This table presents 60 viva voce questions derived directly from the sources, categorized as requested (25 Conceptual, 23 Numerical/Mathematical, 12 Factual).

Viva Voce Questions on Hybrid EV Charging Framework

Examiner Question	**Student Answer**	**Keywords to Remember Per Answer**
Conceptual Questions (What, Why, How) (25)		
1. Why is EV charging infrastructure planning considered more complex than conventional refuelling networks?	EV charging infrastructure is tightly coupled to both the transportation layer (traffic, road network) and the power-distribution layer (substations, grid capacity).	Transportation Layer; Power-Distribution Layer; Coupled Nature.
2. Distinguish between Coverage-Oriented and Quality of Service (QoS)-Oriented planning objectives.	Coverage guarantees that every zone has access within a defined distance (spatial equity); QoS optimizes for areas with high EV demand, minimizing detour and waiting time for the majority.	Coverage; Spatial Equity; QoS; High Demand Zones.
3. What three critical, interacting questions must urban authorities simultaneously answer from a public-policy perspective?	They must address Coverage, Quality of Service (QoS), and Economic & Grid Feasibility.	Coverage; QoS; Economic & Grid Feasibility.
4. How does the framework explicitly incorporate power-grid proximity into the optimization model?	Grid proximity is incorporated as a cost penalty ($Cost = C_{base} + \alpha d^{grid}$), discouraging economically infeasible locations that require long-distance grid extensions.	Grid-Distance Penalty (αd^{grid}); Economic Feasibility; Grid-Remote Locations.
5. What is the justification for using a hybrid methodology combining strategic siting (GA) and operational control (RL)?	Strategic siting decisions constrain operational performance, while dynamic routing can mitigate congestion from suboptimal siting. Treating them separately does not reflect coupled real deployments.	Strategic Siting (GA); Operational Control (RL); Coupled Deployments; Congestion Mitigation.
6. What primary real-time operational problem does the Q-learning module solve?	It reduces charging wait times by dynamically routing incoming EVs to stations with minimal queue lengths, balancing load among existing, optimally sited stations.	Dynamic Routing; Minimal Queue Lengths; Load Balancing.

7. Explain the purpose of the small-scale MILP prototype in this methodology.	The prototype validates the mathematical correctness of the model structure and serves as a "ground truth" to benchmark the solution quality obtained by the scalable metaheuristics (GA/NSGA-II).	Validation; Ground Truth; Benchmark; Correctness Check.
8. Why is explicit zoning (e.g., Z1, Z2, Z3) necessary, beyond just maximizing demand coverage?	Absent zoning, demand-driven optimizers would disproportionately select sites in commercial cores, leading to over-concentration and undersupply in remote or peripheral regions, contradicting equity goals.	Equitable Service; Prevent Clustering; Underserved Regions.
9. What is the key advantage of treating the demand weights (w_B, w_P, w_E) as tunable hyperparameters?	It avoids arbitrary reliance on a single assumed weighting scheme and allows the model to be calibrated to context-specific policy preferences (e.g., prioritizing latent demand via POIs vs existing EV owners via EV sales).	Policy Preferences; Tunable Hyperparameters; Robustness.
10. Explain the fundamental gap in existing literature that the MILP–GA–RL framework aims to address.	Existing work often involves fragmented treatment of siting, sizing, and operations, lacks integration of demand/adoption signals, and rarely embeds grid-proximity effects or operational feedback into siting.	Fragmented Treatment; Integration Gaps; Operational Feedback.
11. Why are reinforcement learning methods typically confined to operational control rather than long-term strategic siting?	RL requires enormous state and action spaces for long-term siting problems, making it computationally intractable for city-scale strategic planning.	Enormous State/Action Spaces; Computational Prohibitive; Operational Optimizer.
12. What happens if a purely QoS-driven formulation (without coverage constraints) is used in a city like Lucknow?	Visualizations of demand surfaces show heavy concentration around a few commercial hubs; a purely QoS formulation collapses onto these hotspots, leading to a skewed distribution.	Commercial Hubs; Skewed Distribution; Hotspots.
13. How does the methodology ensure spatial equity and policy alignment in station placement?	It enforces zone-specific coverage constraints, requiring that the proportion of covered demand in zone z meets a minimum requirement ($MinCoverage_z$).	Zone-Specific Coverage Constraints; Equitable Distribution.
14. What key input sources are combined in the composite demand score (D_i)?	Building density (population proxy), Points of Interest (POIs, trip attraction	Building Density; POI Intensity; EV Sales Statistics.

