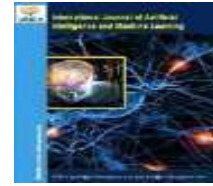




International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Integrated Reliability-Constrained Design of Vehicle-Induced Wind–Battery Systems for Highway Energy Services

Abdulwahab Alfardan¹, Mohamed zaki^{2,3}, Waleed Shaaban⁴, M. M. El-Halwany^{3,5}

¹ Engineering technology and environment management department, Faculty of Engineering, Mansoura University, Elgomhouria St., El-Mansoura 35516, Egypt.

² Electrical Engineering department, Faculty of Engineering, Mansoura University, Elgomhouria St., El-Mansoura 35516, Egypt

³ Faculty of Engineering, Mansoura National University.

⁴ Mechanical Power Engineering department, Faculty of Engineering, Mansoura University, Elgomhouria St., El-Mansoura 35516, Egypt

⁵ Department of Mathematics and Physics Engineering, Faculty of Engineering, Mansoura University, Elgomhouria St., El-Mansoura 35516, Egypt.

*Corresponding author: Abdulwahab Alfardan, E-mail: Eng.Alfardan@gmail.com

Abstract

Roadside wind-energy harvesting can supply distributed highway loads using ambient wind and vehicle-induced wakes. Its feasibility depends on resource variability, storage adequacy, and service requirements. This study develops an integrated wind–battery framework that quantifies the gap between deterministic feasibility and probabilistic robustness and uses the findings to guide service-specific redesign. Applied to the 395 km Riyadh–Dammam highway, the framework combines airflow and storage modeling, lifecycle-cost assessment, and digital-twin supervisory evaluation. Correlated Latin-hypercube Monte Carlo analysis evaluates 10,000 realizations across 54 uncertain inputs. The results show that nominally feasible designs can fail probabilistic service requirements. For the critical-only configuration, targeted redesign increased the probability of limiting annual unserved critical energy to 1% of demand from 31.99% to 95.83%. The redesigned electric-vehicle (EV) charging configuration achieved a 94.07% probability of supplying at least 90% of requested charging energy. These improvements required additional infrastructure and higher lifecycle costs. Digital-twin simulations supported predictive control for critical-only service and resilience-oriented control for EV-enabled operation. The findings establish probabilistic acceptance and the associated cost of redesign as central design considerations for roadside wind–battery systems. The results remain conditional on the reference-synthetic assumptions and require field calibration and experimental validation before deployment.

Keywords: Vehicle-induced wind; roadside wind-energy harvesting; vertical-axis wind turbines; robust optimization; Monte Carlo simulation; digital twin; energy management system; Internet of Things; electric-vehicle charging; smart highways.

1. Introduction

The increasing electrification and digitalization of transportation infrastructure create demand for distributed energy sources for lighting, traffic sensors, communications, safety devices, and electric-vehicle (EV) charging. Supplying dispersed roadside loads can require extensive cabling and grid connections, motivating assessment of local renewable generation. Small vertical-axis wind turbines (VAWTs) offer compact configurations for variable inflow, but their performance depends on rotor geometry, Reynolds number, turbulence, and dynamic stall [1–5]. Storage, monitoring, and energy-management research provides complementary tools for integrating intermittent generation with loads [6–10]. The engineering question is therefore how measured or modeled aerodynamic performance translates into reliable energy services over an entire highway corridor.

Highway traffic provides one such unconventional operating environment. As vehicles move at high speed, aerodynamic drag transfers part of their mechanical energy to the surrounding air, producing transient pressure disturbances and turbulent wakes. Musa et al. [11] used Reynolds-averaged Navier–Stokes simulations to characterize the induced airflow generated by vehicles traveling in tandem and highlighted its potential for highway lighting and emergency signage. Morbiato et al. [12] subsequently assessed traffic-induced wind as a transport-related energy resource using measured relationships between traffic flow and wind-speed occurrence. Santhakumar et al. [13] experimentally investigated a Savonius turbine at different highway locations and under different seasonal wind conditions, demonstrating that both natural wind direction and turbine position materially affect rotor behavior. These studies established an important principle for roadside harvesting: traffic-induced airflow is real and exploitable, but it is intermittent, spatially dependent, and superimposed on the natural wind environment rather than constituting a continuous standalone resource.

Subsequent research focused more directly on the aerodynamic interaction between vehicles and turbines. Tian et al. [14] developed a three-dimensional transient CFD model for a median-installed VAWT and examined different vehicle and road configurations. Hu et al. [15] investigated the structural parameters of an expressway convective-wind-energy collection device and optimized its power coefficient. Tian et al. [16] later compared Banki, Darrieus, and Savonius rotors and investigated turbine arrays and rotor spacing, showing that turbine topology and array configuration strongly influence vehicle-wake energy recovery. Kunkel et al. [17] approached highway VAWTs from a broader site-assessment perspective, highlighting that deployment decisions require considerations beyond aerodynamic performance alone. Collectively, these studies moved the concept from general resource identification toward turbine selection, placement, and highway-scale applicability.

Several studies then extended highway energy harvesting toward hybrid configurations and more application-oriented designs. Kumar et al. [18] experimentally investigated a vehicle-induced VAWT combined with single-axis photovoltaic tracking, while Qi et al. [19] proposed a foldable highway median wind-PV generation system. Rathore et al. [20] examined arrays of low-cost VAWTs for powering highway lighting and traffic-related loads, and Toudarbari et al. [21] evaluated a Darrieus turbine under several vehicle-passing configurations using CFD. A regional feasibility study by Yadav et al. [22] compared helical, troposkien, and flat VAWT configurations for UAE highways, illustrating the relevance of highway wind harvesting to hot-climate Gulf transportation infrastructure.

More recent studies have provided increasingly detailed descriptions of the traffic-induced resource itself. Hu et al. [23] compared several wind-energy collection devices for passenger cars and trucks, while a related study [24] demonstrated an additional highway application in which harvested airflow energy was used to drive a dust-collection system. Their subsequent multi-lane investigation [25] showed that turbine effectiveness varies strongly with lane position, vehicle type, and opposing traffic conditions, and their flow-distribution study [26] demonstrated substantial spatial and temporal variations in vehicle-induced airflow, with trucks generally producing stronger available wake energy than passenger cars. Gallorini and Barelli [27] later developed and experimentally validated a miniature turbine-generator system for recovering vehicle-generated wind in road tunnels. These findings reinforce the need to represent vehicle class, speed, traffic intensity, turbine offset, event duration, and ambient wind simultaneously rather than characterizing highway wind with a single equivalent velocity.

Recent experimental and hybrid-system studies narrow the distance between aerodynamic harvesting and energy use. Bakırcı and Kazal [28] manufactured a combined Savonius–Darrieus rotor and evaluated roadside positioning and different vehicle classes using measured generator voltage and current. Their results provide device-scale evidence of placement sensitivity. Singh et al. [29] modeled a highway solar–wind tower with battery storage for local loads and EV charging, using measured wind inputs and OPAL-RT validation. This is a direct precedent for linking highway wind harvesting to a broader energy architecture. Its hybrid generation estimates, however, are not interchangeable with annual service-constraint probabilities for a wind–battery corridor.

Research remains active at the turbine level. Ulus and Moldovan [30] demonstrated that optimized guide vanes can substantially improve VAWT performance under vehicle-induced highway airflow. Toor et al. [31] investigated VAWT response under different gust configurations, emphasizing the implications of unsteady inflow. Most recently, Guo et al. [32] optimized a Bach-type VAWT specifically for dynamic highway airflow and crosswind conditions, further confirming that turbine behavior under traffic-generated flow differs fundamentally from conventional steady-wind operation. These studies improve understanding of aerodynamic harvesting efficiency but remain primarily concerned with the resource–turbine interface, rather than the complete energy-service system required for long highway corridors.

Table 1(a) compares 22 closely related highway-wind studies, including recent experimental and hybrid-system developments. It separates the topics addressed from the level of validation: coverage of a topic does not imply demonstrated field performance. Table 1(b) extends the comparison to storage sizing, uncertainty, digital supervision, and condition monitoring. Together, the two parts identify connections already established in the literature and the remaining integration requirements relevant to the present corridor study.

Table 1(a). Scope comparison of highway wind-energy studies and the present framework

Study	Year	Focus / evidence	Wake	Amb.	BESS	Scale	UQ	Cost	EV	Ctrl.
Musa et al. [11]	2012	Vehicle-wake resource; 3D RANS	Y	—	—	—	—	—	—	—
Morbiato et al. [12]	2014	Traffic-wind resource assessment; field data	Y	—	—	P	—	—	—	—

Study	Year	Focus / evidence	Wake	Amb.	BESS	Scale	UQ	Cost	EV	Ctrl.
Santhakumar et al. [13]	2017	Savonius highway tests; position and monsoon	Y	Y	—	—	—	—	—	—
Tian et al. [14]	2017	Median VAWT-vehicle interaction; 3D CFD	Y	—	—	—	—	—	—	—
Hu et al. [15]	2018	Highway wind-energy collector optimization	Y	—	—	—	—	—	—	—
Tian et al. [16]	2020	VAWT comparison and turbine-array spacing	Y	—	—	P	—	—	—	—
Kunkel et al. [17]	2020	Highway VAWT siting and stakeholder assessment	—	—	—	P	—	P	—	—
Kumar et al. [18]	2020	Vehicle-wind + solar hybrid prototype	Y	—	P	—	—	—	—	—
Qi et al. [19]	2020	Foldable highway wind-PV generation system	P	P	P	—	—	—	—	—
Rathore et al. [20]	2021	Low-cost highway VAWT array	Y	—	—	P	—	P	—	—
Toudarbari et al. [21]	2021	Darrieus VAWT under highway settings; CFD	Y	—	—	—	—	—	—	—
Yadav et al. [22]	2022	UAE highway VAWT feasibility	Y	P	—	P	—	—	—	—
Hu et al. [23]	2022	Wind collectors under car/truck wakes	Y	—	—	—	—	—	—	—
Hu et al. [24]	2022	Vehicle-wind harvesting for dust collection	Y	—	—	—	—	—	—	—
Hu et al. [25]	2023	Multi-lane wake harvesting and interaction	Y	—	—	P	—	—	—	—
Hu et al. [26]	2023	Multi-lane wake-flow distribution; CFD	Y	—	—	P	—	—	—	—
Singh et al. [29]	2024	Highway PV-wind-BESS; Simulink and OPAL-RT	Y	P	Y	P	—	—	Y	—
Gallorini & Barelli [27]	2024	Tunnel wind-turbine/generator prototype	Y	—	—	—	—	—	—	—
Bakırcı & Kazal [28]	2024	Hybrid rotor; roadside electrical measurements	Y	—	—	P	—	—	—	—
Ulus & Moldovan [30]	2025	Guide-vane optimization for vehicle winds	Y	—	—	—	—	—	—	—
Toor et al. [31]	2026	VAWT response to dynamic gusts; Saudi wind	—	Y	—	—	—	—	—	—
Guo et al. [32]	2026	Bach-type VAWT in dynamic highway airflow	Y	Y	—	—	—	—	—	—
Present study	2026	Integrated traffic-wind-energy-digital framework	Y	Y	Y	Y	Y	Y	Y	Y

Note: Y = explicit coverage; P = partial coverage; — = outside the principal scope. Amb. = ambient/crosswind; Scale = corridor scaling; UQ = reliability/uncertainty; Cost = techno-economics; Ctrl. = IoT/DT/EMS; BESS = battery storage. Coverage does not imply field validation; present-study entries describe reference-synthetic modeling.

Beyond aerodynamic conversion, storage must be sized against the timing and uncertainty of generation and demand. Weng et al. [33] applied sequential Monte Carlo reliability assessment, Huo et al. [34] developed reliability-aware chance-constrained battery sizing, and Gholami et al. [35] examined microgrid reliability metrics. Work on uncertainty representation, multi-objective design, forecast uncertainty, EV integration, and chance-constrained capacity planning provides further foundations [36–40]. These methods establish that nominal energy balance alone is insufficient for storage and service decisions. More recently, Krishna et al. [41] incorporated worst-case uncertainty into multi-objective sizing of isolated PV-wind microgrids with alternative

storage technologies. Qiu et al. [42] coupled prediction intervals, AC-network modeling, and robust operational optimization to address source–load uncertainty. Their work also highlights a useful distinction: robust capacity design and robust operating schedules answer related but different questions.

EV charging makes the service definition consequential: generation adequate for lighting may still be insufficient for charging demand. Wind-powered and hybrid renewable charging configurations [43, 44], together with reviews of charging infrastructure [45], motivate treating charging as an explicit energy service. A particularly close highway precedent is Hammood et al. [46], who integrated PV–battery sizing, annual energy-reliability assessment, road-scale economics, and an IoT monitoring design for a 40 km lighting corridor. Accordingly, the present study does not claim the first integration of highway energy, storage, reliability, and monitoring. It extends that decision context to ambient plus vehicle-induced wind, separate critical and EV service constraints, and probabilistic redesign across resource, storage, electrical, communication, and economic assumptions.

Digital systems connect asset operation with monitoring and control. Chalal et al. [6] experimentally evaluated a bidirectionally connected digital twin for a standalone PV demonstrator; Saleem et al. [7] implemented IoT and cloud-based demand management in buildings; and Al Sumarmad et al. [8] combined simulated fuzzy-logic microgrid control with a monitoring platform. García et al. [9] and Lee et al. [10] provide earlier monitoring and EMS implementations. Gbadega and Loji [47] subsequently combined PV–battery simulation, rule-based management, and an interactive dashboard in a digital-twin-oriented framework. These studies differ in application and validation level, so a monitoring dashboard, a simulated supervisory model, and an experimentally connected digital twin should not be treated as equivalent evidence.

