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Beyond Transport: V2X Integration Turning EVs into Smart Energy Assets

A Comprehensive Tutorial on Vehicle-to-Everything Technologies

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Outline

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- Introduction
  - EV as a Battery-on-Wheels
  - Benefits and Challenges
  - Sample Application Scenarios
- Preliminary
- Individual EV Scenarios
  - Energy-Aware Routing
  - Smart Charging (V2H)
  - Revenue Scheduling
- Fleet-Level Scenarios
  - Revenue-Aware Scheduling for Delivery Fleets
  - Coordinated V2B/V2P Energy Services
  - Grid-Integrated Public Transport
  - Autonomous EV Fleets

Electric Vehicle (EV) as a Battery-on-Wheels

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- Bidirectional charging allow bidirectional flow of energy
  - Grid → EV
  - EV → Grid
- Also called Vehicle-to-Grid (V2G)
- Other related terms
  - V2H: EV ↔ Home
  - V2B: EV ↔ Building
  - V2P: EV ↔ Premise
  - V2V: EV ↔ EV
  - V2X: EV ↔ Everything

Can we use EVs for both transportation and energy storage?

EV Batteries vs Home Batteries

- **Capacity**
  - **Tesla Powerwall:** 13.5 kWh
  - **Tesla Model 3:** 60-82 kWh
  - Typical EVs have enough capacity to meet home energy needs for a couple of days
- **Location**
  - **Home battery:** Installed at home
  - **EV:** Can go anywhere
- **Investment required**
  - **Home battery:** $10,000-$20,000
  - **EV:** Free if buying for traveling anyway
- **Availability**
  - **Home battery:** Always available
  - **EV:** Not always available but …
    - Most vehicles remain parked 95% of the time
    - Average distance a typical person drives per day is 38 km (~10% of battery usage)

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Benefits of V2G

Cost savings

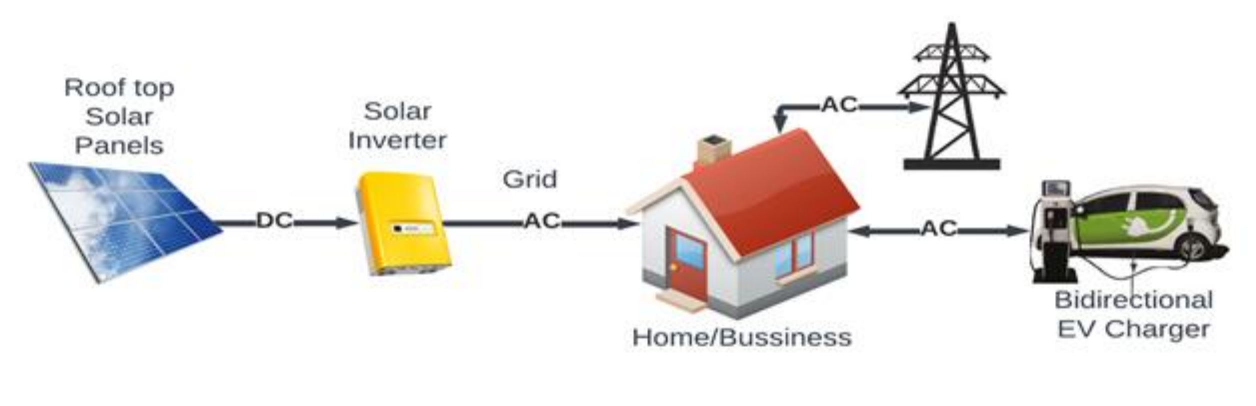
- For vehicle owners
- For grid operators

Reduction in Greenhouse Gas Emissions

- Increased use of renewable energy
- Reduce the need for expensive gas "Peaker" power plants!

Grid support

- Virtual power plants (VPP), demand response programs and peak shaving
- Backup power during outages or emergencies
- Frequency regulation, voltage support, etc



Challenges

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Battery degradation

Policy and regulatory issues

Social and behavioural challenges

....

- **Trials around the world have shown the feasibility and viability of V2G**
- **As technology, infrastructure and EV adoption improve, many of the above concerns will fade**

Economic Benefits of V2G

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Vineyard Profit

- Using Nissan Leaf EV in South Australia
- Transformed $2,000 bill into **$2,500 annual profit**.

UK Grid Savings

- Projected >**4 billion USD/year** network savings by 2040.

System-wide Savings

- Analysis of **50,000 V2G-enabled EVs**.
- Predicted **460 million USD/year** system-wide cost savings.
- Reduced future infrastructure investment.

Charging Cost Reduction

- Achieved **13.6% reduction** in EV charging costs.
- **820–1640 USD** annual savings per EV

Environmental Benefits of V2G

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Emission Reduction

Renewable Integration

Sustainable Transition

1

Global Impact: Massive Emission Cuts

IRENA (2019) study showed

- **61% CO_2** reduction
- **42%** decrease in energy costs
- **3%** peak load reduction

2

UK's Green Leap: CO_2 Eliminated

Oldfield et al. (2022) UK analysis shows using merely **50,000 EVs**

- **3M tonnes CO_2** reduced annually
- Equivalent to removing hundreds of thousands of vehicles

3

Net Negative Emissions: Fleet Advantage

UK comparison of V2G fleets vs. petrol vehicles:

- V2G fleets: **-243 gCO_2/km** (net negative)
- Petrol vehicles: **164 gCO_2/km**
- **400+ gCO_2/km** total emission swing per vehicle