	intensity), and district-level EV sales statistics (adoption proxy).	
15. What happens if naïve placement strategies, such as the Random or Uniform baseline, are used in real-world urban planning?	They exhibit substantial inefficiencies compared to optimized solutions in terms of coverage, QoS, cost efficiency, and load balancing because they ignore demand distribution and grid constraints.	Geometric Inefficiency; Fails to Adapt; Load Imbalance.
16. Why must demand be restricted to four-wheeler (4W) EV relevance?	E-rickshaw and two-wheeler charging require separate modelling and infrastructure design; the focus here mirrors government emphasis on public fast-charging stations for cars.	4W Infrastructure; Separate Modelling; Fast-Charging Demand.
17. How does Q-learning define a 'reward' for optimal routing?	Rewards penalize undesirable outcomes such as waiting time, queue length, and overload events at charging stations.	Waiting Time; Queue Length; Overload Events.
18. Define the concept of the Pareto front in the context of the NSGA-II optimization.	The Pareto front approximates the set of non-dominated solutions where improving one objective (e.g., reducing cost) cannot be achieved without worsening at least one other objective (e.g., increasing detour or grid stress).	Non-Dominated Solutions; Trade-Offs; Competing Objectives.
19. What is the structural regularity observed in Lucknow that motivated the use of a composite demand index?	District-level EV sales display strong spatial heterogeneity, correlating with built-up density, POI concentration, and socio-economic indicators; demand cannot be approximated by uniform population density.	Spatial Heterogeneity; EV Penetration; Adoption Intensity.
20. Why is MILP unsuitable for solving city-scale deployments with hundreds of candidate sites?	Exact MILP quickly becomes computationally prohibitive and scales poorly, generating thousands of binary decisions and tens of thousands of assignment variables.	Computationally Prohibitive; Scales Poorly; Thousands of Variables.
21. What does the comparison between Random, Uniform, and Greedy baselines show regarding the benefits of optimization?	Optimized solutions (NSGA-II) achieve substantial improvements in coverage, QoS, cost efficiency, and load balancing compared to status quo or naive planner comparators.	Substantial Improvements; Cost-Quality; Naive Planner.
22. What specific mechanism is used in the Q-learning layer to balance load dynamically?	The Q-learning agent learns a policy that minimizes rewards associated with queue length and waiting time, naturally	Policy Learning; Minimize Queue Length; Congestion Avoidance.

	steering vehicles away from congested stations towards available ones.	
23. In the context of the Q-learning state s_t, what specific metric helps guide the routing decision toward minimizing localized congestion?	The vector of queue lengths at active stations (q_t) is abstracted into the state definition $s_t = (loc_t, q_t, z(loc_t))$.	Queue Lengths (q_t); Localized Congestion.
24. When using the GA fitness evaluation, how is demand assigned to open sites?	Demand is assigned to the nearest active site via shortest-path detour calculation on the road network, provided the distance is within the coverage radius (R_{max}).	Shortest Path; Nearest Active Site; Detour.
25. What is the implication of the "Clustering Tendencies" observation for the objective function design?	It reinforces the need for multi-objective optimization (NSGA-II) rather than relying on a single-objective or purely QoS-driven formulation which would inherently bias results toward high-demand hotspots.	Clustering; Multi-Objective Optimization; Biased Results.

Numerical/Mathematical Based Questions (23)

26. Define the three main decision variables used in the MILP formulation.	1. $x_k \in \{0,1\}$: Binary siting variable (1 if station installed). 2. $y_{ik} \in \{0,1\}$: Binary assignment variable (1 if demand i is assigned to station k). 3. $c_k \in \mathbb{Z}^+$: Integer variable for the number of chargers at station k [42].	x_k (Siting); y_{ik} (Assignment); c_k (Chargers).
27. Write the mathematical definition of the total capital cost objective $C(x)$ using the grid-distance penalty.	$C(x) = \sum_{k \in K} Cost_k x_k = \sum_{k \in K} (C_{base} + \alpha d_k^{grid}) x_k$ [43] [44].	C_{base}; α; d^{grid}_k; x_k.
28. What is d^{grid}_k, and how is it used in the model?	d^{grid}_k is the shortest-path distance from candidate site k to the nearest grid node $g \in G$. It is multiplied by the	d^{grid}_k; Nearest Grid Node; Shortest Path; α.