Recent digital work provides both enabling methods and stronger validation examples. Jiang et al. [48] constructed an OPAL-RT microgrid model using campus load and weather data and compared its dynamic response with physical assets, supporting predictive control and deployment planning. IoT-enabled wind monitoring is also addressed by Li et al. [49]. Rekeraho et al. [50] integrated encryption and secure cloud communication into solar-system monitoring, while Bonavolontà et al. [51] used distributed power meters, LoRaWAN, and MQTT to track energy exchanges in renewable energy communities. These contributions distinguish measurement integrity, secure data transfer, and energy-flow accounting from the packet-delivery and latency metrics adopted here. Communication availability is one necessary condition for supervision; it does not establish cybersecurity or measurement accuracy.

Condition monitoring offers a further connection between aerodynamic behavior and long-term asset service. Marykovskiy et al. [52] implemented the Aerosense architecture for blade aerodynamic monitoring using sensors, cloud analytics, and prediction functions, explicitly describing the implementation as a digital shadow. Mostafavi and Friedmann [53] released outdoor measurements from a small wind turbine with controlled damage scenarios and heterogeneous sensors, providing an empirical basis for testing diagnostic methods. Maldonado-Correa et al. [54] found in a systematic review that wind-turbine digital twins remain concentrated at component level, with unresolved benchmarking, data heterogeneity, and real-time scalability issues. These findings support examining system-level links, while also requiring clear boundaries: the present simulated fault supervision is not a validated remaining-useful-life estimator or field-proven predictive-maintenance system.

Table 1(b). Established system-level connections and remaining requirements for the present corridor problem

Study	Established connection	Evidence basis	Remaining requirement for this corridor
Singh et al. (2024) [29]	Highway wind + PV + storage + local and EV loads	Simulink; measured wind input; OPAL-RT validation	Translate hybrid yield into separate annual critical/EV constraint-pass probabilities.
Krishna et al. (2024) [41]	Uncertain renewable generation + alternative storage sizing	Worst-case, multi-objective microgrid optimization	Connect sizing to vehicle wakes and corridor communication/electrical constraints.
Qiu et al. (2025) [42]	Prediction intervals + AC power flow + robust operation	Optimization case studies	Relate operating uncertainty to corridor capacity acceptance and redesign.

Study	Established connection	Evidence basis	Remaining requirement for this corridor
Hammood et al. (2026) [46]	Highway PV-battery sizing + annual adequacy + cost + IoT	40 km modeled lighting case; monitoring architecture	Assess traffic-wind inputs, critical/EV service, and correlated redesign together.
Gbadega & Loji (2026) [47]	PV-battery dispatch + SOC + dashboard indicators	Simulation-based digital-twin-oriented framework	Connect supervisory assessment to probabilistically accepted corridor designs.
Jiang et al. (2024) [48]	Microgrid dynamics + predictive control + asset planning	Real-time simulation compared with physical assets	Obtain comparable physical validation for roadside wind-battery supervision.
Rekeraho et al. (2024) [50]	Solar monitoring + encryption + secure cloud transfer	Implemented IoT security architecture	Validate security separately from modeled packet delivery and availability.
Bonavolontà et al. (2025) [51]	Distributed metering + communications + energy accounting	IoT measurement system and community case study	Validate corridor telemetry and align measured energy with service metrics.
Marykovskiy et al. (2024) [52]	Blade sensing + cloud analytics + aerodynamic prediction	Deployed and validated digital-shadow architecture	Link component diagnostics to wind-battery service and maintenance decisions.
Mostafavi & Friedmann (2024) [53]	Turbine measurements + labeled damage scenarios	Outdoor small-turbine monitoring dataset	Collect matched roadside data for diagnostic validation.
Maldonado-Correa et al. (2026) [54]	Condition monitoring + maintenance + remaining useful life	Systematic review of wind-turbine digital twins	Address component-to-system integration and benchmarking with suitable data.
Present study	Wake/ambient generation + annual dispatch + probabilistic redesign + cost + supervision	Reference-synthetic corridor simulations	Field calibration and physical validation remain necessary.

Note: The final column states the connection required for the present research question; it is not a claim that a cited study failed its own objectives. Evidence types are distinguished to avoid equating simulation, a published dataset, and experimental validation. The two parts of Table 1 are complementary scope comparisons, not an exhaustive systematic review.

The reviewed literature establishes several links between aerodynamic harvesting and energy services. Aerodynamic studies resolve vehicle passage and rotor response. Hybrid highway studies connect generation with storage and charging, while microgrid studies address uncertain sizing and operation. Digital systems add supervision and asset monitoring. The remaining gap concerns how these elements jointly inform corridor design decisions. This study links class-dependent wake and ambient-wind assumptions to annual priority dispatch, electrical and communication constraints, and lifecycle cost. Correlated probabilistic assessment then guides redesign and service-specific supervisory evaluation. The contribution is this integrated decision process within a reference case; robust sizing, highway energy integration, and digital twins already have established precedents.

The present study develops an integrated design-to-operation framework for the 395 km Riyadh–Dammam highway corridor. It tests whether designs accepted under nominal conditions remain acceptable under correlated uncertainty. A 10,000-realization Monte Carlo analysis evaluates critical-energy adequacy, EV service, storage, electrical performance, and communications before final economic ranking. Failed probabilistic constraints guide targeted changes in generation, storage, gateway density, and conductor capacity. Ambient and vehicle-induced wind modeling, turbine and drivetrain conversion, LiFePO₄ storage, and

corridor-scale cost assessment provide the physical and economic basis for this process. Critical-only and EV-enabled services are assessed separately. The retained designs then undergo digital-twin evaluation of EMS policies, IoT communications, SOC management, and fault supervision.

The central contribution is a quantified demonstration that correlated uncertainty can change the acceptance of nominally feasible roadside wind-battery designs. Constraint-based redesign then links the identified service risks to infrastructure requirements and lifecycle cost. Building on established probabilistic reliability and robust sizing methods [33, 34, 41], the analysis uses correlated Latin-hypercube sampling across 54 uncertain inputs. Convergence monitoring, Spearman sensitivity analysis, and output percentiles support interpretation. The contribution is assessed through changes in design acceptance and service-specific costs. Supporting contributions include coupled ambient-traffic wake and wind-battery modeling from a roadside node to a 395-cluster corridor; integrated electrical, communication, and lifecycle-cost assessment; and digital-twin evaluation of the retained EV0-R1 and EV22-R1 designs and their supervisory policies. All recommendations remain conditional on the reference-synthetic inputs pending field calibration and experimental validation.

2. Methodology

Figure 1 outlines the integrated methodology, with probabilistic acceptance and redesign providing the link between nominal sizing and final service-track selection. Corridor geometry, traffic, environmental assumptions, and service targets first define the model inputs. Vehicle wake, ambient wind, turbine and drivetrain conversion, and battery dispatch then support single-node feasibility screening and corridor-scale techno-economic optimization. The resulting nominal candidates are evaluated under correlated uncertainty; failed service or technical probability thresholds trigger targeted redesign and reassessment before economic ranking. The retained critical-only and EV-enabled configurations are subsequently evaluated in a digital-twin environment incorporating EMS logic, IoT communications, fault monitoring, and supervisory performance.

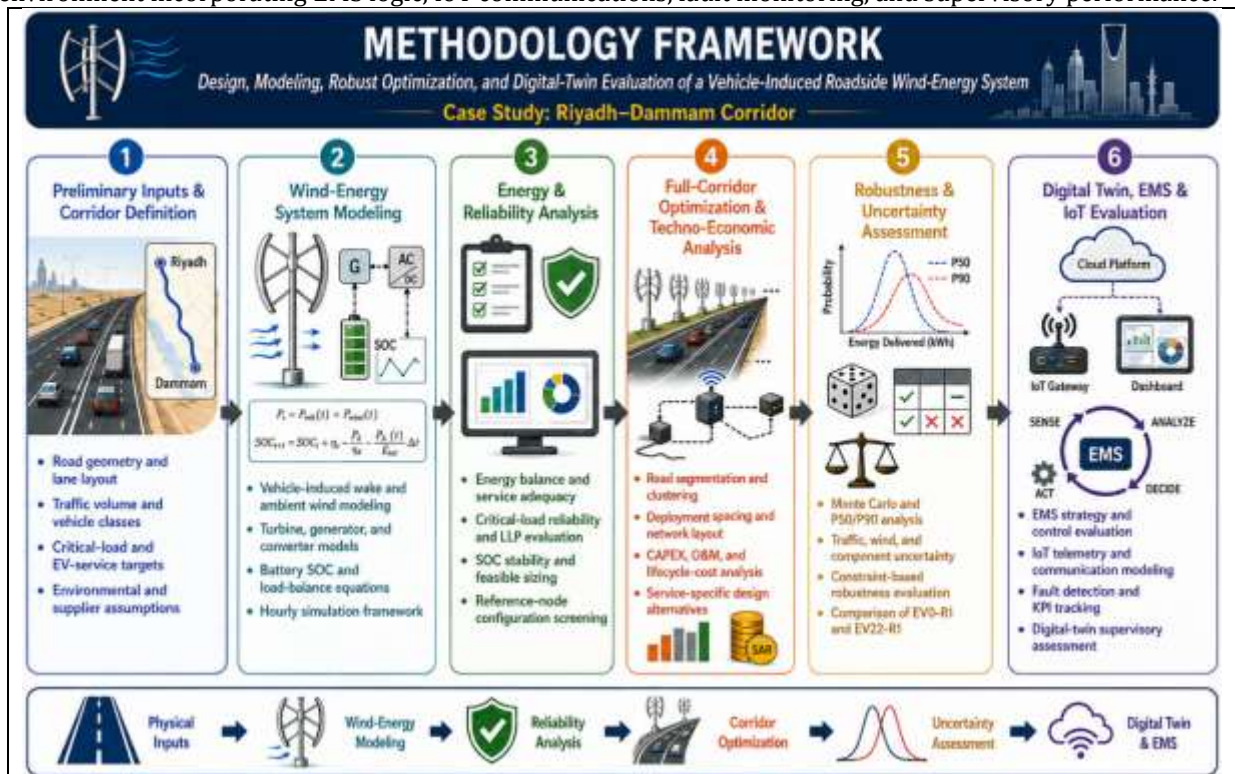


Figure 1. Integrated methodology framework of the proposed study, showing the sequential stages of corridor definition, wind-energy system modeling, reliability analysis, full-corridor optimization, uncertainty assessment, and digital-twin-based evaluation.

2.1. Phase 1: Initial Inputs and Corridor Definition

The first phase defines the physical, operational, and environmental boundaries of the Riyadh-Dammam corridor. Inputs include road length, lane configuration, traffic volume, vehicle-class distribution, and representative vehicle speeds. Critical roadside loads and EV-charging service levels are also specified.

Environmental assumptions, wind-resource parameters, component characteristics, and supplier-related inputs are organized as controlled model inputs.

2.2. Phase 2: Wind-Energy System Modeling

The roadside wind-energy system is then modeled. Effective turbine inflow combines ambient wind and class-dependent vehicle wakes using the adopted superposition rule. The model calculates turbine aerodynamic power, generator output, converter efficiencies, and electrical losses. An hourly simulation couples the resulting electrical generation with battery SOC and load-balance equations.

2.3. Phase 3: Energy and Reliability Evaluation

The third phase evaluates whether each candidate satisfies the energy and service constraints. The hourly simulation calculates generation, served load, unmet critical demand, battery charging and discharging, and SOC. Performance is assessed using the energy-based critical-load loss-of-load index (LLP), energy-service ratio, and SOC constraint violations. Candidates that fail mandatory reliability or battery-operating constraints are excluded from further consideration.

2.4. Phase 4: Full-Corridor Techno-Economic Analysis and Optimization

Feasible single-node configurations are scaled to the full 395 km Riyadh–Dammam corridor. Segments and clusters define turbine and battery allocation, gateway placement, and electrical-network requirements. Alternative spacing and service configurations are compared in terms of energy performance, cable losses, CAPEX, O&M, and lifecycle cost. This phase produces separate optimized candidates for critical-only and EV-enabled operation.

2.5. Phase 5: Probabilistic Acceptance and Targeted Redesign

This phase provides the principal decision test of the framework. A correlated Latin-hypercube Monte Carlo analysis evaluates 54 uncertain inputs using 10,000 realizations, covering resource, component, storage, electrical, communication, and economic variability. Constraint-pass probabilities determine whether nominally feasible candidates meet the prescribed service requirements under the assumed uncertainty model. Convergence monitoring and P5, P10, P50, P90, and P95 output statistics support interpretation, while Spearman sensitivity analysis identifies influential inputs. Failed constraints guide targeted redesign, and the revised configurations are reassessed before final ranking. This process produces EV0-R1 and EV22-R1 as conditional recommendations for their respective service tracks.

2.6. Phase 6: Digital Twin, EMS, and IoT Assessment

The selected configurations are evaluated in a multi-resolution digital-twin environment. Reactive, predictive, and resilience-oriented EMS policies are compared for energy dispatch, SOC management, critical-load prioritization, and EV-service control. The IoT model represents cluster gateways, telemetry, communication availability, latency, packet delivery, fault detection, and KPI reporting. This phase assesses operational and supervisory performance within the same simulation framework.

3. Mathematical Modeling

The modeling chain starts with corridor and traffic characterization, followed by ambient and vehicle-induced wind estimation and electrical-energy conversion. Prioritized battery dispatch supports full-corridor scaling, techno-economic analysis, and probabilistic robustness assessment. Digital-twin, EMS, and IoT evaluation then examines supervisory operation.

3.1. Corridor and Traffic Input Representation

This phase defines the physical and operating boundary of the study. The input representation retains the parameters that control turbine exposure to traffic-induced airflow, hourly vehicle occurrence, service demand, and the spatial scaling of the model.

