Genetic Algorithm-Based Optimization of EV Charging Stations Placement on Long-Distance Routes

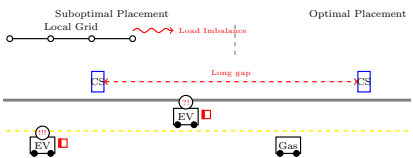
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The EV Adoption Challenge

- Rapid global transition to electric vehicles (EVs) is critical for sustainable transportation
- Range anxiety remains a major barrier to widespread adoption
- Poorly designed charging infrastructure creates:
  - Phase and temporal imbalances in grid systems
  - Adverse effects on power quality and voltage profiles
  - Reduced overall grid reliability
- Recent studies emphasize the importance of considering multiple objectives: energy demand satisfaction, response time, cost minimization, and battery degradation



EV charging infrastructure challenge

The Complex Infrastructure Challenge

- Optimal charging placement involves multiple interdependent factors:
  - Stochastic traffic patterns and driver behavior
  - Diverse EV specifications and battery characteristics
  - Environmental impacts on battery performance
  - Grid infrastructure limitations and capacity constraints
  - Renewable energy integration potential
  - Comprehensive cost considerations
- Traditional planning methodologies often fall short in addressing these complexities
- Need for advanced algorithms capable of handling multiple competing objectives

Research Contributions

- Development of a comprehensive simulation model capturing:
  - Realistic EV energy consumption with temperature effects
  - State-of-charge dynamics and driver behavior
  - Multiple vehicle types and charging processes
- Multi-objective optimization framework balancing:
  - Infrastructure costs
  - Operational efficiency
  - Service reliability metrics
  - Grid stability requirements
- Genetic algorithm implementation tailored to charging infrastructure problems
- Practical validation through extensive computational experiments

Agenda

2. Methodology
3. Genetic Algorithm Implementation
4. Case Study
5. Results and Discussion
6. Conclusion

EV and Battery Models

- Initial state-of-charge (SoC) follows probabilistic distribution:

$$\mathrm{SoC}_{i,0} \begin{cases} 1, & \text{with probability } p_{\text{full}} \\ \mathrm{U}(\mathrm{SoC}_{\text{min_initial}}, 0.5), & \text{otherwise} \end{cases} \tag{1}$$

- Energy consumption model:

$$E_{i,s} = \frac{e_{\text{rate},i} \cdot d_s}{\eta_{\text{temp}}} \cdot f_{\text{road}}(s) \tag{2}$$

- Temperature efficiency:

$$\eta_{\text{temp}} = 1 - (\theta_{\text{avg}} - \theta_{\text{ref}}) \cdot c_\theta \tag{3}$$

- State-of-charge evolution:

$$\mathrm{SoC}_{i,s+1} = \mathrm{SoC}_{i,s} - \frac{E_{i,s}}{C_{\text{battery},i}} \tag{4}$$

Charging Station Model

- Charging initiation criterion:

$$\mathrm{SoC}_{i,s} \leq \mathrm{SoC}_{\mathrm{min_charge}} \tag{5}$$

- Station capacity model:

$$N_{\mathrm{charged},s,t} = \min(N_{\mathrm{need_charge},s,t}, C_{\mathrm{station},s}) \tag{6}$$

- Grid load calculation:

$$L_{\mathrm{grid},s,t} = \max(P_{\mathrm{total_charge},s,t} - P_{\mathrm{renewable},s,t}, 0) \tag{7}$$

- Designed to optimize service while respecting infrastructure constraints

Optimization Framework

- Multi-objective function:

$$J = k_1 \cdot \left(\frac{C_{\text{install}} + C_{\text{operational}}}{C_{\text{max_install_operational}}} \right) + k_2 \cdot \left(\frac{C_{\text{energy}} + C_{\text{demand}}}{C_{\text{max_energy_demand}}} \right) + k_3 \cdot \left(\frac{C_{\text{unserved}}}{C_{\text{max_unserved}}} \right) + k_4 \cdot \left(\frac{C_{\text{stations}}}{C_{\text{max_stations}}} \right) \tag{8}$$

- Key constraints:

$$L_{\text{grid},s,t} \leq L_{\text{grid_max},s} \qquad \forall s \in S, t \in T \tag{9}$$

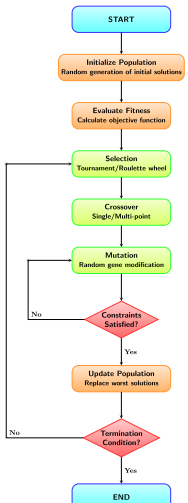
$$0 \leq x_s \leq N_{\text{max_units}} \qquad \forall s \in S \tag{10}$$

$$x_s \in \mathbb{Z} \qquad \forall s \in S \tag{11}$$

- Decision variable: x_s = number of charging units at location s

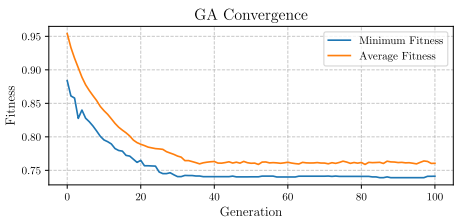
Why Genetic Algorithms?