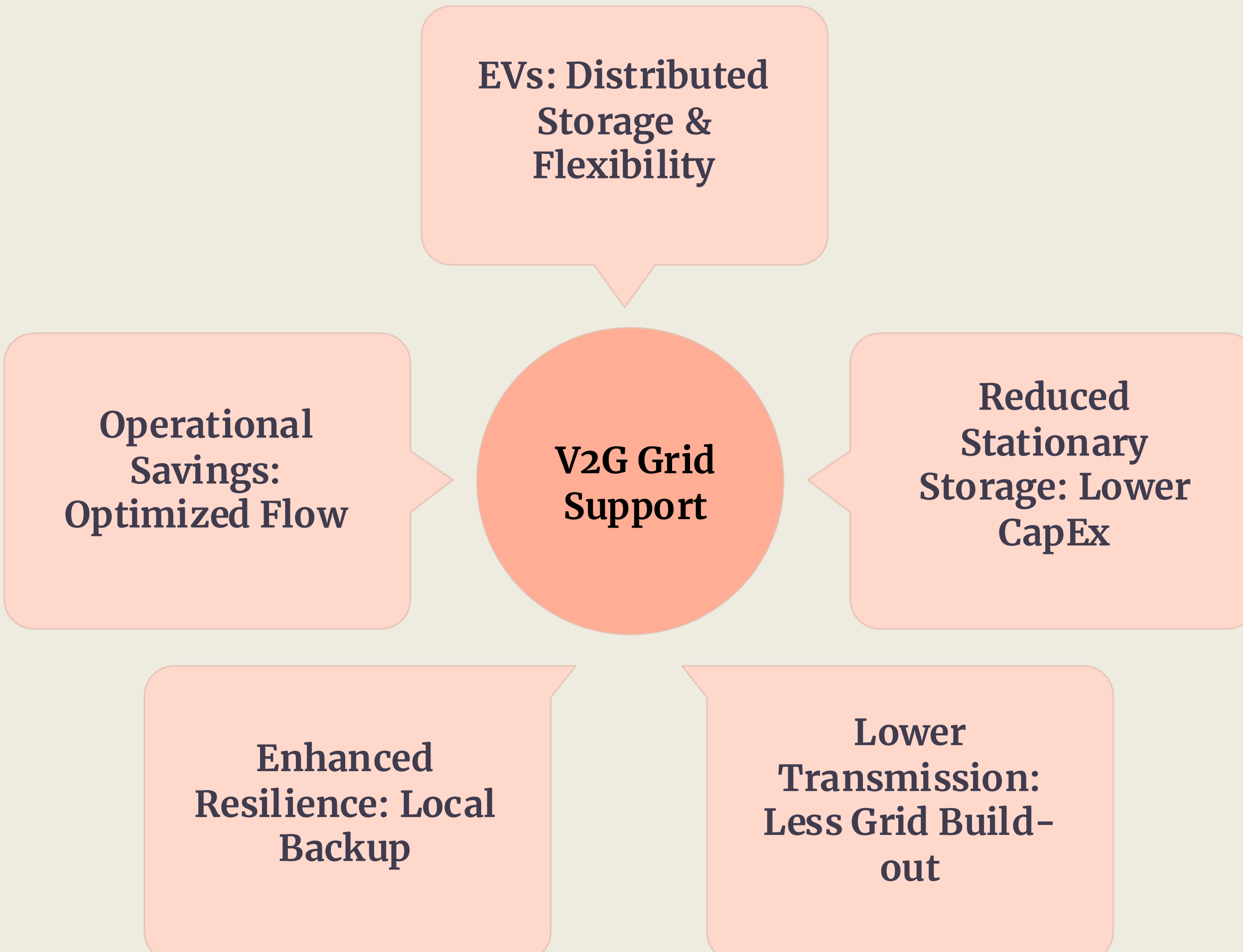
4

Unlocking Renewables: Maximizing Clean Ene

Cenex (2020) UK trials

- Prevented curtailment of valuable renewable energy
- Avoided hundreds of thousands of tonnes of CO_2 annually
- Ensures maximum utilization of clean energy

Grid Support using V2G



Grid Support using V2G

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1

Potential Capital Savings

New England study reports

- 13.9% EV participation in V2G.
- Displaced 14.7 GWh stationary storage.
- 650 Million USD capital savings, 2.2–20.3% system savings when participation increased from 5-80%.

2

Traditional Schemes Vs V2G

Even at 5-10% participation rate, V2G achieves (compared to traditional demand response)

- 337% more savings.
- 10x displacement of storage.

3

Grid Network Cost Saving

The UK Centre of Excellence for Low Carbon and Fuel Cell Technologies reports

- Just by using curtailment of renewable energy
- V2G can save >4 Billion USD per year by 2040 in network costs

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Sample research directions

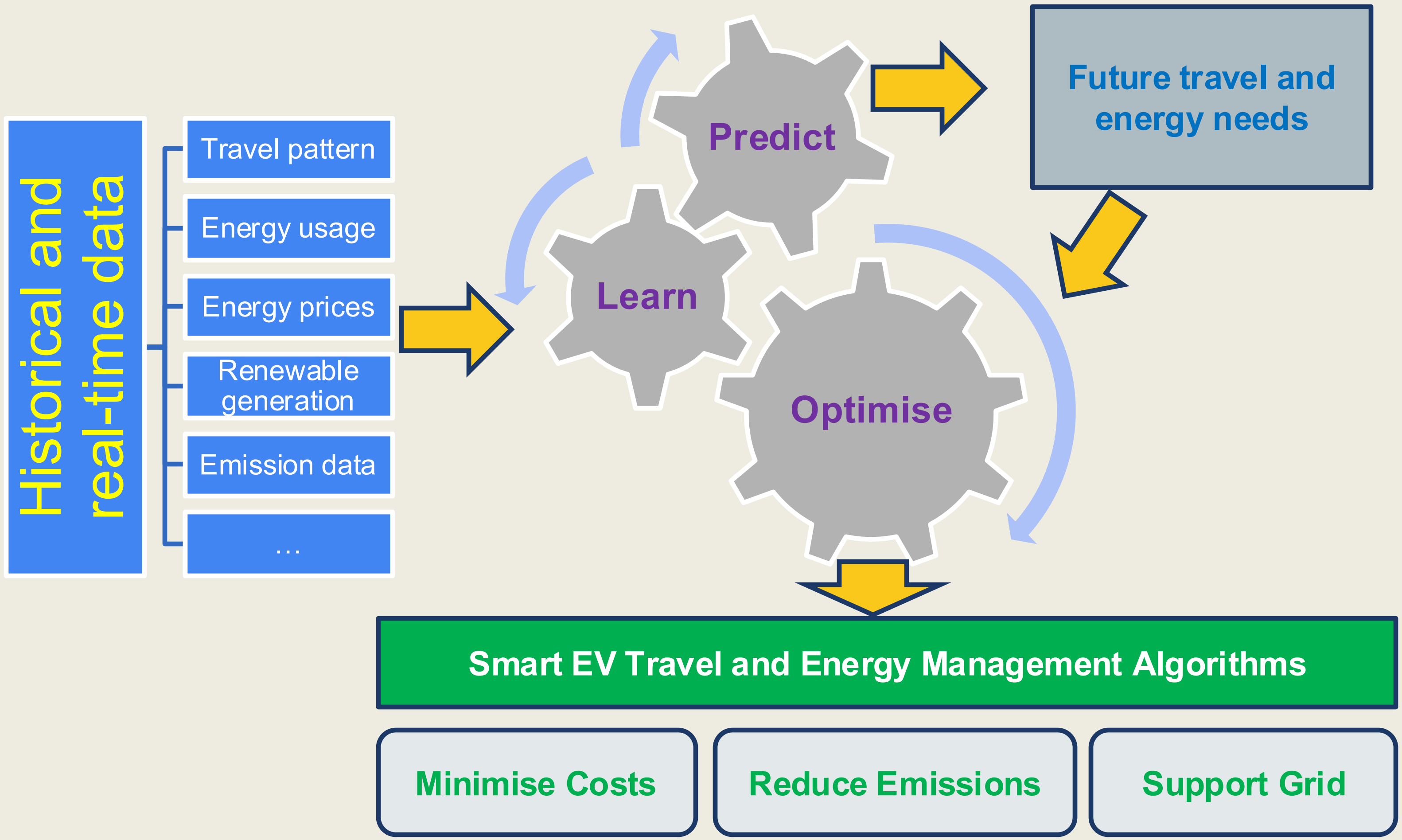
For an EV owner to use V2G, at least two conditions must be met:

1. The EV must always be available for their travelling needs
2. The charging/discharging decisions must be automated

- Design smart travel and energy management techniques for EVs to:
  - reduce emissions; and/or
  - minimise costs; and/or
  - support grid

  for different types of EV stakeholders:

  1. Individual EV owners
  2. EV fleets



Historical and real-time data
Travel pattern
Energy usage
Energy prices
Renewable generation
Emission data
...
Predict
Learn
Optimise
Future travel and energy needs
Smart EV Travel and Energy Management Algorithms
Minimise Costs
Reduce Emissions
Support Grid

Individual EVs for business use

EVs used for ride hailing/delivery or similar business use

EV Fleets

EV fleets, e.g., for last mile deliveries

EV Fleets

Public transport buses

Fire trucks

Net-Zero Premises

Group of EVs parked on-site

Self-driving EVs

Autonomous EVs

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Electric Vehicle

An Introduction to Their Fundamental Components

Electric Vehicle
Introduction to Key Component

- **Battery: Constraints and Dynamics**
  - **Charging Dynamics:**
    - **Linear models assume constant charging rate.**
    - **Non-linear charging slows at high SOC levels.**
    - **Depends on temperature, chemistry, and charger type.**
  - **Battery Degradation:**
    - **Capacity decreases and resistance increases over time.**
    - **Influenced by rate, temperature, and charge cycles.**

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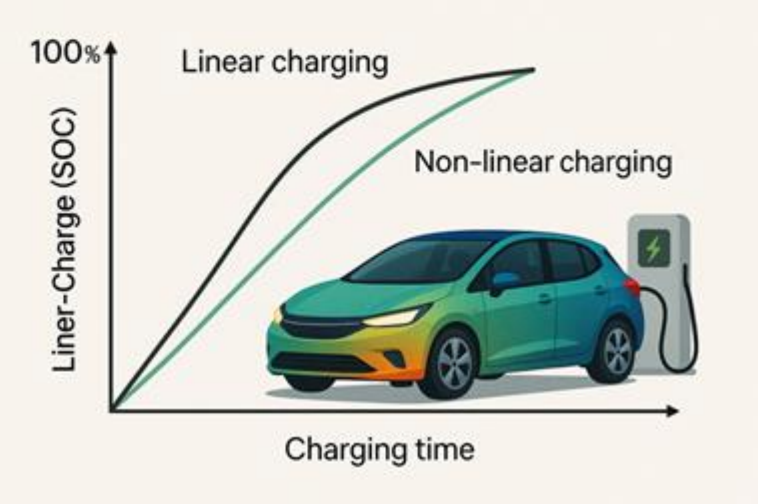

Electric Vehicle
Introduction to Key Component

- **Battery: Constraints and Dynamics**
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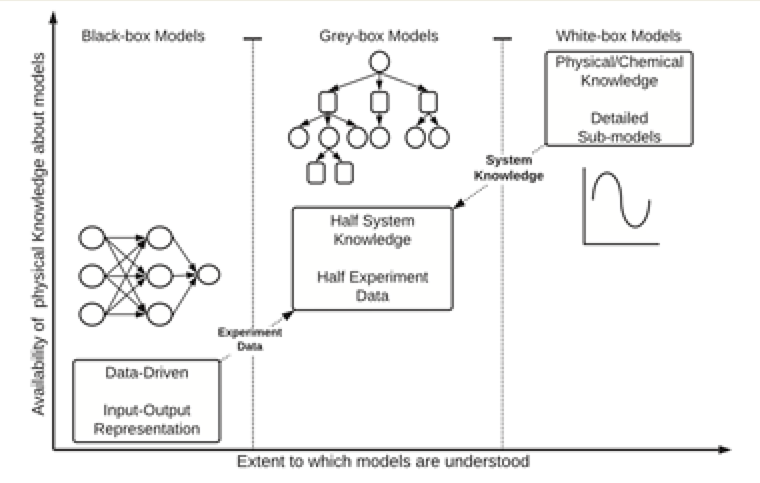
  - **Battery Degradation:**
    - Capacity decreases and resistance increases over time.
    - Influenced by rate, temperature, and charge cycles.
- **Energy Consumption Model**
  - **Black-box (Data-driven):**
    - Learns complex nonlinear energy patterns from data; high accuracy but requires large, diverse datasets.
  - **White-box (Physics-based):**
    - Uses physical laws (drag, resistance, gradient) for transparent modeling; less accurate under real-world variability.
  - **Grey-box (Hybrid):**
    - Blends physics models with data calibration; balances interpretability and adaptability for practical applications.



Electric Vehicle
Introduction to Key Component

- **Charging Station:**
  - **Station Type:**
    - **Battery Charging Station (BCS):**
      - **Fixed location, AC/DC fast charging (7–350 kW);**
    - **Battery Swapping Station (BSS):**
      - **Quick battery exchange; reduces wait time but needs standardization and inventory control.**

Electric Vehicle
Introduction to Key Component

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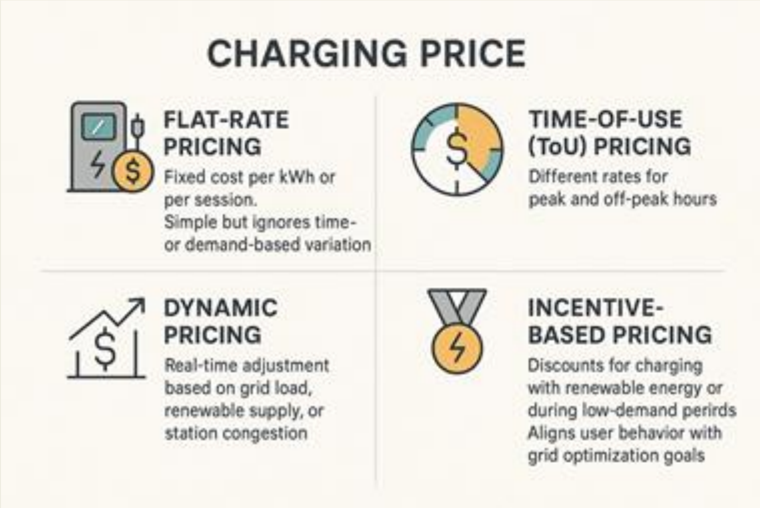
  - **Charging Price:**
    - **Flat-rate Pricing:**
      - **Fixed cost per kWh or per session. Simple but ignores time- or demand-based variation.**
    - **Time-of-Use (ToU) Pricing:**
      - **Different rates for peak and off-peak hours.**
    - **Dynamic Pricing:**
      - **Real-time adjustment based on grid load, renewable supply, or station congestion.**
    - **Incentive-based Pricing:**
      - **Discounts for charging with renewable energy or during low-demand periods.Aligns user behavior with grid optimization goals.**