The principal geometric, traffic, service, and environmental quantities are grouped into one controlled vector. This representation provides a compact interface between the input workbook and the numerical simulation.

$$R = [L, N_{lanes}, w_{lane}, w_{median}, d, AADT, \phi, s, \mu_v, \sigma_v, P_{load}] \quad (1)$$

where R is the complete corridor and operating input vector. L is the modeled corridor length in km. N_{lanes} is the total or direction-specific number of traffic lanes, according to the selected modeling boundary. w_{lane} and w_{median} are the lane and median widths in m. d is the lateral distance between the traffic lane and the turbine rotor in m. $AADT$ is annual average daily traffic in vehicles/day. ϕ is the 24-hour normalized traffic-distribution vector. s is the vector of vehicle-class shares. μ_v and σ_v contain the class-specific mean speeds and speed

deviations. P_{load} contains the critical and flexible load definitions. Equation (1) ensures that all subsequent models use the same corridor geometry, traffic composition, turbine placement, and service boundary. The daily traffic volume is distributed across the 24-hour profile and the considered vehicle classes. A directional exposure factor is included because only a portion of corridor traffic contributes to the airflow incident on a specific roadside node.

$$N_{j,h} = AADT \phi_h s_j \chi_{dir} \quad (2)$$

where $N_{j,h}$ is the expected number of vehicles of class j during hour h . ϕ_h is the fraction of daily traffic occurring during hour h . s_j is the share of vehicle class j , such as passenger cars, light commercial vehicles, buses, or heavy goods vehicles. χ_{dir} is the directional traffic factor assigned to the modeled node. This hourly class count is the direct scaling variable used to convert a single vehicle-wake event into hourly vehicle-induced energy. The temporal and vehicle-class distributions must conserve total traffic volume. These constraints form mandatory input-quality checks before optimization.

$$\sum_{h=1}^{24} \phi_h = 1, \quad \sum_{j=1}^{N_v} s_j = 1 \quad (3)$$

where N_v is the number of modeled vehicle classes. ϕ_h and s_j are the hourly and class shares defined above. If either sum differs from unity, hourly vehicle counts or class-specific wake contributions would be systematically overestimated or underestimated.

3.2. Phase II: Wind-Energy System Modeling

This phase converts the environmental and traffic inputs into an hourly electrical-generation profile. It includes the ambient-wind resource, class-specific vehicle wakes, nonlinear turbine conversion, pulse-overlap correction, multi-turbine spacing effects, and downstream electrical efficiencies.

3.2.1. Ambient-Wind Model

Weibull ambient-wind distribution. The annual screening model represents the ambient wind resource with a two-parameter Weibull distribution. The distribution is suitable for generating a reproducible wind-speed sequence while retaining a physically meaningful positive support.

$$f_V(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right], \quad v \geq 0 \quad (4)$$

where $f_V(v)$ is the probability-density function of ambient wind speed. v is ambient wind speed in m/s. k is the dimensionless Weibull shape parameter. c is the Weibull scale parameter in m/s.

The values of k and c govern the frequency of low, moderate, and high ambient-wind conditions used by the annual turbine model.

To avoid a stationary sequence with no temporal structure, the sampled Weibull wind speed is adjusted by seasonal and diurnal modulation factors. This reproduces the implemented **8,760-hour** screening series.

$$v_{amb}(t) = v_W(t) M_s(t) M_d(t) \quad (5)$$

where $v_{amb}(t)$ is the ambient wind speed at time step t . $v_W(t)$ is the Weibull-sampled base wind speed. $M_s(t) = 1 + a_s \cos[2\pi(D_t - D_0)/365]$ is the seasonal correction factor. $M_d(t) = 1 + a_d \sin[2\pi(H_t - H_0)/24]$ is the diurnal correction factor. a_s and a_d are the seasonal and diurnal modulation amplitudes. D_t and H_t are the day-of-year and hour-of-day indices. D_0 and H_0 are the phase-shift references used to position the seasonal and diurnal peaks. The modulation changes the temporal occurrence of available wind energy while preserving the Weibull-based annual resource distribution.

3.2.2. Vehicle-Induced Wake Model

Vehicle-induced airflow is represented using a reduced-order, class-dependent model informed by published aerodynamic and field studies. Tian et al. [55] examined the effects of vehicle speed and vehicle-to-rotor clearance on wake-energy recovery. Bani-Hani et al. [56] measured roadside wind at several heights in Kuwait, providing a regional empirical comparison for airflow magnitude. Miller et al. [57] documented the dependence of vehicle-induced turbulence on vehicle class, measurement height, and downstream distance. Ulus and Moldovan [30] resolved the transient turbine response during vehicle passage. Table 3(a) summarizes the evidence and its applicability. These studies motivate the model variables and transient

treatment; the numerical coefficients in Table 3(b) remain explicitly specified baseline assumptions, without a demonstrated fit to those studies.

The class-specific peak wake speed is expressed using a dimensionless lateral-distance ratio:

$$v_{pk,j}(d) = \beta_j v_j \left[\frac{\max(d, d_{min})}{d_0} \right]^{-m_j} \quad (6)$$

The post-peak contribution of an individual passing event is approximated by an exponential envelope:

$$v_{wake,j}(\tau, d) = v_{pk,j}(d) \exp\left(\frac{-\tau}{\tau_j}\right), \quad \tau \geq 0 \quad (7)$$

where $\tau \geq 0$ is elapsed time from the idealized event peak and τ_j is the wake-decay time constant in seconds. At $\tau = \tau_j$, the envelope is 1/e of its peak. This parameter is distinct from the finite integration horizon T_j in Equation (10). Published transient turbine-response histories [30] motivate resolving individual events but do not supply the class-specific exponential time constants adopted here. The selected values of 1.50–3.00 s are therefore baseline modeling choices, not measured event durations.

The ambient and wake contributions are combined using the adopted root-sum-square approximation:

$$v_{eff,j}(\tau, d) = \sqrt{v_{amb}^2 + v_{wake,j}^2(\tau, d)} \quad (8)$$

where v_{amb} is the ambient wind speed for the corresponding hour. Equation (8) is a scalar inflow approximation that does not resolve the instantaneous angle between the ambient and wake velocity vectors. Consequently, the modeled peak speeds and energy increments are conditional on the assumed coefficients and superposition rule. Quantitative calibration requires compatible velocity measurements or CFD outputs at matched vehicle speeds, offsets, and measurement heights.

3.2.3. Turbine and Electrical-Conversion Model

Piecewise turbine electrical-power model. The turbine model applies the aerodynamic cubic-power relationship only inside the operational wind-speed range. The converted output is capped at the rated power and set to zero outside the cut-in and cut-out limits.

$$P_T(v) = \begin{cases} 0, & v < v_{ci} \text{ or } v > v_{co}, \\ \min\left[\frac{1}{2}\rho A C_{p,max} \eta_m \eta_g v^3, P_{rated}\right], & v_{ci} \leq v \leq v_{co}. \end{cases} \quad (9)$$

where $P_T(v)$ is the turbine-generator electrical power before the downstream rectifier/MPPT stages in W. ρ is air density in $kg\ m^{-3}$. A is rotor swept area in m^2 . $C_{p,max}$ is the maximum power coefficient used for screening. η_m and η_g are mechanical and generator efficiencies. v_{ci} and v_{co} are the cut-in and cut-out wind speeds. P_{rated} is the rated turbine power. This formulation reproduces the implemented screening power curve: cubic below the rating, bounded by component rating, and inactive outside the permitted speed range.

The incremental contribution of a vehicle event is calculated relative to the power already produced by the ambient wind. Only the positive power increment is integrated over the wake-pulse duration.

$$E_{veh,j,h} = N_{j,h} \int_0^{T_j} \max[P_T(v_{eff,j}) - P_T(v_{amb,h}), 0] d\tau \quad (10)$$

where $E_{veh,j,h}$ is the uncorrected hourly incremental energy from vehicle class j . $N_{j,h}$ is the number of class- j vehicles during hour h . T_j is the numerical integration duration for the wake event. $\max[\cdot, 0]$ retains only positive incremental turbine power. $P_T(v_{amb,h})$ is the ambient-only turbine power baseline. Subtracting the ambient baseline prevents natural wind energy from being counted again as vehicle-induced energy.

At high traffic rates, wake pulses may overlap in time. The hourly occupancy index estimates the combined fraction of an hour occupied by all class-specific wake events.

$$\Omega_h = \sum_{j=1}^{N_v} \frac{N_{j,h} \tau_j}{3600} \quad (11)$$

where Ω_h is the dimensionless hourly wake-occupancy index. $N_{j,h}$ is the number of class- j events during hour h . τ_j is the wake-duration parameter in s. 3600 converts one hour to seconds. A small value indicates isolated wake events, whereas a large value indicates substantial temporal overlap and a higher risk of double counting. The accumulated event energy is reduced using a saturation-style correction when multiple pulses occupy the same period. The factor tends toward unity for sparse traffic and decreases as occupancy increases.

$$F_{ov,h} = \begin{cases} \frac{1 - \exp(-\Omega_h)}{\Omega_h}, & \Omega_h > 0, \\ 1, & \Omega_h = 0. \end{cases} \quad (12)$$

where $F_{ov,h}$ is the hourly wake-overlap correction factor. Ω_h is the occupancy index from Equation (11). The corrected hourly vehicle-induced energy is obtained by multiplying the sum of class-event energies by $F_{ov,h}$. When several turbines are placed at one node, an empirical spacing-efficiency factor represents interaction and diminishing incremental capture. The loss reduces as spacing measured in rotor diameters increases.

$$\eta_{sp} = \max \left[0.70, 1 - 0.08 \exp \left(-\frac{S_D - 3}{2} \right) \frac{N_T - 1}{N_T} \right] \quad (13)$$

where η_{sp} is the multi-turbine spacing efficiency. S_D is the inter-turbine spacing expressed in rotor diameters. N_T is the number of turbines at the node. 0.70 is the lower screening bound imposed on the aggregate spacing efficiency. The equation prevents the optimization from assuming that additional turbines always provide perfectly proportional energy at compact spacing.

Ambient generation and overlap-corrected vehicle-induced energy are combined and passed through the turbine-spacing and power-electronics efficiencies. The result is the hourly energy available at the DC bus.

$$E_{DC,h} = N_T \eta_{sp} \eta_{el} \left[P_T(v_{amb,h}) \Delta t + F_{ov,h} \sum_{j=1}^{N_v} E_{veh,j,h} \right] \quad (14)$$

where $E_{DC,h}$ is net DC energy during hour h in Wh or kWh, according to the selected unit basis. N_T and η_{sp} describe the node turbine arrangement. Δt is the hourly simulation step. $\eta_{el} = \eta_{rec} \eta_{MPPT} \eta_{dc}$ is the combined downstream electrical efficiency. Equation (14) is the principal connection between wind/wake modeling and the battery-dispatch model.

3.3. Phase III: Energy Balance and Reliability Analysis

The generated DC energy is allocated using a priority-based dispatch model. Critical roadside loads are served first, EV charging is served second when included, and any remaining energy is stored subject to battery energy and power limits.

3.3.1. Load Representation

Hourly critical-load demand. The critical demand includes the roadway lighting contribution and the continuously required auxiliary, sensing, control, and communication loads. Alternative operating strategies are represented through an hourly load factor.

$$E_{crit,h} = [P_{aux} + P_{LED} u_s(h)] \Delta t \quad (15)$$

where $E_{crit,h}$ is critical energy demand during hour h . P_{aux} is the aggregate critical auxiliary power. P_{LED} is nominal road-lighting power. $u_s(h)$ is the hourly operating factor for load strategy s . Δt is the simulation interval in h. Changing the control strategy modifies both the annual critical demand and the storage requirement while preserving the same physical load inventory.

The flexible EV service is represented by a specified charging tier and an hourly availability schedule. The no-EV service track is obtained by setting the charger power to zero.

$$E_{EV,h} = P_{EV} q_h \Delta t \quad (16)$$

where $E_{EV,h}$ is requested EV energy during hour h . P_{EV} is the selected EV charging power in kW. q_h is the fraction of the charging session assigned to hour h . $P_{EV} = 0$ defines the EV0 service track. This formulation enables the same energy architecture to be screened for critical-only service and for an EV-enabled operating requirement.

3.3.2. Priority-Based Energy Dispatch

Direct and battery-supported critical service. Available generation is allocated to the critical load before any flexible demand is considered. A remaining critical deficit may be supplied from the battery subject to the battery power and stored-energy limits.

$$E_{crit,h}^{served} = \min[E_{crit,h}, E_{DC,h} + \min(P_{bat,max} \Delta t, B_h \eta_d)] \quad (17)$$

where $E_{crit,h}^{served}$ is total critical energy served during hour h . $E_{DC,h}$ is the current DC generation available before flexible-load service. $P_{bat,max}$ is the maximum battery charge/discharge power. B_h is stored usable battery energy before dispatch. η_d is discharge efficiency. The nested minimum operator enforces critical-load priority while respecting the battery power and stored-energy limits.

EV charging is evaluated only after the critical load has been served. The flexible demand therefore uses the remaining generation and any unused battery-discharge capability.

$$E_{EV,h}^{served} = \min[E_{EV,h}, E_{rem,h} + \min(P_{rem,h} \Delta t, B'_h \eta_d)] \quad (18)$$

where $E_{rem,h}$ is generation remaining after direct critical-load service. $P_{rem,h}$ is the unused battery-discharge power after critical service. B'_h is battery energy remaining after critical-load discharge. $E_{EV,h}^{served}$ is the total EV

energy delivered during hour h . The priority rule prevents flexible charging demand from increasing the energy-based critical-load LLP.

After the critical and EV demands have been processed, the remaining generation is used to charge the battery. Charging is limited by the remaining capacity and the maximum battery power.

$$E_{ch,h} = \min \left(E_{sur,h}, P_{bat,max} \Delta t, \frac{E_{use} - B_h''}{\eta_c} \right) \quad (19)$$

where $E_{ch,h}$ is energy accepted by the battery charging path. $E_{sur,h}$ is energy remaining after direct load service. E_{use} is total usable battery capacity. B_h'' is stored energy after all discharging during hour h . η_c is charging efficiency. Any remaining energy that cannot be served or stored is recorded as spilled energy.