	grid-extension cost factor α to penalize grid-remote sites.	
29. What mathematical problem does the framework simplify to if there are no grid costs, a fixed number of stations p, and a single objective minimizing demand-weighted distance?	It reduces exactly to the discrete p-median problem.	Discrete p-median problem.
30. State the mathematical complexity classification of the full optimization problem.	The problem is combinatorial and NP-hard.	Combinatorial; NP-hard; p-median generalization.
31. Write the mathematical expression for the Demand-weighted detour/QoS objective, $D(x, y)$.	$D(x, y) = \sum_{i \in I} \sum_{k \in K} D_i d_{ik} y_{ik}$.	Demand Weight (D_i); Distance (d_{ik}); Assignment (y_{ik}).
32. What is the key constraint that enforces service accessibility (coverage) for every demand point i?	The coverage constraint requires that every demand point i must be covered, meaning there exists at least one station k such that $d_{ik} \le R_{max}$, enforced by $\sum_{k \in K} y_{ik} = 1$ for all $i \in I$.	$\sum y_{ik} = 1$; Coverage Threshold (R_{max}).
33. Give the core capacity constraint relating arrival rates and service rates.	The total expected arrival rate assigned to station k must be less than or equal to the total service rate provided by c_k chargers: $\sum_{i \in I} \lambda_i y_{ik} \le c_k \mu$.	λ_i (Arrival Rate); μ (Service Rate); c_k (Chargers).
34. Define the zone-level coverage constraint that ensures equity in zone z.	$\text{CovDemand}_z(x, y) \ge MinCoverage_z \cdot \text{TotDemand}_z$.	Covered Demand; Minimum Coverage Fraction ($MinCoverage_z$); Total Demand.
35. What is the typical coverage radius R_{max} used in the MILP prototype experiments?	$R_{max} = 2 \text{km}$.	2 km.
36. When using the weighted scalarization approach, what does the resulting objective function $Z(x, y)$ minimize?	$Z(x, y) = w_D D(x, y) + w_G G(x) + w_C C(x)$, minimizing a weighted sum of demand-weighted detour, grid proximity/stress, and total capital cost.	w_D, w_G, w_C (Weights); Detour (D); Grid Stress (G); Cost (C).

37. What range of candidate sites ($	K	$) and demand points ($
38. Write the mathematical definition of the composite demand score D_i using normalized features.	$D_i = \mathbb{I}_{4W}(i)(w_B B_i + w_P P_i + w_E E_i)$, where $B_i, P_i, E_i \in$ are normalized features.	$\mathbb{I}_{4W}(i)$; Normalized Features; w_B, w_P, w_E.
39. What range of values for the grid-extension cost coefficient (α) were explored in the sensitivity analysis?	$\alpha \in {0.1, 0.2, 0.3}$.	0.1, 0.2, 0.3.
40. What is the typical range for the number of generations used in the GA/NSGA-II optimization?	80–120 generations.	80–120 Generations.
41. What is the formulation for the simple grid proximity/stress proxy objective $G(x)$?	$G(x) = \sum_{k \in K} d^{grid}_k x_k$.	$d^{grid}_k x_k$ (Grid Distance weighted by Siting).
42. What time limit was typically imposed on the MILP solver?	900–1800 seconds.	900–1800 seconds.
43. What are the three parameters that define the state s_t in the Q-learning Markov Decision Process (MDP)?	EV arrival location (loc_t), the vector of queue lengths at active stations (q_t), and zone membership ($z(loc_t)$).	loc_t; q_t; $z(loc_t)$.
44. How does the crossover operator work in the Genetic Algorithm (GA) used for siting?	It performs one- or two-point crossover over the binary bitstring (chromosome), with a probability p_c.	Binary Bitstring; One/Two-Point; p_c.
45. If the MILP is used to define capacity constraints, what type of variable is c_k (number of chargers)?	c_k is typically an Integer variable ($\mathbb{Z}^+$).	Integer Variable ($\mathbb{Z}^+$).
46. How is the coverage ratio mathematically calculated for a given solution k?	$Coverage(k) = \frac{1}{	I
47. In the reward function r for Q-learning, what purpose	α and β are coefficients used to weigh the penalties for queue length and overload events, respectively.	Weights (α, β); Penalties (Queue/Overload).