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Individual EV Scenarios: Routing, Charging, and Scheduling

Three interconnected optimization challenges for individual EV users integrating travel needs, charging strategies, and economic considerations

Energy-Aware Routing

Minimize energy consumption while preserving battery capacity for V2X services

Smart Charging (V2H)

Transform vehicles into household energy assets for cost reduction and resilience

Revenue Scheduling

Balance energy efficiency with economic returns for commercial EV users

Energy-Aware Routing

Minimize energy consumption while preserving battery capacity for V2X services

Energy-Aware Routing Problem

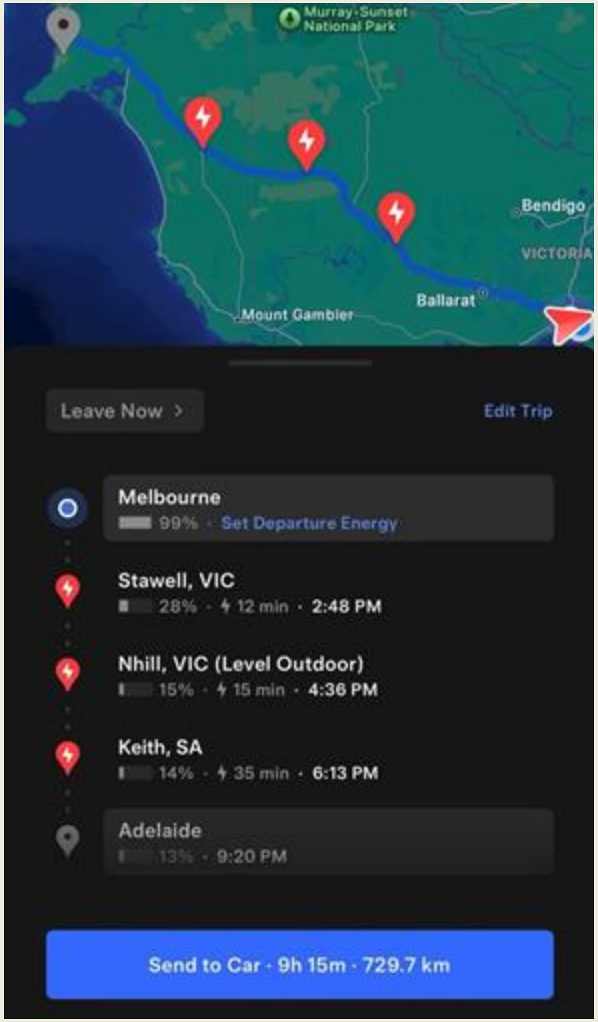
Introduction

Introduction

- EVs face limited driving range, sparse charging, and lengthy recharging times.
- Routing is an essential component for supporting connected and automated vehicles.
- Vehicle-to-Everything (V2X) relies on dynamic routing for energy-efficient navigation.

Goals

- Determine paths that minimize overall trip time, accounting for inevitable charging stops.



Energy-Aware Routing Problem

Key Challenges in Energy-Aware Routing Problem

- **Computational Intractability:**
  - The problem is an NP-hard constrained shortest path instance
  - Multi-criteria search leads to huge, exponentially growing solution sets

Energy-Aware Routing Problem

Key Challenges in Energy-Aware Routing Problem

- **Computational Intractability:**
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- **Battery Limitations and Route Feasibility:**
  - Limited battery capacity restricts EV cruising range
  - Route must guarantee vehicle feasibility, avoiding zero charge

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  - Route must guarantee vehicle feasibility, avoiding zero charge
- **Integrating Dynamic and Real-world Factors**
  - Need account for travel time variability due to traffic conditions
  - Need realistic modeling of variable speeds and charging procedures

Energy-Aware Routing Problem

Recent Applications and Advancements

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Scaling Algorithms for Large Networks

- Baum et al. [1]: CHArge optimally solves NP-hard routing on continental road graphs.

Integrating Temporal and Charging Dynamics

- Alam et al. [2]: Network addresses time-dependent traffic and charging waiting times.
- Baum et al. [4]: Algorithms integrate battery charge procedures that are non-linear over time.

Improving Query Runtime with Approximation

- Storandt. [3]: Simplifying assumptions (e.g., constant time, full charge) boost efficiency.It trades solution quality for speed, reducing runtime significantly.

Energy-Aware Routing Problem

Recent Applications and Advancements

Search-Based Approaches

- Model the problem as a constrained shortest path.
- Apply algorithms such as Dijkstra’s or A*.

Indexing-Based Approaches

- Use indexing-based approaches to accelerate query processing.
- Apply algorithms such as Contraction Hierarchies (CH) or Hub Labeling (HL).

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Smart Charging (V2H)

Transform vehicles into household energy assets for cost reduction and resilience

Vehicle-to-Home(V2H)

Introduction to V2H

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Introduction

- Vehicle-to-Home (V2H) technology allows electric vehicles (EVs) to supply electricity to homes.
- Transforms EVs into energy storage units.
- Works with Home Energy Management Systems (HEMS) for optimized energy use.

Goals

- Minimize household energy cost, improve reliability and renewable use, and cut emissions via scheduled charge/discharge.

Vehicle-to-Home(V2H)

Key Challenges in V2H

- **Complexity in Optimal Scheduling and Dynamic Variables:**
  - Scheduling requires managing uncertain.
  - Must integrate prices, emissions, solar, mobility patterns, and loads.

Vehicle-to-Home(V2H)

Key Challenges in V2H

- **Complexity in Optimal Scheduling and Dynamic Variables:**
  - Scheduling requires managing uncertain.
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- **User Participation and Mobility Compromise:**
  - Users fear unpredictable impact on EV energy availability.
  - Difficult to separate battery energy for mobility versus V2H use.