The battery state is advanced from one hourly interval to the next by adding efficiently stored charging energy and subtracting the internal energy required to support discharge. Clipping enforces the usable energy limits.

$$B_{h+1} = \text{clip} \left[B_h + \eta_c E_{ch,h} - \frac{E_{dis,h}}{\eta_d}, 0, E_{use} \right] \quad (20)$$

where B_{h+1} and B_h are stored usable energies at the end and beginning of the interval. $E_{dis,h}$ is total battery energy delivered to critical and EV loads. $\text{clip}(x, 0, E_{use})$ limits the result to the usable range. This energy-state equation is the core recursive relationship of the annual dispatch simulation.

The internal usable-energy state is mapped to the reporting interval bounded by the selected minimum and maximum SOC values. This keeps operational SOC limits explicit in the results.

$$SOC_h = SOC_{min} + \frac{B_h}{E_{use}} (SOC_{max} - SOC_{min}) \quad (21)$$

where SOC_h is the reported state of charge at hour h . SOC_{min} and SOC_{max} are the permitted lower and upper SOC fractions. B_h/E_{use} is the fraction of usable storage currently occupied. A candidate is rejected when the selected configuration cannot maintain the required SOC operating range or cannot provide the requested power.

3.3.3. Reliability and Service Metrics

Energy-based critical-load loss-of-load index. An energy-based loss-of-load probability (LLP) is defined here as the ratio of annual unserved critical energy to annual critical energy demand. Accordingly, LLP quantifies the fraction of requested critical energy that remains unsupplied over the simulated year. It does not represent the probability of a shortfall in a particular hour, the fraction of hours with insufficient supply, or the frequency of interruption events. This energy-based definition is used consistently throughout the study and forms the basis of the critical-load adequacy constraint.

$$LLP_{crit} = \frac{\sum_{h=1}^{8760} E_{unmet,crit,h}}{\sum_{h=1}^{8760} E_{crit,h}} \quad (22)$$

where LLP_{crit} is the annual energy-based critical-load loss-of-load index, $E_{unmet,crit,h}$ is the unserved critical energy during hour h , and $E_{crit,h}$ is the requested critical energy during that hour. Both energy quantities are expressed in kWh. The index ranges from 0 to 1 and is multiplied by 100 when reported as a percentage. The adopted constraint, $LLP_{crit} \leq 0.01$, permits at most 1% of annual critical energy demand to remain unserved; it does not impose a 1% limit on the number or duration of shortfall events.

The complementary served-critical-energy fraction is calculated using Equation (23). This quantity expresses the proportion of annual critical energy demand supplied by the system and is used for reporting and comparison.

$$R_{crit} = 1 - LLP_{crit} \quad (23)$$

where R_{crit} is the annual served-critical-energy fraction and LLP_{crit} is defined by Equation (22). For example, $LLP_{crit} = 0.01$ corresponds to supplying 99% of annual critical energy demand. This energy-based service measure does not, by itself, establish uninterrupted supply or quantify interruption frequency and duration.

EV charging performance is evaluated as the fraction of requested charging energy that is actually delivered. The metric is applied only to EV-enabled configurations.

$$EVSR = \frac{\sum_{h=1}^{8760} E_{served,EV,h}}{\sum_{h=1}^{8760} E_{EV,h}} \quad (24)$$

where $EVSR$ is the annual EV energy-service ratio. $E_{served,EV,h}$ is EV energy supplied during hour h . $E_{EV,h}$ is requested EV charging energy. For EV0, the EV demand is absent and the metric is treated as not applicable rather than being used to favor the no-EV design.

A configuration is declared deterministically feasible only when it passes the applicable reliability, service, and SOC constraints. Economic ranking is performed after this screening.

$$LLP_{crit} \leq 0.01, \quad EVSR \geq 0.90, \quad SOC_{min} \leq SOC_h \leq SOC_{max} \quad (25)$$

where 0.01 is the maximum annual unserved critical-energy fraction (LLP). 0.90 is the minimum annual EV service ratio for EV-enabled designs. SOC_h must remain within the selected operational bounds for every simulated hour. This hard-screening rule prevents an inexpensive but technically inadequate configuration from being selected by a weighted economic score.

3.4. Phase IV: Full-Corridor Optimization and Techno-Economic Modeling

Feasible node configurations are scaled to the full Riyadh–Dammam corridor. The corridor model accounts for spatial clustering, asset quantities, electrical collection losses, gateways, battery replacements, lifecycle cost, and service-specific design alternatives.

3.4.1. Spatial and Electrical Scaling

Number of corridor clusters. The corridor is divided into repeatable operational clusters. The ceiling function ensures that the complete road length is represented even when the final segment is shorter than the nominal cluster length.

$$N_c = \text{ceil}\left(\frac{L}{L_c}\right) \quad (26)$$

where N_c is the number of corridor clusters. L is the corridor length. L_c is the nominal cluster length. **Clustering** provides a common unit for energy aggregation, cable routing, IoT telemetry, and corridor-level maintenance analysis.

The electrical energy generated by all turbines assigned to a cluster is aggregated and reduced by conversion, cable, storage, and auxiliary losses.

$$E_{c,c,h} = \sum_{i=1}^{N_{T,c}} E_{i,h} - E_{loss,c,h} \quad (27)$$

where $E_{c,c,h}$ is the net energy of cluster c during hour h . $N_{T,c}$ is the number of turbines in cluster c . $E_{i,h}$ is hourly energy from turbine i . $E_{loss,c,h}$ is the total cluster loss. The equation supports nonuniform asset allocation when corridor segments have different traffic, wind, load, or reliability multipliers.

The complete corridor energy profile is obtained by summing the net output of all clusters. This profile is used for annual energy, service, and economic calculations.

$$E_{road,h} = \sum_{c=1}^{N_c} E_{c,c,h} \quad (28)$$

where $E_{road,h}$ is net corridor energy at hour h . $E_{c,c,h}$ is the net energy of cluster c . N_c is the cluster count. The same summation structure is used to aggregate critical demand, EV demand, storage, and communication events across the corridor.

Cluster power is converted into DC feeder current using the selected bus voltage. Higher bus voltage reduces current and consequently reduces resistive losses for the same transmitted power.

$$I_{c,h} = \frac{P_{c,h}}{V_{bus}} \quad (29)$$

where $I_{c,h}$ is feeder current for cluster c at hour h . $P_{c,h}$ is power transmitted through the feeder. V_{bus} is the selected DC bus voltage. The current is used to size cables and evaluate conductor losses under candidate deployment layouts.

Cable resistance is calculated from conductor geometry and corrected for operating temperature. This avoids treating a long roadside collection circuit as lossless.

$$R_c = \rho_e \frac{\ell_c}{A_c} [1 + \alpha_T (T_c - T_{ref})] \quad (30)$$

where R_c is the conductor resistance of circuit c in ohms. ρ_e is conductor resistivity at the reference temperature. ℓ_c is conductor length. A_c is conductor cross-sectional area. α_T is the conductor temperature coefficient. T_c and T_{ref} are operating and reference temperatures. Longer routes and smaller conductor areas increase resistance and may make an otherwise energy-feasible deployment electrically unacceptable.

Resistive cable loss is obtained from the feeder current and resistance. The corresponding voltage-loss fraction is evaluated as a mandatory corridor-design constraint.

$$P_{loss,c,h} = I_{c,h}^2 R_c, \quad \delta_{V,c,h} = \frac{I_{c,h} R_c}{V_{bus}} \quad (31)$$

where $P_{loss,c,h}$ is resistive power loss. $\delta_{v,c,h}$ is the relative voltage drop. $I_{c,h}$, R_c , and V_{bus} are defined above. The candidate cable network is accepted only when the maximum route voltage loss remains below the prescribed limit, typically 5% in this study.

3.4.2. Techno-Economic Model

Initial capital expenditure. Initial investment includes the quantities of turbines, generators, power-electronic units, batteries, gateways, cables, and civil/integration work. The component-level formulation allows the optimizer to penalize asset-intensive designs.

$$CAPEX = \sum_{q=1}^{N_q} n_q C_q + C_{civil} + C_{installation} + C_{integration} \quad (32)$$

where N_q is the number of component categories. n_q and C_q are the installed quantity and unit cost of component category q . C_{civil} , $C_{installation}$, and $C_{integration}$ are project-level allowances. CAPEX is evaluated at node, cluster, and corridor scales depending on the optimization stage.

Components with a calendar life shorter than the project horizon require scheduled replacement. Each replacement is discounted to its present value.

$$C_{rep,PV} = \sum_{y \in \mathcal{Y}_{rep}} \frac{C_{rep,y}}{(1+r)^y} \quad (33)$$

where $C_{rep,PV}$ is the present value of all replacements. $\mathcal{Y}_{rep}$ is the set of replacement years. $C_{rep,y}$ is the replacement cost incurred in year y . r is the real discount rate. Battery replacement schedules are particularly important because storage capacity and lifecycle cost are both sensitive to battery calendar life.

Lifecycle cost combines initial investment, discounted operation and maintenance, discounted replacement cost, and residual value. It is the primary long-term economic indicator used in the robust comparison.

$$LCC = CAPEX + \sum_{y=1}^Y \frac{C_{O\&M,y} + C_{rep,y}}{(1+r)^y} - \frac{C_{salvage}}{(1+r)^Y} \quad (34)$$

where LCC is total lifecycle cost in SAR. Y is project lifetime in years. $C_{O\&M,y}$ is operation and maintenance cost in year y . $C_{salvage}$ is the residual value at the end of the project. Unlike a simple initial-cost comparison, LCC captures the economic consequences of maintenance and component replacement over the full study period. The levelized cost is calculated using discounted served energy rather than gross generated energy. This penalizes configurations that produce energy but fail to deliver it to the required services.

$$LCOE = \frac{LCC}{\sum_{y=1}^Y \frac{E_{served,y}}{(1+r)^y}} \quad (35)$$

where $LCOE$ is the levelized cost per kWh of served energy. $E_{served,y}$ is total critical and applicable EV energy served in year y . LCC , Y , and r are defined above. This definition aligns the economic denominator with the actual service delivered by the system.

After hard feasibility screening, the deterministic candidates are ranked using normalized reliability, service, utilization, and cost indicators. The score mirrors the relative priorities used in the single-node optimizer.

$$S_{det} = 0.30S_C + 0.20S_L + 0.30S_R + 0.15S_{EV} + 0.05S_E \quad (36)$$

where S_{det} is the deterministic candidate score. S_C and S_L are the inverse-normalized LCC and LCOE scores. S_R is the **inverse-normalized annual energy-deficit score**. S_{EV} and S_E reward EV service and critical served energy. The score ranks feasible configurations; it does not permit a failed hard constraint to be offset by a favorable cost score.

3.5. Phase V: Robustness and Uncertainty Modeling

Correlated Monte Carlo assessment is the principal acceptance and redesign mechanism linking deterministic optimization to final design selection. Each nominal candidate is evaluated across the specified uncertainty model to estimate service and technical constraint-pass probabilities, downside energy, and upper-tail lifecycle cost. Candidates that fail an applicable probability threshold require redesign before economic ranking.

Convergence monitoring and sensitivity analysis support interpretation of these decisions, while the probabilistic results determine which service-track configurations proceed to digital-twin evaluation.

The probabilistic results quantify uncertainty within the specified model structure and input distributions. They do not independently validate the baseline wake coefficients in Table 3(b); the reported compliance probabilities remain conditional on this parameterization.

The uncertainty model groups the principal sources of variability that affect generation, service, communications, and cost. Individual distributions and correlation groups are defined in the uncertainty register.

$$U = [U_{resource}, U_{component}, U_{system}, U_{economic}] \quad (37)$$

where $U_{resource}$ groups traffic, ambient-wind, and vehicle-wake uncertainty. $U_{component}$ groups turbine, generator, converter, and battery uncertainty. U_{system} groups electrical-loss, availability, and RF-communication uncertainty. $U_{economic}$ groups CAPEX, O&M, replacement, and discount-rate uncertainty. This grouping provides a traceable link between uncertain inputs and reliability, energy, communication, and economic outputs.

Each candidate design is evaluated repeatedly using one sampled realization of the uncertain parameter vector. The deterministic system model is therefore treated as a mapping from design and uncertainty to outputs.

$$Y^{(m)} = \mathcal{M}(x, U^{(m)}), \quad m = 1, \dots, N_{MC} \quad (38)$$

where $Y^{(m)}$ is the output vector from Monte Carlo realization m . $\mathcal{M}$ is the complete energy, reliability, cost, and communication model. x is the candidate design vector. $U^{(m)}$ is the sampled uncertainty vector. N_{MC} is the number of Monte Carlo realizations. The final study uses the empirical output distributions rather than relying on a single nominal simulation.

Output percentile. Percentiles summarize the simulated output distribution and provide a consistent basis for reporting central and downside performance. The same definition is applied to energy and economic outputs.

$$P_q(Y) = Q_q(Y^{(1)}, Y^{(2)}, \dots, Y^{(N_{MC})}) \quad (39)$$

where $P_q(Y)$ is percentile q of output Y . $Q_q(\cdot)$ is the empirical quantile operator. $Y^{(m)}$ is the output in realization m . P50 is the median outcome; P90 cost is a high-cost risk case, whereas P10 served energy is used as a downside service indicator.

Robust feasibility is measured by the fraction of Monte Carlo realizations in which a mandatory constraint is satisfied. This converts deterministic acceptance into an explicit probability of compliance.

$$p_k = \frac{1}{N_{MC}} \sum_{m=1}^{N_{MC}} \mathbb{I}[g_k(Y^{(m)}) \leq 0] \quad (40)$$

where p_k is the probability estimate for satisfying constraint k . $g_k(Y) \leq 0$ defines the acceptable region for constraint k . $\mathbb{I}[\cdot]$ is the indicator function, equal to 1 when the condition is true and 0 otherwise. The pass probability distinguishes a design that barely passes in the nominal case from a design that remains feasible under input variability.

