data
Digital Twin	Simulation	Physics-based modeling	Physics predictions
AI Prediction	Intelligence	Pattern recognition	Risk scores, RUL
User Interface	Visualization	Display insights & alerts	Actionable reports

Core Flow (Flow Diagram)

Driver App Flow -Q



Core Flow (Flow Diagram)
System Flow



Realistic set of rules (Example Battery Condition Classification Rules)

Let's say the model will predict following:

Category	Color	State of Health (SoH)	State of Charge (SoC)	Temperature (°C)	Health Score
Healthy	Green	≥ 85 %	≥ 50 %	15 – 40	≥ 85
Warning	Yellow	70 – 84 %	20 – 49 %	41 – 45	70 – 84
Critical	Red	< 70 %	< 20 %	> 45	< 70

Project Terms:

Term	Plain-English definition	Why it matters
Digital Twin	A live, digital copy of a physical asset (battery/bus) built from sensor data.	Lets you monitor, predict failures, and test what-if plans without touching the bus.
SOH (State of Health)	How much life/capacity a battery has left vs. new.	Core KPI for maintenance and replacement planning.
SOC (State of Charge)	Current charge level, like a fuel gauge.	Input to range prediction and charging strategy.
RUL (Remaining Useful Life)	Estimated time/cycles left before maintenance or replacement.	Optimizes cost and reduces unexpected failures.
Telemetry	Sensor data automatically sent from the bus to the cloud.	Feeds the twin and AI models.
CAN / J1939	Vehicle network and protocol used by heavy vehicles to share data.	Where you read signals safely without altering controls.
Edge Gateway	Small computer on the bus that reads CAN and sends data over LTE.	First hop for data; can run simple AI rules locally.
IoT SIM / APN	Machine data plan; APN is a private lane on the carrier network.	Connectivity and security for moving buses.
Sampling Rate	How often values are recorded (e.g., every 1–5 seconds).	Directly sets data volume and cost.
Payload	Size of each message you send.	With sampling rate, determines cellular and cloud bills.
Time-Series DB	Database optimized for timestamped measurements.	Fast charts/alerts for sensor histories.
Amazon Timestream	AWS's managed time-series database.	Convenient for time-based queries without server management.
Amazon S3	Durable, low-cost storage for files.	Stores raw data long-term; use tiers to save money.
AWS IoT Core	Service to securely connect and manage devices.	Standard ingest for telemetry at scale.

Kinesis/Firehose	Streaming pipeline to move data into storage/DBs.	Reliable ingestion with minimal ops work.
CloudWatch	Monitoring and logging in AWS.	Track health and control log costs.
Data Egress	Data leaving the cloud to the public internet.	Can incur costs; keep dashboards efficient.
Cross-AZ Traffic	Data sent between availability zones in a region.	Small fees that add up; co-locate services.
SageMaker	AWS platform for training and deploying ML.	One place for training, endpoints, and experiments.
Inference Endpoint	Always-on API that returns model predictions.	Enables real-time alerts and recommendations.
Retraining	Updating models with fresh data.	Keeps predictions accurate as conditions change.
IAM / KMS	Identity/Access control and encryption key management.	Security, auditability, and compliance.
VPC	Private cloud network boundary.	Reduces attack surface; keeps services private.
Direct Connect	Private link from data center to AWS.	Optional; lowers latency and egress costs.
UI / Dashboard	Web/mobile screens for drivers/ops.	Where insights turn into action.
Charge Abort	Charging session that fails or is stopped early.	Reduce to improve availability and schedule adherence.
Road Call	Emergency roadside repair dispatch.	Expensive; predicting failures avoids them.
Contingency	Budget buffer for unknowns.	Protects plan from surprises.
Pilot	Time-boxed first deployment to prove value.	Validates costs/benefits before scaling.