Vehicle-to-Home(V2H)

Key Challenges in V2H

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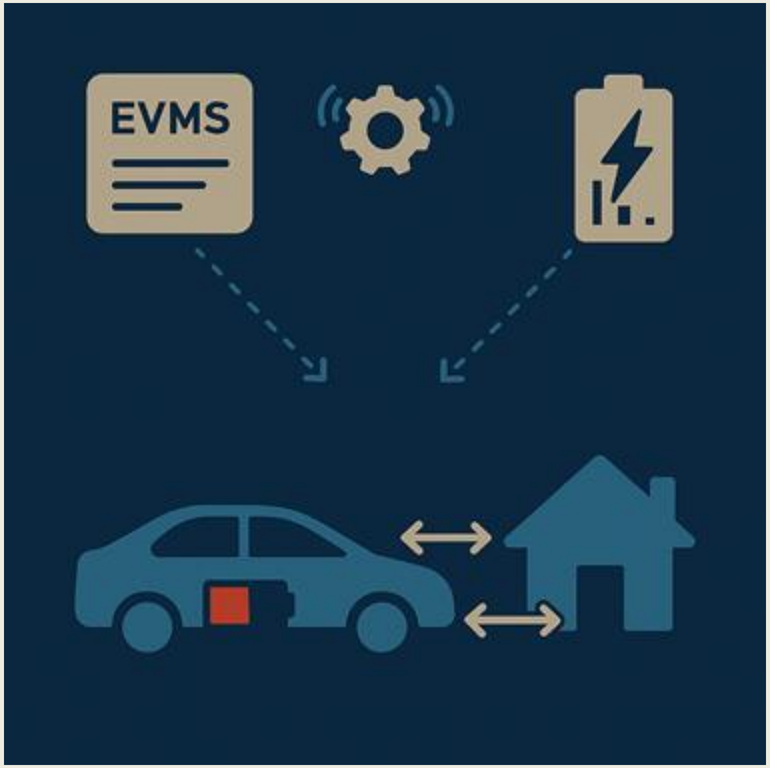
- **User Participation and Mobility Compromise:**
  - Users fear unpredictable impact on EV energy availability.
  - Difficult to separate battery energy for mobility versus V2H use.
- **Technical Implementation and Interoperability Standards:**
  - Requires addressing practical implementation within EV management systems.
  - Need communication standards for interoperability with different services.
  - V2H use may increase equivalent cycles of the battery.



Vehicle-to-Home(V2H)

Recent Applications and Advancements

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Integration with Home Energy Management Systems (HEMS)

- Li et al. [5] developed a HEMS that optimizes charging and discharging under real-time pricing, using centralized control to coordinate household loads and minimize energy costs.

Renewable Energy Optimization

- Bonfiglio et al. [7]: Utilizes EV battery capacity to store solar energy.
- Bonfiglio et al. [9] introduced virtual battery partitioning to use EV capacity for home support, reducing the need for dedicated storage.

Advanced Forecasting and Smart Charging

- Al-Amin et al. [8] used spatiotemporal forecasting to optimize scheduling, lowering costs and emissions while enabling informed trading and discharging decisions.

Vehicle-to-Home(V2H)

Algorithmic Methods

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Optimization-Based Techniques

- Dynamic programming optimizes charging and discharging decisions
- Mixed-Integer Linear Programming (MILP) minimize household electricity costs and grid dependence

Heuristic & Metaheuristic Methods

- Evolutionary Algorithms (EA) solves the HEMS model.
- Located and generalized search strategies are used within EA.

Learning-Based Approaches

- Gradient Boosting algorithm predicts dynamic operational attributes.
- Machine Learning models input predicted values to scheduling algorithms.

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Revenue-Aware Scheduling

Balance energy efficiency with economic returns for commercial EV users

Revenue-Aware Scheduling

Introduction

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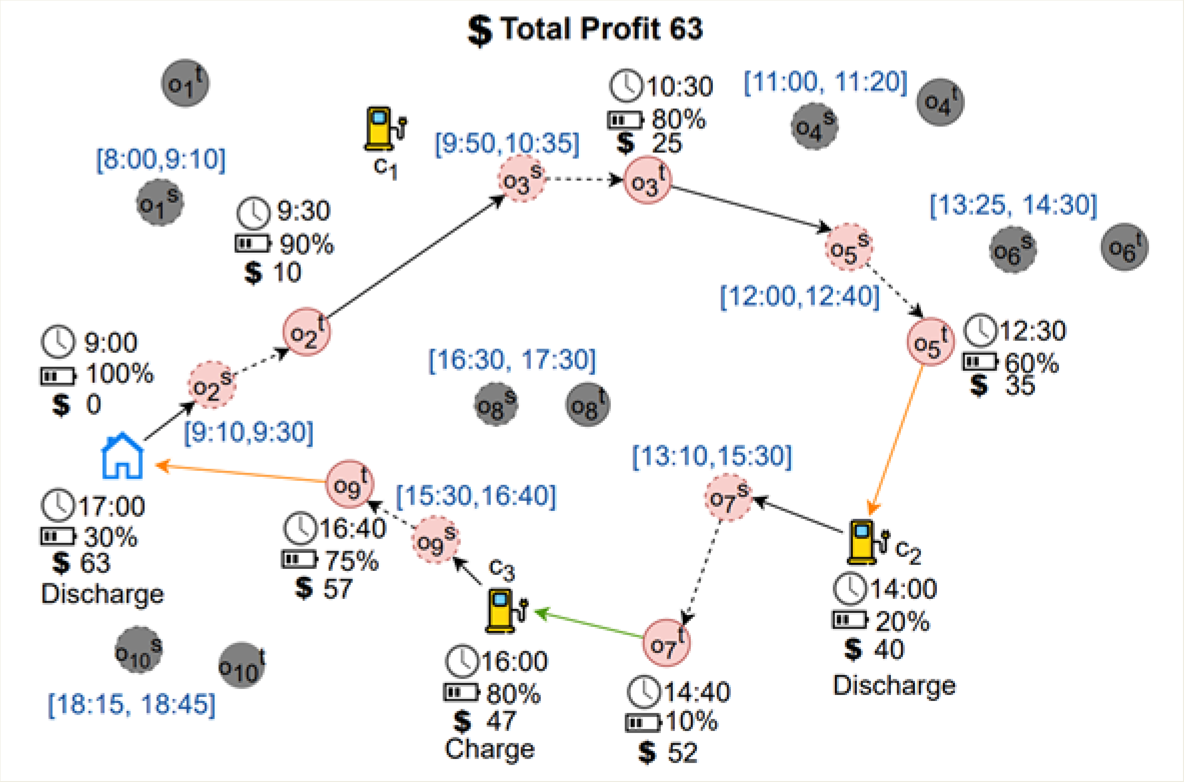
Introduction

- Commercial EV users (e.g., ride-hailing, delivery) must balance energy usage and profitability.
- Traditional routing (e.g., *Traveling Salesman Problem*) minimizes distance only — not profit.
- Emerging V2G (Vehicle-to-Grid) discharging enables EVs to sell energy back to the grid, offering an additional source of income.
- These combined revenue streams motivate joint optimization of routing, charging, and discharging strategies.

Goals

- Maximize profit by jointly planning trips and energy actions—i.e., choose which customers to serve and when to charge or discharge—so total revenue from transport plus V2G energy sales is highest under time/energy constraints.

- **The Electric Vehicle Orienteering Problem (EVOP)**
  - The EV selects a subset of customers to serve within limited time or battery capacity.
  - The vehicle starts and ends at a depot, maximizing total collected revenue.
  - Key Benefit: Allows selective service, greater flexibility than models requiring visits to all customers.



Revenue-Aware Scheduling

Key Challenges in EVOP

- **Limited Battery Capacity and Driving Range:**
  - Limited battery capacity restricts distance traveled.
  - Vehicles must detour to charging stations to recharge.