The reliability, EV-service, and communication requirements are enforced probabilistically. The required pass probabilities depend on the role and criticality of each metric.

$$p_{LLP} \geq 0.95, \quad p_{EV} \geq 0.90, \quad p_{PDR} \geq 0.95 \quad (41)$$

where $p_{LLP} = Pr(LLP_{crit} \leq 0.01)$ is the probability that a Monte Carlo realization satisfies the annual critical-energy adequacy constraint. It is estimated as the fraction of realizations in which unserved critical energy does not exceed 1% of annual critical energy demand. Thus, LLPcrit is an energy-deficit fraction within a realization, whereas pLLP is a compliance probability across realizations. Neither quantity represents the probability of a supply interruption in an individual hour. Similarly, $p_{EV} = Pr(EVSR \geq 0.90)$ applies to the EV-enabled track, and $p_{PDR} = Pr(PDR \geq 0.98)$ represents communication compliance. The required compliance probabilities are 0.95, 0.90, and 0.95, respectively. A candidate must satisfy every applicable probability threshold to qualify as robust.

Eligible designs are compared using reliability probability, EV-service probability, downside energy, lifecycle-cost risk, initial budget, asset complexity, and communication probability. The score is evaluated only after the mandatory gates are checked.

$$S_{rob} = \sum_{r=1}^7 w_r z_r, \quad \sum_{r=1}^7 w_r = 1 \quad (42)$$

where S_{rob} is the normalized robust score. z_r are the normalized metrics $[p_{LLP}, p_{EV}, S_{P90,LCC}, S_{P10,served}, S_{P50,CAPEX}, S_{complexity}, p_{PDR}]$. $w_r = [0.30, 0.20, 0.20, 0.10, 0.10, 0.05, 0.05]$ are the adopted metric weights. The economic and complexity terms are normalized so that lower cost or complexity

gives a higher score. The weighting places the greatest emphasis on **compliance with the annual critical-energy deficit limit**, followed by EV service and lifecycle-cost risk.

3.6. Phase VI: Digital-Twin, EMS, and IoT Modeling

The selected EV0-R1 and EV22-R1 configurations are carried into a multi-resolution digital twin. The twin evaluates energy dispatch, EMS policies, telemetry, communication quality, fault detection, repair response, maintenance risk, and operational KPI gates at **one-second, one-minute, and hourly resolutions**.

The digital twin stores the energy, storage, service, communication, and health variables required to describe one corridor cluster at time t . The vector is updated at the resolution of the selected simulation scale.

$$x_{c,t} = [E_{gen}, E_{crit}, E_{EV}, SOC, PDR, A_g, L_{95}, H, a]_{c,t} \quad (43)$$

where $x_{c,t}$ is the state of cluster c at time t . E_{gen} , E_{crit} , and E_{EV} are generation and service energies. SOC is battery state of charge. PDR , A_g , and L_{95} are **packet-delivery ratio**, gateway availability, and P95 latency. H is the asset-health index. a is the vector of active alarms and fault states. The state vector allows the twin to connect physical energy behavior with communication and maintenance performance.

The next digital state depends on the current state, the EMS action, and external disturbances. This generic transition encompasses the deterministic energy dispatch as well as communication and fault-state updates.

$$x_{t+1} = \mathcal{F}(x_t, u_t, w_t) \quad (44)$$

where $\mathcal{F}$ is the digital-twin transition function. x_t is the current corridor state. u_t is the control action selected by the EMS. w_t contains traffic, wind, load, communication, and fault disturbances. The equation separates physical state evolution from policy choice, allowing several EMS strategies to be compared using identical disturbances.

The EMS selects charging, discharging, load-priority, buffering, or resilience actions using the present state, predicted disturbances, and desired service references. Different policy mappings represent EMS-BASE, EMS-PRED, and EMS-RES.

$$u_t = \pi_p(x_t, \hat{w}_{t+1}, r_t) \quad (45)$$

where π_p is EMS policy p . $\hat{w}_{t+1}$ is the forecast or estimated next-step disturbance. r_t contains operational references, reserves, and service priorities. u_t is the resulting supervisory control action. The predictive policy uses future energy information, whereas the resilient policy gives greater priority to reserves, communications, and fault-tolerant operation.

IoT communication performance is quantified by the proportion of transmitted telemetry messages successfully received. Retransmissions and redundancy influence this value in the digital-twin simulation.

$$PDR = \frac{N_{received}}{N_{transmitted}} \quad (46)$$

where PDR is **packet-delivery ratio**. $N_{received}$ is the number of successfully received packets. $N_{transmitted}$ is the number of transmitted packets. PDR is a mandatory operational metric because unreliable telemetry can conceal energy stress or faults even when the physical energy system remains operational.

Gateway uptime and end-to-end delay are evaluated separately because a system may have high packet delivery but still respond too slowly to alarms or supervisory commands.

$$A_g = \frac{T_{online}}{T_{total}}, \quad L_{95} = Q_{0.95}(t_{received} - t_{sent}) \quad (47)$$

where A_g is gateway availability. T_{online} and T_{total} are online and observed durations. L_{95} is the 95th-percentile end-to-end latency. t_{sent} and $t_{received}$ are packet timestamps. The digital-twin gate requires high availability and bounded latency for both service tracks.

Fault performance is evaluated using detection coverage and the time required to restore or close detected events. These metrics connect monitoring accuracy to maintainability.

$$R_f = \frac{TP}{TP + FN}, \quad MTTR = \frac{1}{N_{rep}} \sum_{i=1}^{N_{rep}} (t_{repair,i} - t_{detect,i}) \quad (48)$$

where R_f is fault-detection recall. TP and FN are true-positive and false-negative fault counts. $MTTR$ is mean time to repair in h. N_{rep} is the number of repaired events. $t_{detect,i}$ and $t_{repair,i}$ are detection and repair timestamps. High recall reduces undetected faults, while low $MTTR$ reduces the duration and energy impact of known failures.

A numerical conservation check is applied to verify that generation, battery exchange, served energy, and spilled energy close over the simulated horizon. This is a validation metric rather than a design objective.

$$\varepsilon_E = \frac{|\sum_t (E_{gen,t} + E_{dis,t} - E_{ch,t} - E_{served,t} - E_{spill,t})|}{\sum_t E_{gen,t}} \quad (49)$$

where ε_E is normalized energy-balance error. $E_{gen,t}$ is generated energy. $E_{dis,t}$ and $E_{ch,t}$ are battery discharge and charge energies. $E_{served,t}$ is total served energy. $E_{spill,t}$ is unused surplus energy. A small value demonstrates that the time-step implementation does not create or destroy **energy** through numerical bookkeeping errors. A design-policy pair receives an operational conditional pass only when every applicable energy, storage, communication, fault, and numerical-validation KPI is satisfied.

$$k_{DT} \leq k_{lim} \quad (50)$$

where k_{DT} is the vector of digital-twin KPI results. k_{lim} contains the equivalent limits: $LLP \leq 0.01$, $EVSR \geq 0.90$ for EV22, $0.20 \leq SOC \leq 0.95$, $PDR \geq 0.98$, $A_g \geq 0.95$, $L_{95} \leq 5$ s, $R_f \geq 0.90$, $MTTR \leq 4$ h, and $\varepsilon_E \leq 0.001$. $\leq$ denotes satisfaction of the direction-specific upper and lower KPI limits. The conditional pass describes performance inside the digital-twin study and is not equivalent to measured field acceptance.

3.7. Integrated Optimization Statement

The complete research problem is a constrained multi-objective design task. A candidate must first satisfy the deterministic and robust technical constraints; feasible candidates are then compared according to reliability, service capability, lifecycle cost, asset complexity, and operational performance.

The selected system is obtained by searching the design space for configurations that jointly reduce economic and reliability penalties while increasing delivered service and communications performance. The design vector contains the physical, electrical, spatial, and control decisions varied across the implemented phases.

$$x_{opt} = \operatorname{argmin}_{x \in \mathcal{F}} J(x) \quad (51)$$

where x_{opt} is the selected feasible design. $J(x)$ combines LCC, LCOE, **energy-based critical LLP**, unmet EV service, communication risk, and asset complexity. $\mathcal{F}$ is the feasible set defined by the deterministic, robust, electrical, and digital-twin constraints. S is turbine or node spacing. d is lateral distance from the traffic lane. N_T is turbine count per node or cluster. E_{bat} is usable storage capacity. V_{bus} and A_{cable} are DC-bus voltage and cable area. L_g is gateway-sector length or communication spacing. p_{EMS} identifies the evaluated EMS policy. $C_{complexity}$ represents the maintenance and integration burden associated with total assets. The two final research recommendations, EV0-R1/EMS-PRED and EV22-R1/EMS-RES, correspond to different service tracks and therefore should not be interpreted as interchangeable alternatives.

4. Results

4.1. Corridor, Traffic, and Wind Resource Characterization

This section describes the reference corridor, traffic, and wind conditions used to generate the energy and optimization results. The values define a controlled simulation case. Scenario-based traffic, geometry, and wake parameters are distinguished from fixed computational settings.

4.1.1. Riyadh–Dammam Corridor and Traffic Characteristics

The Riyadh–Dammam highway was modeled as a 395 km intercity corridor divided into 395 energy clusters, each 1 km long. The reference roadway had two traffic lanes in each direction, a lane width of 3.65 m, and an initial turbine offset of 1 m from the traffic lane. These parameters provided a consistent spatial basis for scaling the single-node model to the full corridor.

Three traffic-demand scenarios were considered. The medium scenario, with 25,000 vehicles/day, was selected as the reference case. Low and peak demand corresponded to AADT values of 10,000 and 45,000 vehicles/day, respectively [58]. The hourly profile had a morning peak during 07:00–08:00 and a larger afternoon peak during 16:00–17:00, reaching approximately 2026 vehicles/h. Minimum modeled traffic occurred at 03:00, at approximately 152 vehicles/h.

The modeled traffic comprised passenger cars (72%), light commercial vehicles (13%), heavy goods vehicles (10%), and buses (5%). Their respective mean speeds were 115, 105, 85, and 90 km/h. Passenger cars accounted for most passing events. Heavy vehicles contributed fewer events but remained relevant because of their larger aerodynamic size and stronger assumed wakes.

The traffic and road values in Table 2 represent the controlled reference-synthetic case used by the computational model rather than a completed corridor-wide field survey. The model therefore supports comparative evaluation and sensitivity analysis, while the final deployment values would require official classified traffic counts and segment-specific geometric measurements.

Table 2. Main corridor, traffic, environmental, service, and simulation parameters used in the reference analysis.

Category	Parameter	Value	Unit/status
Corridor	Studied road	Riyadh–Dammam Highway	Reference case

Category	Parameter	Value	Unit/status
Corridor	Total modeled length	395	km
Deployment	Energy-cluster length	1	km
Deployment	Number of clusters	395	clusters
Road geometry	Lanes per direction	2	scenario
Road geometry	Lane width	3.65	m
Turbine placement	Lateral distance from lane	1.0	m, reference
Traffic	Low-demand scenario	10,000	vehicles/day
Traffic	Medium-demand scenario	25,000	vehicles/day; default
Traffic	Peak-demand scenario	45,000	vehicles/day
Traffic	Directional split	0.50	fraction
Environmental	Air density	1.074	kg/m ³
Environmental	Weibull shape parameter, (k)	2.0	dimensionless
Environmental	Weibull scale parameter, (c)	4.5	m/s
Simulation	Time resolution	1	h
Simulation	Annual time steps	8,760	h/year
Reliability	Maximum annual unserved critical-energy fraction (LLP)	0.01	fraction
EV service	Minimum EV service ratio	0.90	fraction

Note: The LLP limit of 0.01 corresponds to a maximum annual unserved critical-energy fraction of 1%. It does not specify the permitted fraction of hours with supply shortfalls.

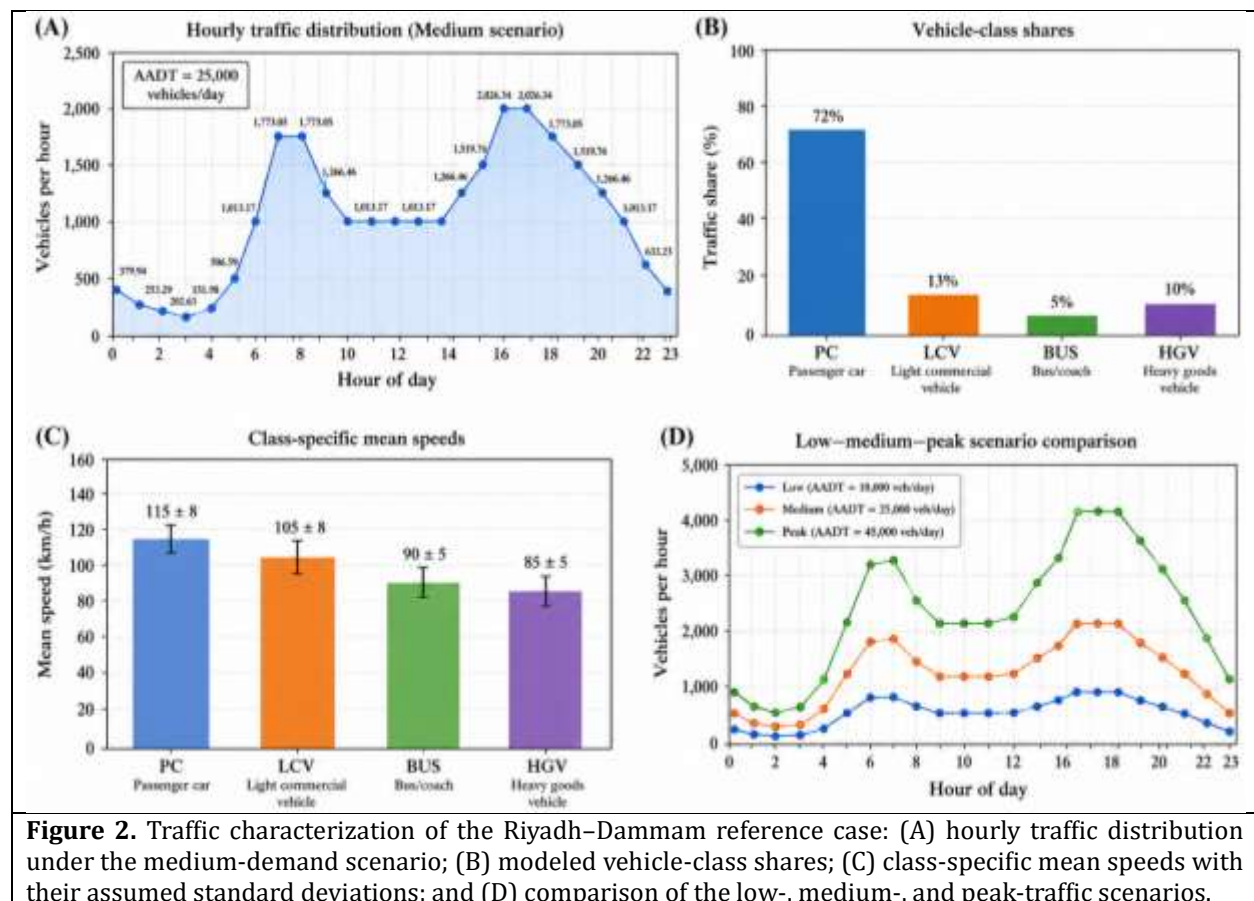


Figure 2. Traffic characterization of the Riyadh-Dammam reference case: (A) hourly traffic distribution under the medium-demand scenario; (B) modeled vehicle-class shares; (C) class-specific mean speeds with their assumed standard deviations; and (D) comparison of the low-, medium-, and peak-traffic scenarios.