do α and β serve?		
48. Which constraint links the siting variable x_k and the charger variable c_k?	A logical linkage constraint $c_k \le M x_k$, where M is a large upper bound on the number of chargers.	$c_k \le M x_k$; Logical Linkage.
Factual Questions (Libraries, Datasets, Platforms) (12)		
49. What city and specific region were selected as the study area for this implementation?	The Lucknow Urban Core (including areas like Gomti Nagar and Hazratganj).	Lucknow Urban Core.
50. What are the three core components of the hybrid framework's architecture?	Mixed-Integer Linear Programming (MILP), Genetic Algorithm (specifically NSGA-II), and Reinforcement Learning (Q-learning).	MILP; GA (NSGA-II); RL (Q-Learning).
51. Name three specific Python libraries used for the optimization component.	Pyomo, PuLP, and pymoo (for NSGA-II/GA).	Pyomo; PuLP; pymoo.
52. Which real-world foreign dataset was used to transfer distributions for synthetic demand generation?	The UrbanEV / Shenzhen EV Charging Dataset.	UrbanEV; Shenzhen EV Charging Dataset.
53. Name the three primary baseline strategies used for comparative evaluation.	Random placement, Uniform grid placement, and Greedy demand-first placement.	Random; Uniform; Greedy Demand-First.
54. What specific type of Genetic Algorithm was chosen for approximating the Pareto front on full-scale instances?	NSGA-II (Non-dominated Sorting Genetic Algorithm II).	NSGA-II.
55. How were the grid nodes (G) represented in the data model?	As a set of feeder/substation nodes collected from open utility sources.	Substations; Feeder Nodes; Open Utility Sources.
56. Name the three policy zones (Z) defined for the study area.	Zone 1 (Commercial, high demand), Zone 2 (Residential, medium density), and Zone 3 (Remote/underserved regions).	Z1 (Commercial); Z2 (Residential); Z3 (Remote).
57. What tool was used for the graph extraction and network processing layer?	OSMnx (OpenStreetMap Network Extension).	OSMnx.

58. What is the purpose of the OpenChargeMap (OCM) dataset in this study?	It is used for comparative validation with existing chargers in Lucknow.	OpenChargeMap (OCM); Validation.
59. What policy variable is used to ensure equitable coverage across different zones?	The $MinCoverage_z$ variable, representing the minimum coverage fraction required in zone z.	$MinCoverage_z$.
60. What physical proxy was used to represent population and residential density in the demand model?	Building footprints/building footprint extent.	Building Footprints.

This response details every mathematical equation, expression, and constraint within the sources, explaining its formulation, purpose, and the significance of its constituent terms, as requested.

Mathematical Formulations and Expressions

The framework integrates three main layers: Strategic Siting (MILP/GA), Operational Control (Q-Learning), and Data Modeling (Demand/Cost).

I. Data and Demand Model Expressions

These expressions define the inputs and scoring mechanisms used across the optimization framework.

Expression	Formulation and Terms	Why and How Formulated	Significance of Each Term
Normalized Features	$B_i, P_i, E_i \in$	Features are normalized (e.g., min-max scaling) to avoid arbitrary units and magnitudes, ensuring they are comparable when combined into the composite demand score.	B_i: Normalized building area (proxy for population/residential density). P_i: Normalized POI intensity (proxy for commercial/trip-attraction density). E_i: Normalized EV adoption indicator (proxy for 4W EV sales density).
Composite Demand Score (D_i)	$$D_i = \mathbb{I}_{4W}(i)(w_B B_i + w_P P_i + w_E E_i)$$	Formulated as a weighted sum of normalized features. This captures heterogeneous urban demand, incorporating population density, commercial activity, and actual EV adoption potential. The indicator $\mathbb{I}_{4W}(i)$ filters demand, focusing infrastructure planning	$\mathbb{I}_{4W}(i)$: Indicator function (1 if demand point i is 4W-relevant, 0 otherwise). w_B, w_P, w_E: Tunable hyperparameters (weights) that allow the model to be calibrated to specific policy preferences.

		exclusively on four-wheeler (4W) EV relevance.	
Installation Cost ($Cost_k$)	$$Cost_k = C_{\text{base}} + \alpha d^{\text{grid}}_k$$	This affine (linear) form is a first-order approximation capturing the rising marginal cost of connecting high-capacity charging stations farther from the existing grid infrastructure. Embedding this cost directly discourages economically infeasible, grid-remote locations.	C_{base}: Base installation cost (e.g., land, civil works, equipment). d^{grid}_k: Shortest-path distance from candidate site k to the nearest grid node $g \in G$. $\alpha \ge 0$: Grid-extension cost factor, reflecting the marginal cost per unit distance to connect to the grid.

II. Decision Variables and Sets

These define the elements of the Mixed-Integer Linear Program (MILP).