- Complex search space:
  - Multi-dimensional with nonlinear constraints
  - Discrete decision variables (integer charging units)
  - Multiple competing objectives
- GA advantages:
  - Population-based global search
  - Natural handling of discrete variables
  - Effective navigation of complex search spaces
  - Proven effectiveness in similar infrastructure problems



GA Implementation Details

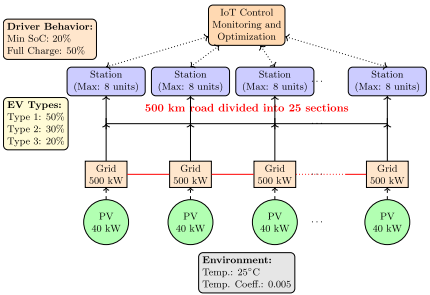
- Implementation environment:
  - Python 3.12 with DEAP 1.4 framework
  - 20 processing threads, 40GB RAM
  - Parallel fitness evaluations
- GA parameters:
  - Population size: 1000
  - Max generations: 100
  - Uniform crossover (prob. 0.8)
  - Mutation probability: 0.2



Convergence analysis

Case Study Overview

- 500 km corridor representing typical long-distance route
- Divided into 25 discrete sections for optimization
- Each section with unique:
  - Traffic profiles
  - EV adoption rates
  - Grid constraints
- 24-hour simulation period with sinusoidal traffic variation ($\pm 30\%$)



Key Simulation Parameters

Charging Station Parameters

- Charger power: 150 kW
- Charging efficiency: 90%
- Max units per station: 3
- Capacity per unit: 25 charging points
- Renewable capacity: 40 kW per station

Traffic Parameters

- EV adoption rate: 15% (833 vehicles/hour)

Grid Parameters

- Grid capacity: 500 kW per section
- Environmental conditions: 25 °C

Electric Vehicle Types

Type	Range (km)	Battery Capacity (kWh)	Consumption Rate (kWh/km)
1	400	60	0.15
2	300	50	0.167
3	200	40	0.20

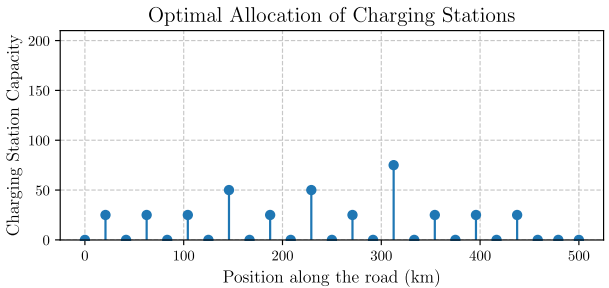
- Type distribution: 50% Type 1, 30% Type 2, 20% Type 3
- Representative of real-world EV market segmentation
- Different range capabilities create varied charging demand patterns

Optimal Charging Station Configuration

Position (km)	Units	Capacity
20.83	1	25
62.50	1	25
104.17	1	25
145.83	2	50
187.50	1	25
229.17	2	50
270.83	1	25
312.50	3	75
354.17	1	25
395.83	1	25
437.50	1	25

- Non-uniform distribution aligned with traffic patterns
- Strategic capacity concentration at key points (km 312.50)
- Average inter-station distance: 41.67 km
- Total of 15 charging units across 11 stations
- Total capacity: 375 charging points

Spatial Distribution Visualization



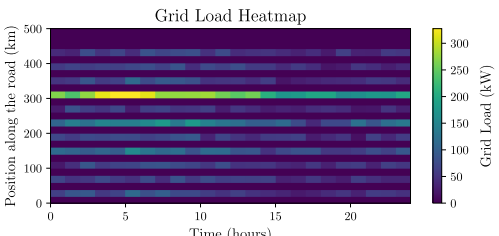
- Marker size indicates station capacity
- Strategic clustering around high-demand zones
- Consistent coverage for all EV types
- Capacity concentration at kilometer 312.50 (3 units, 75 capacity)

Economic and Performance Analysis

- Capital Investment:
  - Total infrastructure cost: $1.85M
  - 27% reduction vs. uniform distribution ($2.53M)
- Operational Efficiency:
  - Annual operational costs: $75,000
  - 32% reduction vs. baseline approaches ($110,300)
- Service Quality:
  - 99.7% service reliability
  - 4.7 percentage point improvement vs. baseline (95%)
  - Average station utilization: 76.3%

Grid Integration Performance

- Grid stability:
  - Peak loads maintained below 90% of grid capacity
  - Effective management of temporal and spatial demand
- Renewable integration:
  - 23.5% reduction in grid dependency
  - Improved environmental footprint



Grid load heatmap

Key Findings

- Genetic algorithm optimization successfully balances:
  - Infrastructure costs and operational efficiency
  - Service reliability and grid stability
- Non-uniform station distribution outperforms conventional approaches:
  - 27% reduction in capital investment
  - 32% reduction in operational costs
  - 4.7 percentage point improvement in service reliability
- Strategic capacity allocation enhances resource utilization:
  - 76.3% average station utilization
  - Effective temporal load balancing
- Renewable energy integration reduces grid dependency by 23.5%

Thank you!

Questions welcome

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