4.1.2. Ambient and Vehicle-Induced Wind Characteristics

Ambient wind was modeled using a two-parameter Weibull distribution with $k = 2.0$ and $c = 4.5$ m/s. Seasonal and diurnal factors modulated a reproducible 8,760-hour wind sequence. This profile represented ambient inflow before the addition of short-duration wake pulses from passing vehicles.

Under the baseline coefficients in Table 3(b), Equation (6) gives peak induced speeds of 2.56, 3.21, 4.50, and 5.19 m/s at a 1 m offset for passenger cars, light commercial vehicles, buses, and heavy goods vehicles, respectively. At a 3 m offset, the corresponding model outputs are 0.68, 0.86, 1.20, and 1.39 m/s. These values are calculated scenario outputs; their decrease with offset follows the prescribed attenuation exponent [59].

The ambient contribution is retained as the reference generation component, and vehicle-induced energy is evaluated as the incremental output during each modeled event. This formulation avoids counting the ambient baseline twice. The class ranking and distance response should be interpreted within the reduced-order model described in Section 3.2.2.

Table 3 separates the published evidence supporting the modeling approach from the numerical assumptions used to generate the reference case. Quantitative transfer to the Riyadh–Dammam corridor requires matched observations of vehicle speed, lateral position, measurement height, and transient airflow. The reported resource and downstream system results remain conditional on the baseline wake parameterization.

Table 3. Literature basis and baseline inputs for the vehicle-induced wake model: (a) published evidence and limits of transfer; (b) prescribed reference-scenario parameters.

(a) Published evidence and limits of transfer

Study	Published evidence	Use in this study	Limit of transfer
Tian et al. [55], 2017	Car speeds: 15–30 m/s; body-to-rotor gaps: 0.5–2.0 m (Table 2).	Supports explicit speed and clearance dependence.	Does not establish the four class-specific (β_j) values or ($m_j=1.20$).
Bani-Hani et al. [56], 2018	Reported mean winds of 4.6 and 5.6 m/s on the two highway sides at 1.5 m measurement height (Table 2 and accompanying text).	Regional field evidence for roadside airflow magnitude.	Height is not lateral offset; these means are not HGV-specific peak measurements.
Miller et al. [57], 2019	Measured turbulence varies with vehicle class, height, and downstream distance.	Supports class dependence and spatially varying wake behavior.	Downstream TKE decay is not the lateral peak-speed law in Equation (6).
Ulus and Moldovan [30], 2025	Vehicle translation speed: 32 m/s; transient run: 7 s; car/bus response histories (Table 6; Section 5; Figures 8–9).	Supports event-resolved modeling and vehicle-geometry dependence.	Total run length and turbine-power histories do not directly determine (τ_j).

(b) Prescribed reference-scenario parameters

Vehicle class	Traffic share (%)	Mean speed (km/h)	Speed SD (km/h)	(β_j) at ($d_0 = 1$ m)	Lateral exponent (m_j)	Decay time constant (τ_j) (s)
Passenger car (PC)	72	115	8	0.08	1.20	1.50
Light commercial vehicle (LCV)	13	105	8	0.11	1.20	1.80
Bus/coach (BUS)	5	90	5	0.18	1.20	2.50
Heavy goods vehicle (HGV)	10	85	5	0.22	1.20	3.00

Notes: Table 3(a) documents supporting literature; Table 3(b) preserves the reference-scenario inputs. No reviewed source directly substantiates the complete numerical set of (β_j), (m_j), and (τ_j) in Table 3(b). The class shares, vehicle-speed statistics, and wake coefficients are scenario inputs, not a classified traffic survey or a fitted roadside-flow dataset. Ambient assumptions remain: air density 1.074 kg/m³, Weibull shape ($k=2.0$), and scale ($c=4.5$) m/s. The evaluated lateral offsets are 1, 2, and 3 m. The literature comparisons do not calibrate these ambient-wind parameters.

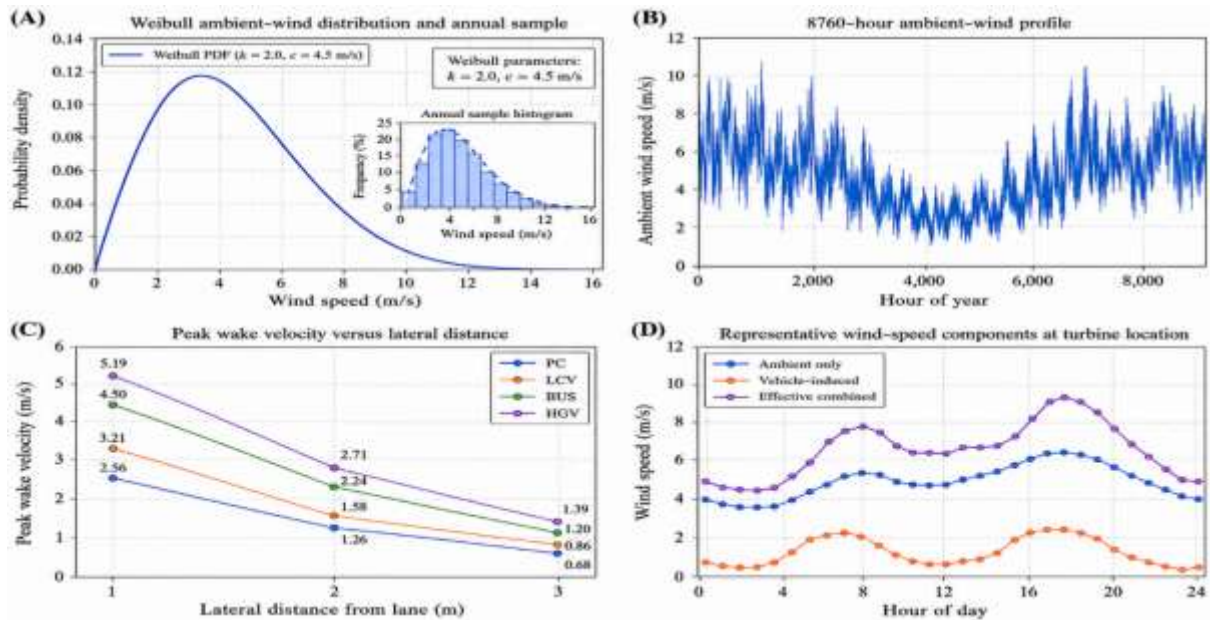


Figure 3. Reference-scenario wind-resource and vehicle-wake characterization: (A) prescribed Weibull ambient-wind distribution and generated annual sample; (B) synthetic **8,760-hour** ambient-wind profile; (C) calculated class-specific peak wake speeds at the evaluated lateral offsets using Equation (6) and Table 3(b); and (D) illustrative ambient, wake, and effective inflow profiles using Equations (7)–(8). The wake curves represent model outputs under the stated assumptions.

4.2. Single-Node Wind-Energy Conversion Results

The single-node analysis evaluated the conversion of ambient and vehicle-induced airflow into usable electrical energy before full-corridor scaling. Candidate turbine topologies were compared using common assumptions for wind, traffic, siting, generators, and power electronics. The selected conversion train was then coupled with battery dispatch to evaluate critical-load service, storage performance, and annual energy adequacy.

4.2.1. Turbine and Electrical-Conversion Performance

The principal turbine topologies were evaluated at a 5-kW reference rating with one turbine located 1 m from the traffic lane to allow for a consistent comparison. All configurations used a 94% efficient PMSG model followed by a 96% efficient rectifier and a 95% efficient wind MPPT, corresponding to a combined downstream conversion efficiency of 91.2%. The scaled turbine library specified rated electrical power, swept area, C_p , and cut-in/cut-out limits. A separate rated wind-speed parameter was not specified, as the modeled output was capped directly at the rated power.

Table 4. Performance and electrical characteristics of the investigated turbine-generator configurations.

Turbine topology	Rated power (kW)	Swept area (m ²)	$C_{p,max}$	Cut-in/cut-out (m/s)	Ambient AEP (kWh/year)	Vehicle-induced AEP (kWh/year)	Net DC AEP (kWh/year)	Vehicle share (%)
H-Darrieus VAWT	5.0	18.75	0.35	3.5/20	2839.60	202.22	3041.82	6.65
Helical Darrieus VAWT	5.0	18.75	0.32	2.5/20	2725.25	184.89	2910.14	6.35
Hybrid Savonius-Darrieus	5.0	18.75	0.28	2.0/20	2382.94	160.04	2542.98	6.29
Savonius VAWT	5.0	24.00	0.18	2.0/20	1964.91	131.69	2096.59	6.28

Note: All configurations use the GEN-PMSG-1000L generator model with five parallel 1 kW units, together with five PE-RECT-1K rectifiers and five PE-MPPT-1K converters. The reported AEP is the reference-synthetic output after generator, rectifier, and MPPT conversion losses.

The H-Darrieus configuration produced the highest annual net energy output, at 3041.82 kWh/year. Ambient wind contributed 2839.60 kWh/year, while vehicle wakes added 202.22 kWh/year, or 6.65% of the total. The Savonius and hybrid designs had lower cut-in speeds, but their lower power coefficients resulted in lower annual output. The 5 kW H-Darrieus configuration was therefore retained for battery and dispatch analysis.

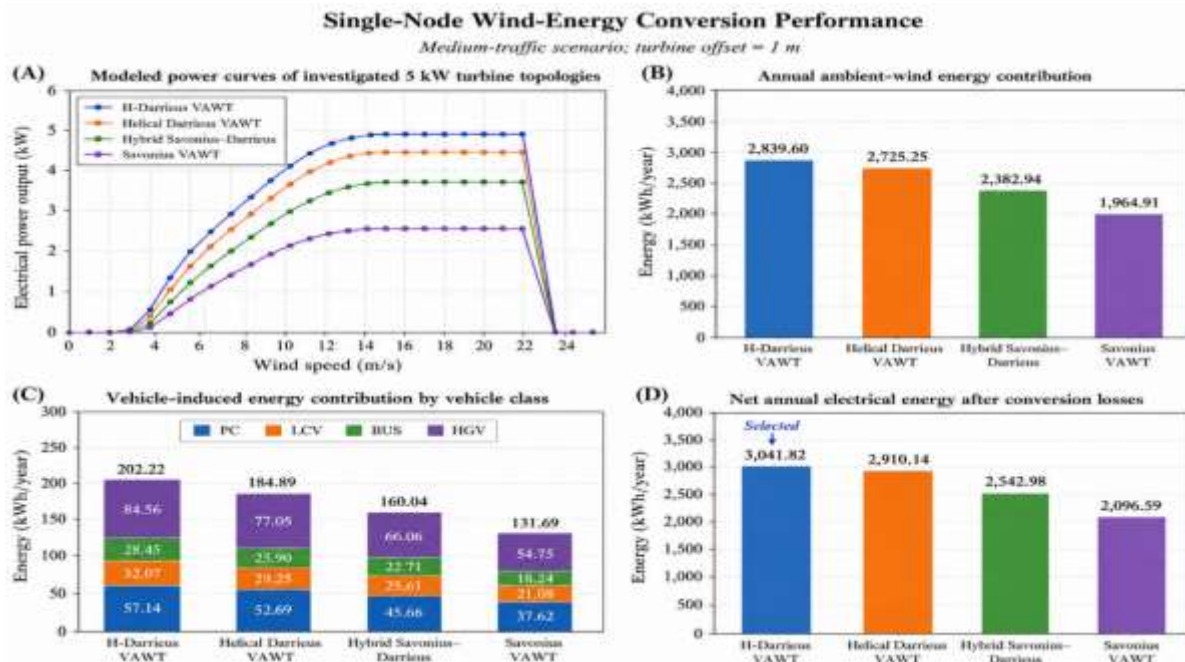


Figure 4. Single-node wind-energy conversion performance under the medium-traffic scenario and a 1 m turbine offset: (A) modeled power curves of the investigated 5 kW turbine topologies; (B) annual ambient-wind energy contribution; (C) class-resolved vehicle-induced energy contribution; and (D) net annual electrical energy after generator, rectifier, and MPPT conversion losses.

The retained configuration connected one 5 kW H-Darrieus turbine to the 48 V DC bus through the scaled PMSG-rectifier-MPPT chain. The parallel 1 kW components served as screening surrogates [60]. Final implementation would require a matched 5 kW generator, rectifier, and MPPT set supported by verified manufacturer data.

4.2.2. Battery and Energy Dispatch Performance

Battery options were assessed with the turbine and electrical-conversion system fixed and with no EV charging demand. Annual generation was 3041.82 kWh, compared with critical demand of 1434.93 kWh. Every configuration in Table 5 supplied the full critical-energy demand. Storage selection therefore depended on SOC margin, component count, and lifecycle cost [61].