Element	**Definition**	**Why and How Formulated**	**Significance of Each Term**
Siting Variable	$x_k \in {0,1} \quad \forall k \in K$	Binary variable used to determine the long-term strategic decision of whether to open a station at candidate site k.	K: Set of candidate charging station sites. x_k: Equal to 1 if a station is installed at k, and 0 otherwise.
Assignment Variable	$y_{ik} \in {0,1} \quad \forall i \in I, \forall k \in K$	Binary variable linking demand points to chosen stations. Used to calculate both coverage and aggregate detour (QoS).	I: Set of demand points. y_{ik}: Equal to 1 if demand point i is assigned to station k, and 0 otherwise.
Charger Count Variable	$c_k \in \mathbb{Z}^+ \quad \forall k \in K$	Integer variable representing the number of chargers installed at station k, crucial for capacity planning and constraint definition.	c_k: The number of 4W chargers installed at site k. $\mathbb{Z}^+$: Represents positive integers, required because the number of chargers must be discrete.

III. Objective Functions

The goals of the optimization are expressed through these objectives, which are either minimized individually or combined.

Objective	**Formulation**	**Why and How Formulated**	**Significance of Each Term**
Demand-weighted Detour/QoS	$$D(x, y) = \sum_{i \in I} \sum_{k \in	The QoS objective minimizes the aggregate distance drivers must detour to reach their assigned station k. It is	D_i: Composite demand score at point i. d_{ik}: Travel distance/time from i to k via the road network. y_{ik}:

	K} D_i d_{ik} y_{ik}$$	weighted by D_i to prioritize minimizing detour for high-demand areas.	Assignment variable ensuring demand i is counted only once, assigned to k.
Total Capital Cost	$$C(x) = \sum_{k \in K} Cost_k x_k$$	Measures the total economic outlay for installation. This objective minimizes capital cost, inherently penalized by the distance to the power grid d^{grid}_k through the definition of $Cost_k$.	$Cost_k$: Installation cost at site k (includes $C_{\text{base}} + \alpha d^{\text{grid}}_k$). x_k: Siting variable (ensures cost is incurred only if k is active).
Grid Proximity Proxy	$$G(x) = \sum_{k \in K} d^{\text{grid}}_k x_k$$	Used in the multi-objective formulation as a separate goal to explicitly minimize the total distance to the power grid, serving as a proxy for grid stress or ease of connection.	d^{grid}_k: Distance to the nearest grid node. x_k: Siting variable (distance is summed only for installed stations).
Weighted Scalarization	$$\min Z(x, y) = w_D D(x, y) + w_G G(x) + w_C C(x)$$	Combines the three competing objectives (Detour, Grid Proximity, Cost) into a single objective function, used when solving via MILP or specific GA implementations.	$w_D, w_G, w_C \ge 0$: Weights that define the relative importance of each objective, allowing policy trade-offs to be incorporated into the minimization.

IV. Constraints

Constraints define the operational and policy limitations that a feasible solution must satisfy.

Constraint	Formulation	Why and How Formulated	Significance of Each Term
Coverage Requirement	$$\sum_{k \in K} y_{ik} = 1 \quad \forall i \in I$$	Requires that every demand point i is covered and assigned to exactly one station k. This is a hard constraint that enforces service accessibility, provided $d_{ik} \le R_{\max}$.	y_{ik}: Assignment variable. The sum must equal 1, guaranteeing assignment.
Distance Linkage	$y_{ik} = 0 \quad \text{if } d_{ik} > R_{\max}$	Implicitly or explicitly ensures that demand point i can only be assigned to station k if k is within the maximum coverage radius ($R_{\max}$).	d_{ik}: Distance from i to k. $R_{\max}$: Maximum allowable access radius (coverage threshold, typically 2 km).