Revenue-Aware Scheduling

Key Challenges in EVOP

- **Limited Battery Capacity and Driving Range:**
  - Limited battery capacity restricts distance traveled.
  - Vehicles must detour to charging stations to recharge.
- **Complexities of Charging Operations:**
  - Recharge and discharge rates vary across stations.
  - Prices fluctuate by station and time.
  - Limited chargers cause waiting time and station congestion.

Revenue-Aware Scheduling

Key Challenges in EVOP

- **Limited Battery Capacity and Driving Range:**
  - Limited battery capacity restricts distance traveled.
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- **Complexities of Charging Operations:**
  - Recharge and discharge rates vary across stations.
  - Prices fluctuate by station and time.
  - Limited chargers cause waiting time and station congestion.
- **Computational and Modeling Challenges:**
  - Joint routing and scheduling requires complex hybrid methods.
  - NP-hard problem: Finding optimal routes requires exponential computation.
  - Combinatorial explosion: Route and charging choices grow factorially (n!).

Revenue-Aware Scheduling

Recent Applications and Advancements

Charging Strategies

- Full Recharging: Lee et al. [11] Standard assumption for simplicity.
- Partial Charging: Du et al. [15] Increases route flexibility.
- Battery Swapping: Chen et al. [13] Enables rapid turnaround.

Charging Delay Modeling

- Lee et al. [11]: Accounts for queueing and charging delays at stations

Time-Window Constraints

- Wang et al. [12]: Ensures punctual customer service through time-based restrictions.

Range Anxiety & Sparse Infrastructure

- Chen et al. [13]: Addressed range anxiety by formulating a bi-objective optimization problem to minimize range anxiety and maximize profit.

Vehicle-to-Grid (V2G) Discharging

- Du et al. [14]: Requires co-optimization of travel routes, charging, and discharging windows. EVs can feed excess energy back into the grid when idle or waiting..

Revenue-Aware Scheduling

Algorithmic Methods

Optimization-Based Techniques

- Mixed Integer Programming (MIP) models are formulated.
- Reformulation-Linearization Technique converts nonlinear terms to linear.

Heuristic & Metaheuristic Methods

- Large Neighborhood Search efficiently explores broad solution spaces.
- Evolutionary Algorithms use natural selection for iterative improvement.
- Variable Neighborhood Search guides local exploration and diversification.

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Fleet-Level Scenarios: Coordination Beyond Individual Vehicles

Fleet-scale EV deployment introduces spatial and temporal coordination challenges across logistics, transit, and autonomous services

Revenue-Aware Scheduling for Delivery Fleets

Optimize routes and charging for commercial EV fleets serving customers with energy constraints and time windows

Coordinated V2B/V2P Energy Services

Leverage multiple EVs to support commercial buildings and parking facilities with peak shaving and load balancing

Grid-Integrated Public Transport

Enable electric buses and taxis to provide V2G services while maintaining reliable transportation operations

Autonomous EV Fleets

Centrally manage autonomous EVs for simultaneous optimization of mobility and grid support services

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Revenue-Aware Scheduling for Delivery Fleets

Optimize routes and charging for commercial EV fleets serving customers with energy constraints and time windows

Revenue-Aware Scheduling for EV Fleets

Introduction

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Introduction

- Growth in commercial EV fleets for delivery, logistics, and ride services.
- Traditional Vehicle Routing Problems (VRPs) focus on distance or cost only.
- Emerging V2G capabilities enable fleets to discharge energy back to the grid, turning vehicles into mobile energy assets.

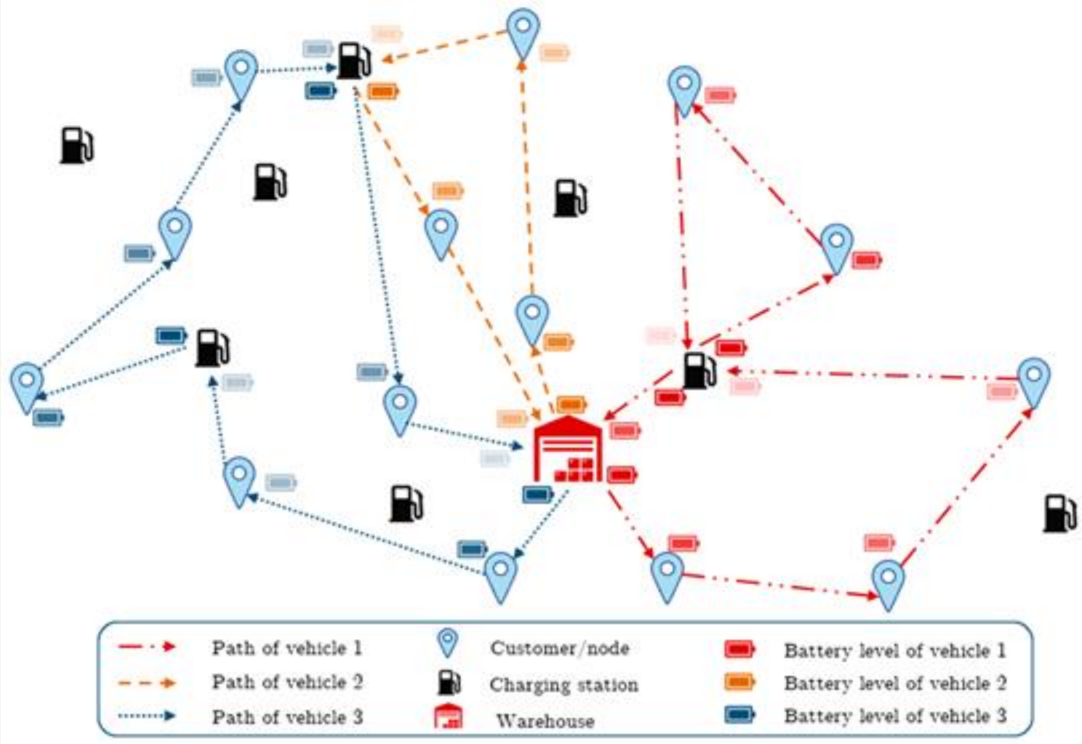
Goals

- Minimize the total operating cost of the fleet while serving all customers and scheduling optimal charging and discharging operations. The cost includes travel, energy purchase, and battery degradation expenses, offset by any revenue earned from vehicle-to-grid (V2G) energy discharge.

Revenue-Aware Scheduling for EV Fleets

Introduction

- **Electric Vehicle Routing Problem (EVRP)**
  - The Electric Vehicle Routing Problem (EVRP) extends the classical Vehicle Routing Problem (VRP) by incorporating: Battery limitations, Charging operations, and Energy consumption models.
  - A fleet of EVs departs from and returns to one or more depots, serving customers while respecting range, load, and time constraints.
  - The objective is typically to: Minimize total energy use or operational cost.