Table 5. Battery-storage and dispatch results for the feasible single-node configurations.

Battery bank	Units layout /	Usable storage (kWh)	Cont. power (kW)	Energy-based critical LLP	Min. SOC (%)	Mean SOC (%)	Spilled energy (kWh/year)	Total LCC (SAR)	Decision
51.2 V-100 Ah LiFePO ₄	1; 1S × 1P	4.096	2.56	0.000	22.24	84.70	1561.79	104,724.74	Selected
25.6 V-200 Ah LiFePO ₄	2; 2S × 1P	8.192	5.12	0.000	58.62	89.84	1560.10	116,939.45	Feasible; larger storage
12.8 V-200 Ah LiFePO ₄	4; 4S × 1P	8.192	5.12	0.000	58.62	89.84	1560.10	118,996.67	Feasible; higher unit count

Note: All rows use the selected 5 kW H-Darrieus conversion train, the S0 reference load profile, and the EVO service case. The simulated annual generation and critical demand were fixed at 3041.82 and 1434.93 kWh/year, respectively. LLP denotes the ratio of annual unserved critical energy to annual critical energy

demand. Values marked (%) express this ratio as a percentage. LLP does not represent the fraction of hours with supply shortfalls or the frequency of interruption events.

The 51.2 V–100 Ah LiFePO₄ bank was selected as the lowest-cost feasible configuration. It maintained SOC between 22.24% and the imposed upper limit of 95%, supplied all critical energy in the reference-synthetic annual simulation, and required one battery unit. Doubling usable storage raised minimum SOC to 58.62% but provided no additional critical-energy service. It also increased lifecycle cost by more than 12,000 SAR. The reference node comprised one 5 kW H-Darrieus VAWT, one scaled PMSG–rectifier–MPPT conversion chain, and one 51.2 V–100 Ah LiFePO₄ battery. It provided the baseline for reliability-constrained design comparison and full-corridor scaling. Its reported performance represents reference-synthetic screening and requires component-level verification.

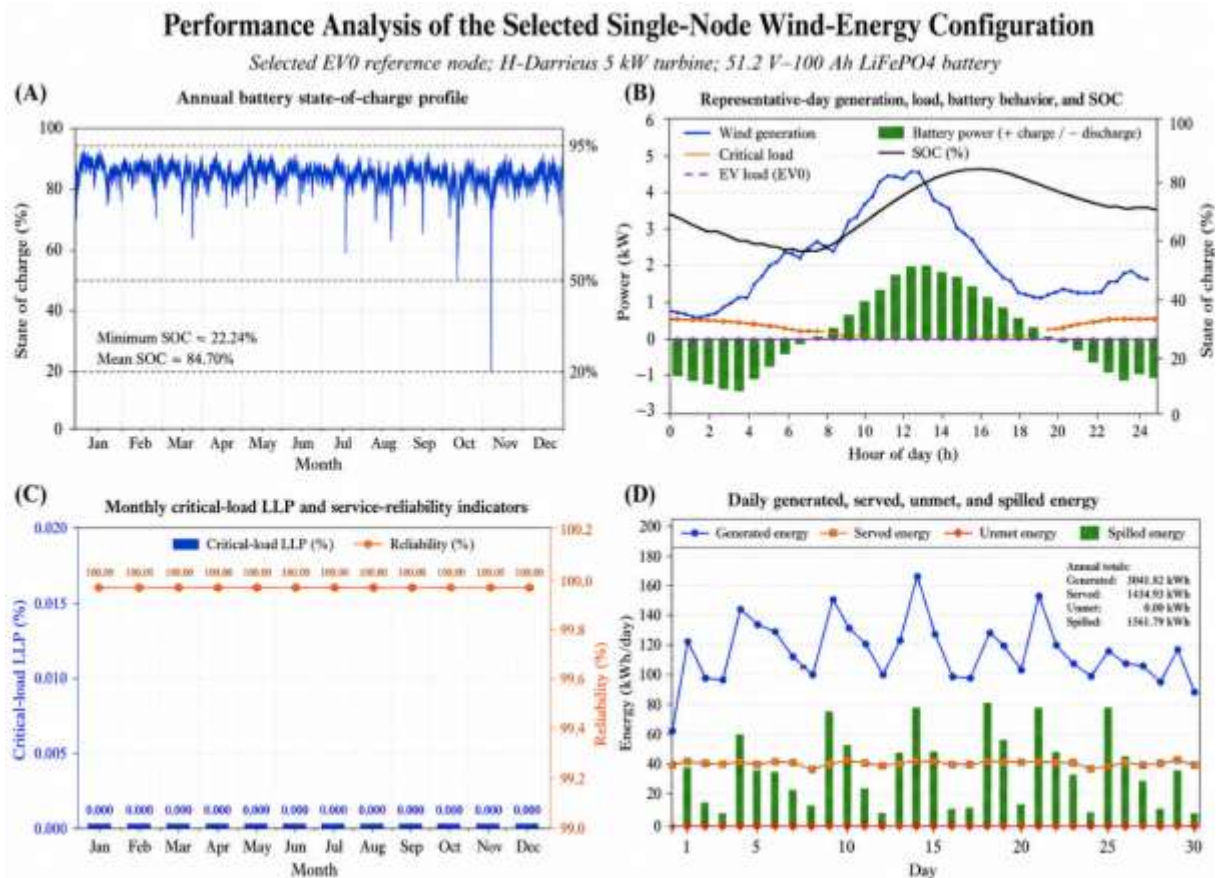


Figure 5. Performance analysis of the selected single-node wind-energy configuration: (A) annual battery state-of-charge profile; (B) representative-day wind generation, critical load, EV load—zero for the selected EV0 reference case—battery charging/discharging behavior, and SOC; (C) monthly energy-based critical-load LLP and served-critical-energy fractions; and (D) daily generated, served, unmet, and spilled energy. In panel (C), LLP refers to the energy-deficit fraction for the reported month; “Reliability (%)” denotes the corresponding served-critical-energy percentage, not the percentage of interruption-free hours.

4.3. Reliability-Constrained Single-Node Design Selection

Single-node optimization evaluated 3840 combinations of four EV-service tiers, load strategies, turbine counts and spacing, and battery configurations. Each candidate was assessed using the complete hourly energy balance before economic ranking. Only configurations satisfying the service and component constraints proceeded to cost comparison.

4.3.1. Feasibility Screening

A candidate was retained if its annual unserved critical-energy fraction (LLP) did not exceed 1%, its EV service ratio reached at least 90% for EV-enabled cases, and its generator, BMS, inverter, and EVSE were electrically

compatible. Hourly dispatch enforced battery charging and discharging power limits and the 20–95% SOC operating range. Insufficient storage or discharge capacity therefore increased LLP or reduced EV service. Table 6 summarizes the screening results. The EV0 tier retained 480 feasible configurations, while the more demanding EV22 tier retained 288. No feasible configurations were found for the 50- and 150-kW charging tiers because the evaluated generation, storage, and compatible EVSE options could not meet the minimum EV-service requirement.

Table 6. Feasibility screening of the investigated single-node alternatives.

EV-service tier	Tested cases	Feasible cases	Annual energy-deficit constraint violations	EV-service failures	SOC-specific failures	Component-incompatibility cases	Overall screening outcome
EV0: critical loads only	960	480	0	N/A	0	480	Feasible alternatives retained
EV22: 22 kW charging	960	288	200	444	0	480	Feasible alternatives retained
EV50: 50 kW charging	960	0	200	960	0	960	Excluded due to EV service and component incompatibility
EV150: 150 kW charging	960	0	200	960	0	960	Excluded due to EV service and component incompatibility

Note: Failure counts are non-exclusive because one configuration may violate more than one constraint. No candidate was classified separately as “Excluded due to SOC” because the dispatch algorithm enforced the SOC limits directly; storage inadequacy was reflected in LLP or EV-service performance. Annual energy-deficit constraint violations count configurations for which the annual unserved critical-energy fraction exceeds 0.01; they do not count interruption events.

The results indicate that a relatively small node can supply critical roadside loads under the modeled conditions. The 22 kW charging tier was also feasible but required substantially greater turbine and battery capacity. The best EV50 and EV150 alternatives supplied only 80.89% and 29.70% of requested charging energy, respectively, below the 90% requirement.

4.3.2. Reliability versus Cost Trade-Off

Economic ranking followed mandatory constraint screening. The multicriteria score for feasible configurations combined lifecycle cost, LCOE, energy-based critical-load LLP, EV service, and served critical energy. Candidates that failed a mandatory reliability, service, or component-compatibility requirement were excluded regardless of cost.

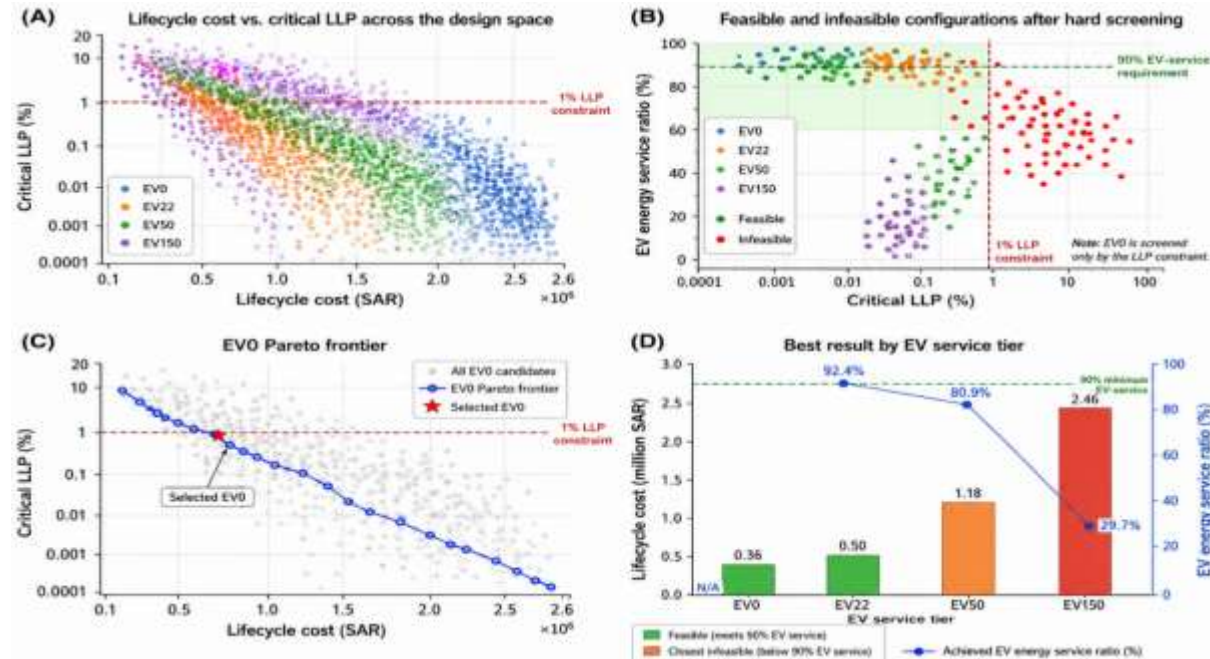


Figure 6. Reliability-constrained selection of the investigated single-node configurations: **(A)** relationship between lifecycle cost and **energy-based critical-load LLP** across the complete design space; **(B)** separation of feasible and infeasible configurations after applying the mandatory technical constraints; **(C)** **lifecycle-cost-energy-deficit Pareto frontier** for the EV0 critical-load service track; and **(D)** lifecycle cost and achieved EV service ratio of the best feasible—or closest infeasible—configuration at each charging tier. **LLP in the graphic denotes the energy-based critical-load index defined in Equation (22).**

Figure 6A–B separates configurations that satisfy the LLP and service constraints from lower-cost but technically inadequate alternatives. Figure 6C identifies the non-dominated EV0 solutions, while Figure 6D shows that only the EV0 and EV22 tiers cross the applicable service threshold. The optimization therefore retained the lowest-cost feasible solution within each valid service tier rather than the lowest-cost solution across the unrestricted design space.

Table 7. Selected single-node configuration by service tier.

EV tier	Load mode	Turbine configuration	Battery configuration	Usable storage (kWh)	Battery power (kW)	Energy-based critical LLP (%)	EV service ratio (%)	Min. SOC (%)	Lifecycle cost (SAR)	Selection status
EV0	S0	1 $\times$ 5 kW H-Darrieus VAWT	1 $\times$ 51.2 V–100 Ah LiFePO ₄	4.096	2.56	0.000	N/A	22.24	104,724.74	Feasible—retained
EV22	S0	4 $\times$ 5 kW H-Darrieus VAWTs	10 $\times$ 25.6 V–200 Ah LiFePO ₄ ; 2S $\times$ 5P	40.960	25.60	0.022	92.43	20.00	504,101.65	Feasible—retained
EV50	S2	6 $\times$ 5 kW H-Darrieus VAWTs	40 $\times$ 25.6 V–200 Ah LiFePO ₄ ; 2S $\times$ 20P	163.840	102.40	$\approx$ 0.000	80.89	20.00	1,181,000.63	Closest infeasible—aggregation required
EV150	S2	6 $\times$ 5 kW H-Darrieus VAWTs	114 $\times$ 25.6 V–200 Ah LiFePO ₄ ; 2S $\times$ 45P	466.940	291.84	$\approx$ 0.000	29.70	20.00	2,459,373.19	Closest infeasible—aggregation required

Note: LLP denotes the ratio of annual unserved critical energy to annual critical energy demand. Values marked (%) express this ratio as a percentage. LLP does not represent the fraction of hours with supply shortfalls or the frequency of interruption events.

The EV0 configuration was retained as the reference node for critical roadside loads, while the EV22 configuration was retained as the feasible EV-enabled node. These two alternatives were carried forward as separate service-track inputs to the full-corridor optimization. The EV50 and EV150 tiers were not transferred as independent single-node designs because they require multi-node aggregation, cluster-level storage, or an additional energy source.