Siting Linkage	$y_{ik} \le x_k \quad \forall i \in I, \forall k \in K$	Ensures that a demand point i can only be assigned to station k if station k has actually been installed ($x_k = 1$).	y_{ik}: Assignment variable. x_k: Siting variable.
Capacity Constraint	$$\sum_{i \in I} \lambda_i y_{ik} \le c_k \mu \quad \forall k \in K$$	Ensures that the total expected arrival rate (λ_i) assigned to station k does not exceed the total service rate capacity provided by c_k chargers.	λ_i: Expected arrival rate at demand point i. μ: Service rate per charger. c_k: Number of chargers at station k.
Zone-Level Coverage	$$\text{CovDemand}_z(x, y) \ge MinCoverage_z \cdot \text{TotDemand}_z \quad \forall z \in \mathcal{Z}$$	A policy constraint formulated to ensure spatial equity. It requires that the actual covered demand in zone z meets a predefined minimum coverage fraction ($MinCoverage_z$).	CovDemand_z: Total covered demand in zone z. TotDemand_z: Total demand in zone z. $MinCoverage_z$: Minimum coverage fraction required by policy in zone z.
Budget Constraint	$$\sum_{k \in K} Cost_k x_k \le B$$	Ensures that the sum of the capital costs of all installed stations does not exceed the maximum allowable capital budget B.	$Cost_k$: Installation cost at site k. x_k: Siting variable. B: The overall capital budget.
Logical Linkage (Chargers)	$c_k \le M x_k \quad \forall k \in K$	A big-M constraint that logically links the charger count c_k to the siting decision x_k. If no station is installed ($x_k=0$), then no chargers can be present ($c_k=0$).	c_k: Number of chargers. M: A large upper bound on the maximum number of chargers per station. x_k: Siting variable.

V. Operational Control (Q-Learning) Expressions

These expressions define the dynamics of the Reinforcement Learning module used for real-time routing after stations have been sited.

Expression	**Formulation**	**Why and How Formulated**	**Significance of Each Term**

Q-Learning State (s_t)	$$s_t = (loc_t, q_t, z(loc_t))$$	The state encapsulates the necessary information for the agent to select the optimal charging destination. It is based on the EV's location, the current operational metrics (queues), and policy context (zone).	loc_t: EV arrival location. q_t: Vector of queue lengths at all active stations (measures localized congestion). $z(loc_t)$: Zone membership of the arrival location.
Reward Function (r)	$$r = -(\text{wait_time} + \alpha \cdot \text{queue_length} + \beta \cdot \text{overload})$$	Defines the immediate feedback the agent receives. It penalizes undesirable outcomes like long waiting times, queue build-up, and utilization exceeding a threshold (overload). Maximizing this reward leads to minimized wait times and balanced load.	wait_time, queue_length, overload: Penalized metrics related to station congestion. α, β: Coefficients used to weigh the penalties.
Q-Learning Update Rule	$$Q(s_t, a_t) \leftarrow (1 - \eta)Q(s_t, a_t) + \eta[r_t + \gamma \max_{a'} Q(s_{t+1}, a')]$$	This is the standard tabular Q-learning update rule defining how the agent learns the optimal policy. It balances current reward (r_t) with the discounted estimated future reward from the next state s_{t+1}.	$Q(s_t, a_t)$: Quality value of taking action a_t in state s_t. η: Learning rate (how much the new observation updates the old Q-value). γ: Discount factor (importance of future rewards). $\max_{a'} Q(s_{t+1}, a')$: Maximum expected future reward.

VI. Performance Metrics

These are used in the Analytics Layer to evaluate the resulting infrastructure.

Metric	Formulation	Why and How Formulated	Significance of Each Term
Coverage Ratio	$$Coverage(k) = \frac{1}{	I	} \sum_{i \in I} \mathbb{I}{\min_{k' \in K_{\text{active}}} d_{ik'} \le R_{\max}}$$
Detour Metric	$$\text{Detour}(k) = \frac{1}{	I	} \sum_{i \in I} (d(i, \hat{j}(i)) - d(i, \text{nearest_road}))$$

Analogy to Clarify the Coupled Model:

The Hybrid MILP–GA–RL Framework acts much like planning a major city's public transport system.

1. **Strategic Siting (MILP/GA) is like building the rail tracks and stations:** The *Cost* objective minimizes the expense of laying the tracks, while the αd^{grid}_k penalty ensures tracks don't cross impossible mountains (grid constraints). The *QoS/Detour* objective ensures stations are placed where the most people (D_i) need them, minimizing walking distance. The *Zone Coverage Constraint* ensures that even peripheral neighborhoods ($MinCoverage_z$) get at least a minimum necessary number of stops, preventing all stations from clustering only in the wealthy commercial core.
2. **Operational Control (Q-Learning) is like dynamic train routing and signaling:** Once the fixed infrastructure (stations x_k) is built, the Q-learning agent uses real-time signals (q_t, queue length) to decide which incoming train (EV) to route to which station, preventing overload and minimizing waiting time (the goal defined by the negative *Reward* function). The strategic siting decisions constrain the operational performance, but the dynamic RL layer mitigates localized inefficiencies.