Revenue-Aware Scheduling for EV Fleets

EVRP vs. EVOP – Key Differences

Aspect	EVOP (Single EV)	EVRP (Fleet-level)
Scope	One EV selects a subset of profitable customers	Multiple EVs coordinate routes to serve all customers
Objective	Maximize profit under time and energy limits	Minimize total energy or operational cost
Decision Focus	Route selection and charging schedule for one vehicle	Fleet assignment, routing, and charging coordination
Applications	Ride-hailing or delivery driver	Delivery/logistics company with multiple EVs

Revenue-Aware Scheduling for EV Fleets

Recent Applications and Advancements

Charging Strategies	• Full Recharging: Afroditi et al. [6] Standard assumption for simplicity. • Partial Charging: Keskin and Catay [15] Increases route flexibility. • Battery Swapping: Chen et al. [16] Enables rapid turnaround.
Charging Models	• Lam et al. [19]: Propose a branch-and-cut-and-price algorithm with piecewise-linear charging functions for large-scale EVRPs.
Time-Window Constraints	• Schneider et al. [17]: Ensures deliveries meet strict deadlines.
V2G-Enabled Fleets	• Lin et al. [18]: Incorporate vehicle-to-grid discharging for additional revenue or grid support.
Two-Echelon EVRP (2E-EVRP)	• Moradi et al. [20]: Adds a two-tier delivery structure—main depots to micro-depots, then small EVs for last-mile delivery.

Revenue-Aware Scheduling for EV Fleets

Algorithmic Methods

Optimization-Based Techniques

- Formulates problems as MILP, often using Lagrangian Relaxation.
- Advanced exact methods like Branch-and-Cut-and-Price are utilize.

Heuristic & Metaheuristic Methods

- Adaptive Large Neighborhood Search (ALNS) is widely implemented.
- Uses Tabu Search, VNS, or Iterated Local Search for improvement.
- Includes methods like EA.

Learning-Based Approaches

- Machine Learning enhances planning, prediction.
- Reinforcement Learning addresses dynamic and real-time routing challenges.

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Coordinated V2B/V2P Energy Services

Leverage multiple EVs to support commercial buildings and parking facilities with peak shaving and load balancing

Coordinated V2B/V2P Energy Services

Introduction

Introduction

- Traditional V2H systems involve a single EV powering a private residence during outages or high-price periods.
- In contrast, V2B (Vehicle-to-Building) and V2P (Vehicle-to-Premises) systems coordinate multiple EVs to support commercial, institutional, or campus-scale energy needs.
- These fleet-based systems transform EVs into distributed energy resources (DERs) that can:
  - Provide peak shaving and load balancing.
  - Offer backup power and demand response capabilities.

Goals

- Enhance energy resilience, reduce operational costs, and support renewable integration at scale.

Coordinated V2B/V2P Energy Services

V2H vs. V2B/V2P

Aspect	V2H (Vehicle-to-Home)	V2B / V2P (Fleet-Based)
Scope	Single EV + Private Home	Multiple EVs + Commercial / Institutional Buildings
Objective	Individual energy resilience	Collective demand management and grid support
Energy Source	One EV battery	Aggregated fleet capacity
Control Complexity	Simple scheduling (home-level)	Multi-vehicle, multi-site coordination
Applications	Backup power, cost savings	Peak shaving, load shifting, grid stabilization

V2B/V2P extend the concept of resilience from homes to campuses, offices, and public facilities, leveraging fleet energy as a shared resource.

Coordination enables larger-scale optimization of energy use and grid interaction.

Coordinated V2B/V2P Energy Services

Key Challenges in Coordinated V2B/V2P Energy Services

- **Financial Investment and Costs:**
  - High costs for required bidirectional charging infrastructure.
  - Rising equipment and infrastructure expenditures

Coordinated V2B/V2P Energy Services

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- **Regulatory and Transactional Barriers:**
  - Regulation typically prohibits building-EV electricity trading.
  - Buildings and EV owners are separate entities.

Coordinated V2B/V2P Energy Services

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- **Regulatory and Transactional Barriers:**
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  - Buildings and EV owners are separate entities.
- **Technical Management and Operational Constraints:**
  - Uncoordinated charging creates significant peak power demand.
  - Uncertain parking patterns reduce system flexibility.
  - Interoperability is difficult across different vehicle manufacturers.

Coordinated V2B/V2P Energy Services

Recent Applications and Advancements

Peak Shaving and Load Balancing

- Jiang et al. [21], Liu et al. [22], Rehman et al. [23]: Studies demonstrate coordinated discharging from EV fleets to reduce peak demand in commercial buildings.

Dynamic Scheduling and Pricing Optimization

- Moura et al. [24], Trimboli et al. [25]: Researchers develop real-time optimization frameworks that integrate dynamic pricing and EV availability.
- Lee et al. [11]: zone-specific optimization reduces both cost and grid congestion across metropolitan areas.

Integration with Renewables

- Lo et al. [26]: demonstrates that V2B + solar PV significantly lowers electricity costs and improves the performance of zero-energy buildings (ZEBs).

Coordinated V2B/V2P Energy Services

Algorithmic Methods

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Optimization-Based Techniques

- Formulated using Mixed-Integer Linear Programming (MILP).
- Uses multi-objective models for competing perspectives/goals.
- Employs bi-level models to optimize tariffs and scheduling.

Heuristic & Metaheuristic Methods

- Includes Rule-Based Control (RBC) as a benchmark or method.
- Utilises metaheuristic methods like Particle Swarm Optimisation (PSO).

Learning-Based Approaches

- Machine learning predicts power demand and develops optimal plans.
- Reinforcement Learning (RL) optimizes policy through environment interaction.

Outline

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- Introduction
  - EV as a Battery-on-Wheels
  - Benefits and Challenges
  - Sample Application Scenarios
- Preliminary
- Individual EV Scenarios
  - Energy-Aware Routing
  - Smart Charging (V2H)
  - Revenue Scheduling
- Fleet-Level Scenarios
  - Revenue-Aware Scheduling for Delivery Fleets
  - Coordinated V2B/V2P Energy Services
  - Grid-Integrated Public Transport
  - Autonomous EV Fleets

Grid-Integrated Public Transport

Enable electric buses and taxis to provide V2G services while maintaining reliable transportation operations

Grid-Integrated Public Transport

Introduction

Introduction

- Electrification of public transport fleets (buses, taxis, school transport) is reshaping sustainable urban mobility.
- Transition to Electric Buses (EBs) and Electric Taxis (ETs) reduces emissions and fuel dependency.
- Integration with Vehicle-to-Grid (V2G) enables energy exchange between fleets and the grid.
- Requires intelligent scheduling and real-time coordination to balance transportation service and grid stability.

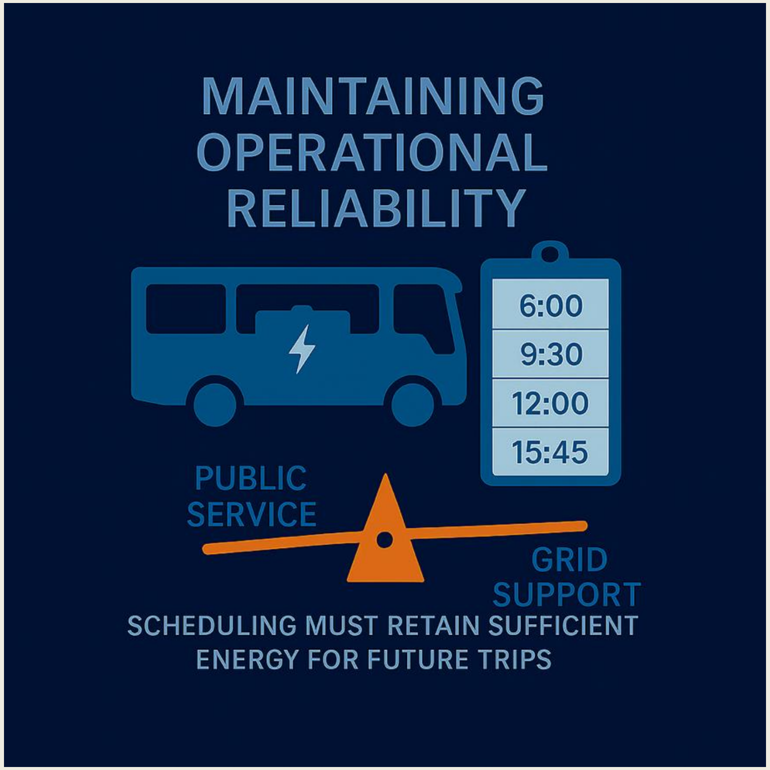
Goals

- Achieve cost-effective, reliable public transport operations and support power grid stability using V2G integration strategies under uncertainty

Grid-Integrated Public Transport

Key Challenges in Grid Integrated Public Transport

- **Maintaining Operational Reliability:**
  - Prioritize reliable public service over grid support.
  - Scheduling must retain sufficient energy for future trips.



Grid-Integrated Public Transport

Key Challenges in Grid Integrated Public Transport

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- **Mitigating Battery Degradation Costs:**
  - Degradation costs may exceed V2G revenue.
  - Frequent V2G cycles shorten battery lifespan.

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  - Energy consumption is uncertain (traffic, weather).
  - Discharging prices and battery efficiency fluctuate wildly.

Grid-Integrated Public Transport

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- **Overcoming Grid Integration and Infrastructure Barriers:**
  - Disorderly access risks transformer overload and load peaks.
  - Grid infrastructure capacity upgrades face institutional barriers.

Grid-Integrated Public Transport

Recent Applications and Research Advancements

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Battery Swapping Optimization	• Hu et al. [27]: Optimized swapping strategies under variable temperature conditions, improving reliability and turnaround.
Battery Degradation Modeling	• Manzolli et al. [28]: Semi-empirical models simulate aging and efficiency loss under operational and environmental stress.
Predictable Idle Utilization (School & City Buses)	• Khwanrit et al. [29]: Electric school buses ideal for V2G due to consistent idle periods. Enable energy discharge to grid without disrupting service schedules.
Electric Taxi Fleet Integration	• Yu et al. [30]: ET fleets can provide V2G services with minimal impact on passenger operations.

Grid-Integrated Public Transport

Algorithmic Methods

Optimization-Based Techniques

- Utilizes MILP/LP for solving complex scheduling problems.
- Employs two-stage stochastic and robust optimization methods.

Heuristic & Metaheuristic Methods

- Greedy strategy rapidly matches battery swapping demands.
- Algorithms like ALNS solve complex scheduling problems.
- Includes methods like EA.

Learning-Based Approaches

- Clustering algorithms enhance stochastic optimization efficiency.
- Reinforcement Learning guides optimal charging/scheduling strategies.

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Autonomous EV Fleets

Centrally manage autonomous EVs for simultaneous optimization of mobility and grid support services

Autonomous EV Fleets

Introduction

Introduction

- Autonomous Electric Vehicles (AEVs) combine electrification + automation, creating dual-role assets that serve both mobility and energy functions.
- Unlike conventional EV fleets, which depend on human drivers and fixed charging patterns, AEV fleets feature:
  - Autonomy: Self-driving and self-dispatching without human intervention.
  - Centralized Coordination: Fleet-level control allows joint optimization of routing, charging, and V2G participation.
  - Dynamic Adaptability: Respond in real time to traffic, demand, and grid conditions.
- These features position AEV fleets as grid-responsive, data-driven transport networks—a step beyond static EV operations.

Goals

- Enhance urban sustainability, grid stability, and transport reliability through intelligent autonomy.

Autonomous EV Fleets

V2H vs. V2B/V2P

Aspect	Private EVs	Autonomous EVs / SAEVs
Control	Individually owned and operated	Centrally managed, coordinated fleet
Charging Behavior	Typically once/twice daily at home	Dynamic, continuous charging/discharging between trips
Grid Interaction	Limited or uncontrolled	Actively participate in V2G and V2X services.
Availability	Tied to owner schedule	Can be optimized fleet-wide for transport and energy objectives
System Impact	Adds load variability due to personal constraints	Enables grid balancing and renewable integration

AEVs are grid-responsive transport assets capable of real-time optimization across dispatch, routing, and charging.

AEVs can charge or discharge whenever idle, creating continuous energy flexibility at the city scale.

Autonomous EV Fleets

Recent Applications and Advancements

Ride-hailing for AV Fleets

- Iacobucci et al. [33]: Scalable simulation-optimization framework framework lowers charging costs, preserves service quality.
- Iacobucci et al. [34]: Two-layer MPC balances electricity costs and passenger wait times.

EVOP for AV Fleets

- Zhang et al. [32]: Uses Deep Reinforcement Learning for joint AV/V2G optimization. Strategically enables AEVs to charge low, discharge high, maximizing revenue.

Co-Optimization to Ensure Grid Reliability

- Bagherinezhad et al. [10]: Rolling horizon optimizes AEV routing and charging in real-time. Coordinated model prevents PDS current flow constraint violations.

Autonomous EV Fleets

Algorithmic Methods

Optimization-Based Techniques

- Uses Model Predictive Control (MPC) over defined horizons
- Problems formulated as Mixed-Integer Linear Programs (MILP)
- Employs two-layer optimization for transport and charge time scales

Heuristic & Metaheuristic Methods

- Uses heuristics-based charge scheduling to lower electricity costs
- Applies an online heuristic for charging and re-balancing decisions
- Includes simpler behaviors such as a greedy model for comparison

Learning-Based Approaches

- Machine Learning enhances planning and prediction.
- Leverages Multi-Agent Reinforcement Learning (MARL).
- Uses Deep Reinforcement Learning (DRL) algorithms for strategic scheduling

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Thank you

Questions?

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