4.3.3. Final Reference-Node Configuration

The lowest-lifecycle-cost configuration satisfying the critical-load requirements was selected as the reference node. It comprised a single 5 kW H-Darrieus VAWT, a PMSG-based conversion stage, rectification, wind MPPT control, and a 48/51.2 V DC bus. Storage consisted of a 51.2 V–100 Ah LiFePO₄ battery pack with 4.096 kWh usable capacity, supported by a suitable BMS and a 5-kW inverter. In the reference-synthetic simulation, the node generated 3041.82 kWh/year and supplied the full annual critical demand of 1434.93 kWh.

Table 8 summarizes the physical, electrical, storage, load, sensing, and communication components retained for the reference node. Parallel 1 kW modules represented the generator, rectifier, and MPPT stages, providing an equivalent 5 kW conversion capacity. A manufacturer-matched 5 kW drivetrain set is required for implementation while retaining the selected functional architecture.

Table 8. Final selected single-pole configuration of the reference roadside wind-energy node.

Component	Final selected configuration
Wind turbine	1 × 5 kW H-Darrieus VAWT
Turbine location	Roadside/median installation at a 1 m reference lateral offset
Generator stage	PMSG; 5 × 1 kW screening modules, equivalent to 5 kW
Rectifier stage	5 × 1 kW three-phase rectifier modules
Wind MPPT stage	5 × 1 kW wind MPPT modules
Local DC bus	48/51.2 V DC
Battery technology	LiFePO ₄
Battery configuration	1 × 51.2 V–100 Ah battery
Nominal battery energy	5.12 kWh
Usable battery energy	4.096 kWh
Continuous battery power	2.56 kW
BMS	LiFePO ₄ -compatible BMS with current and temperature monitoring
Inverter/load interface	1 × 5 kW bidirectional inverter and protected critical-load interface
Load strategy	S0 reference critical-load profile
EV service	EV0; no EV charging demand at the reference node
Daily critical-load energy	3.931 kWh/day
Annual critical-load energy	1434.93 kWh/year
Annual generated energy	3041.82 kWh/year
Energy-based critical-load LLP	0.000%
Minimum/mean SOC	22.24% / 84.70%
Local controller	Industrial local acquisition, dispatch, and protection controller
IoT edge gateway	Raspberry Pi/industrial edge-gateway equivalent
Communication interface	4G/LTE and MQTT-based communication
Sensors	Voltage, current, wind speed, temperature, and vibration sensors

Note: LLP denotes the ratio of annual unserved critical energy to annual critical energy demand. Values marked (%) express this ratio as a percentage. LLP does not represent the fraction of hours with supply shortfalls or the frequency of interruption events.

The corresponding physical arrangement and hardware interconnection are illustrated in Figure 7. Figure 7a presents the turbine, conversion cabinet, battery, sensing units, controller, and IoT gateway as an integrated roadside installation. Figure 7b shows the associated power path from the ambient and vehicle-induced airflow to the critical loads, together with the sensor-data, cloud-communication, and supervisory-control paths. This architecture forms the repeatable reference node subsequently scaled to the complete Riyadh–Dammam corridor.

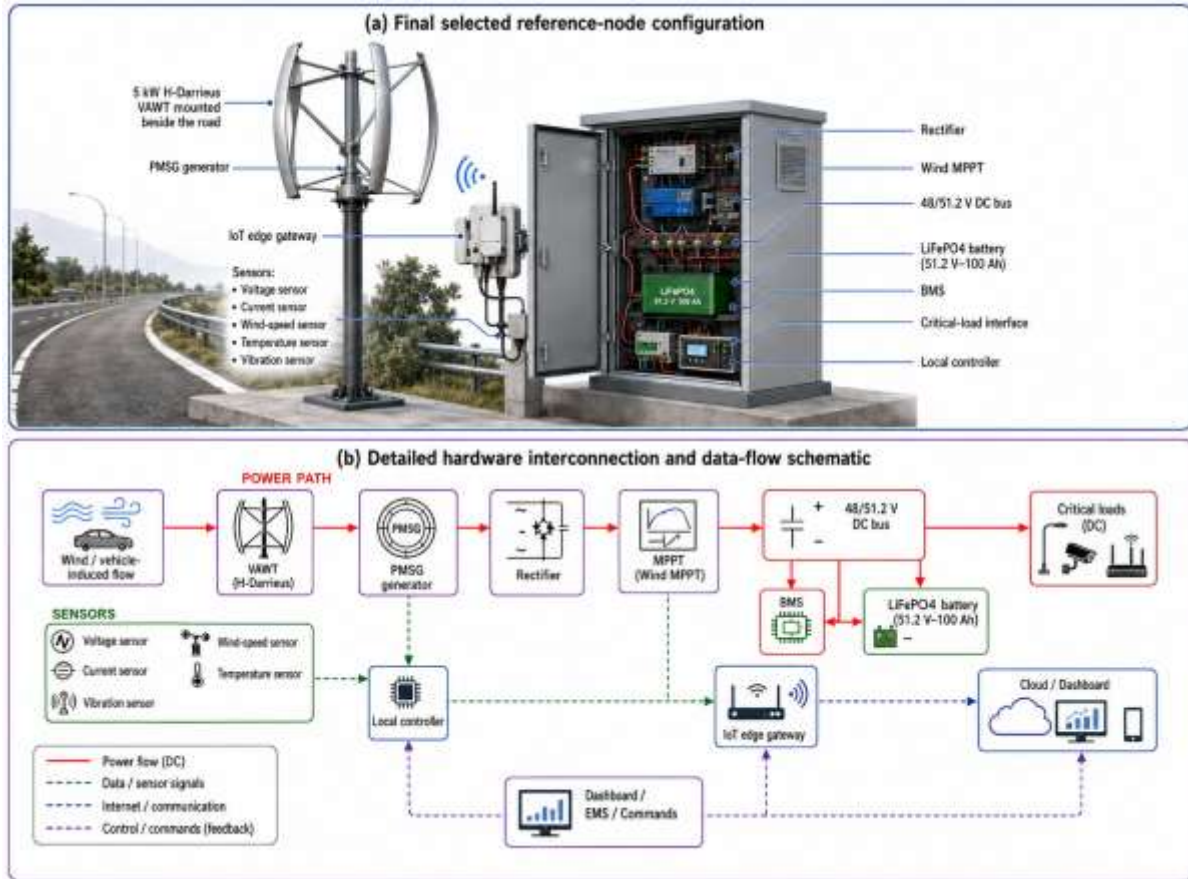


Figure 7. Reference-node architecture: (a) physical arrangement of the 5 kW H-Darrieus turbine, conversion stage, DC bus, LiFePO₄ battery, BMS, critical-load interface, sensors, controller, and IoT gateway; and (b) power and data connections, including rectification, wind MPPT, cloud communication, and EMS supervisory feedback.

4.4. Full-Corridor Design and Techno-Economic Results

The reference node selected through reliability screening was scaled to the 395 km Riyadh–Dammam corridor. The turbine and local conversion components from Section 4.3 were retained. Corridor-level variables included turbine density, cluster configuration, storage distribution, collection-bus voltage, conductor size, gateway coverage, and service level. The deterministic deployment analysis used 395 one-kilometer energy clusters grouped into eight macro-segments.

4.4.1. Corridor Deployment Architecture

Three deterministic configurations were compared: the initial corridor baseline, the critical-only candidate CAND-EV0, and the EV-enabled candidate CAND-EV22. Reducing turbine density from four to two per km yielded 790 turbines for CAND-EV0. CAND-EV22 required eight turbines per km, totaling 3160 turbines (Table 9). Local 48 V node buses fed the 380 V DC collection architecture. All configurations used 395 clusters.

Table 9. Deterministic full-corridor deployment alternatives derived from the selected reference-node architecture.

Parameter	Baseline	CAND-EV0	CAND-EV22
Service track	Critical only	Critical only	Critical + EV22
Cluster length (km)	1	1	1
Number of clusters	395	395	395
Turbines per cluster	4	2	8
Turbine spacing (m)	250	500	125
Total turbines	1580	790	3160
Road rated capacity (MW)	7.90	3.95	15.80
Battery units per cluster	3	2	8

Parameter	Baseline	CAND-EV0	CAND-EV22
Total battery units	1185	790	3160
Storage architecture	Cluster-centralized	Distributed	Distributed
Local / collection DC bus	48 / 380 V	48 / 380 V	48 / 380 V
Gateway coverage (km)	5	5	5
Number of gateways	79	79	79
Load strategy	S0	S1	S0
Deterministic status	Reference baseline	Feasible optimum	Feasible optimum

Figure 8 shows the corridor architecture. Generation and storage are organized into repeating one-kilometer clusters. Turbine outputs are conditioned at the low-voltage DC level and connected to the 380 V collection bus. Sector gateways link groups of clusters to the supervisory platform. This arrangement connects the single-node design with the subsequent electrical, economic, and digital-twin analyses.

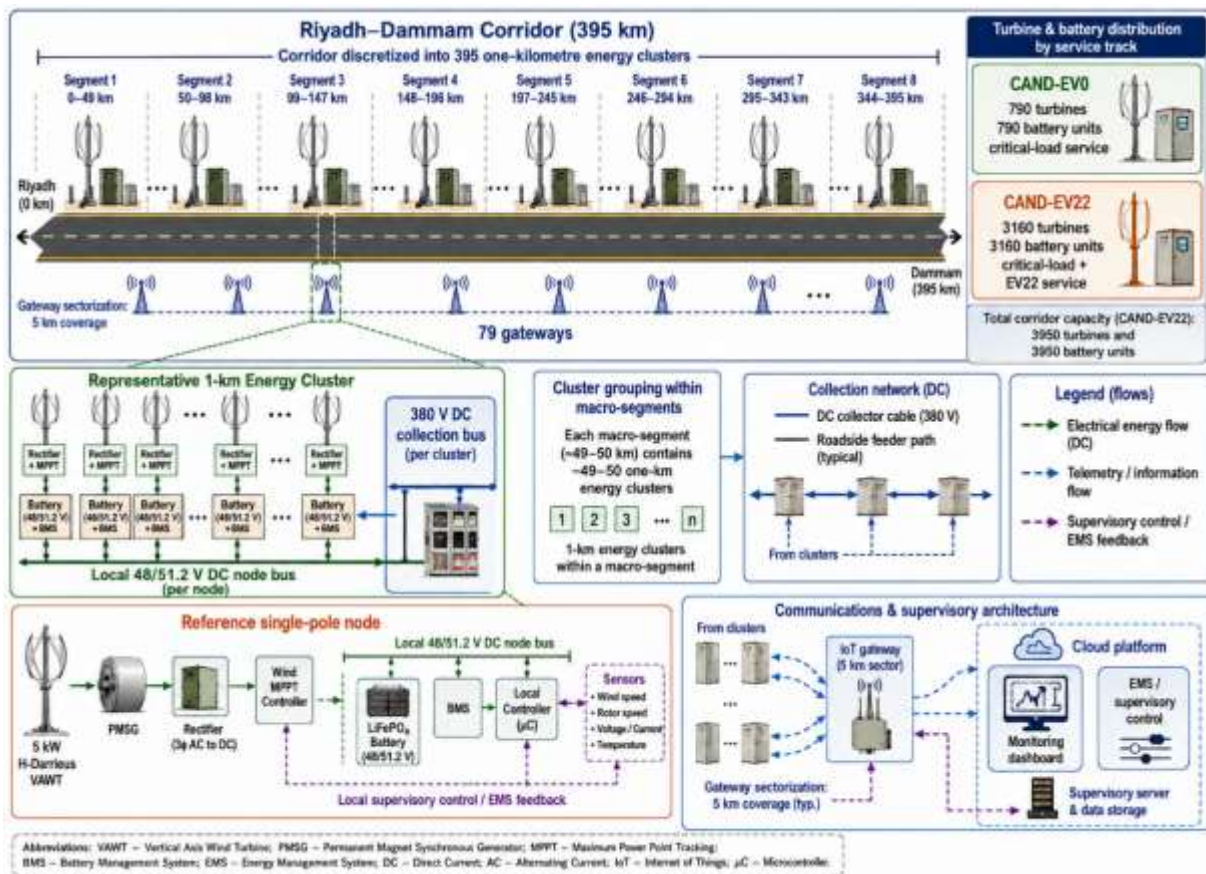


Figure 8. Full-corridor deployment architecture of the proposed roadside wind-energy system along the Riyadh–Dammam highway, showing the eight macro-segments, one-kilometer energy clusters, turbine and battery distribution, local-to-collection DC-bus hierarchy, gateway sectorization, electrical collection network, and the associated energy and information flows.

4.4.2. Electrical Losses and Cable Sizing

Conductor sizing depended on deployment power density and the allowable electrical loss. The 380 V collection bus was retained to limit feeder current, and conductor area was selected subject to a maximum rated loss of 5%. Table 10 summarizes the deterministic screening results. CAND-EV0 satisfied the constraint with a 35 mm² conductor and approximately 2.08% rated loss. The higher-power CAND-EV22 design required a 70 mm² conductor, with approximately 4.16% rated loss.

Table 10. Cable-sizing and electrical-loss comparison for the deterministic corridor configurations.

Configuration	Collection bus (V DC)	Conductor area (mm ²)	Rated cable loss (%)	Installed cable cost (SAR/m)	Approx. road collection-cable CAPEX (M SAR)	Electrical status
Baseline	380	35	4.155	80	9.48	Pass
CAND-EV0	380	35	2.078	80	9.48	Pass
CAND-EV22	380	70	4.155	160	18.96	Pass

Note: The cable CAPEX values are screening estimates based on a 300 m one-way collection route per cluster and the installed cable-cost assumptions used by the deterministic optimizer. The model treats the cluster collection conductor as the governing feeder at this stage; a separate corridor-length main feeder is not claimed as an independently sized circuit. The cable-cost scaling and loss calculations were explicitly incorporated into the corridor cost model.

As illustrated in Figure 9, increasing the conductor cross-section progressively reduces resistive loss but increases cable investment. Consequently, conductor selection was treated as a constrained trade-off rather than simply choosing the largest available cable.

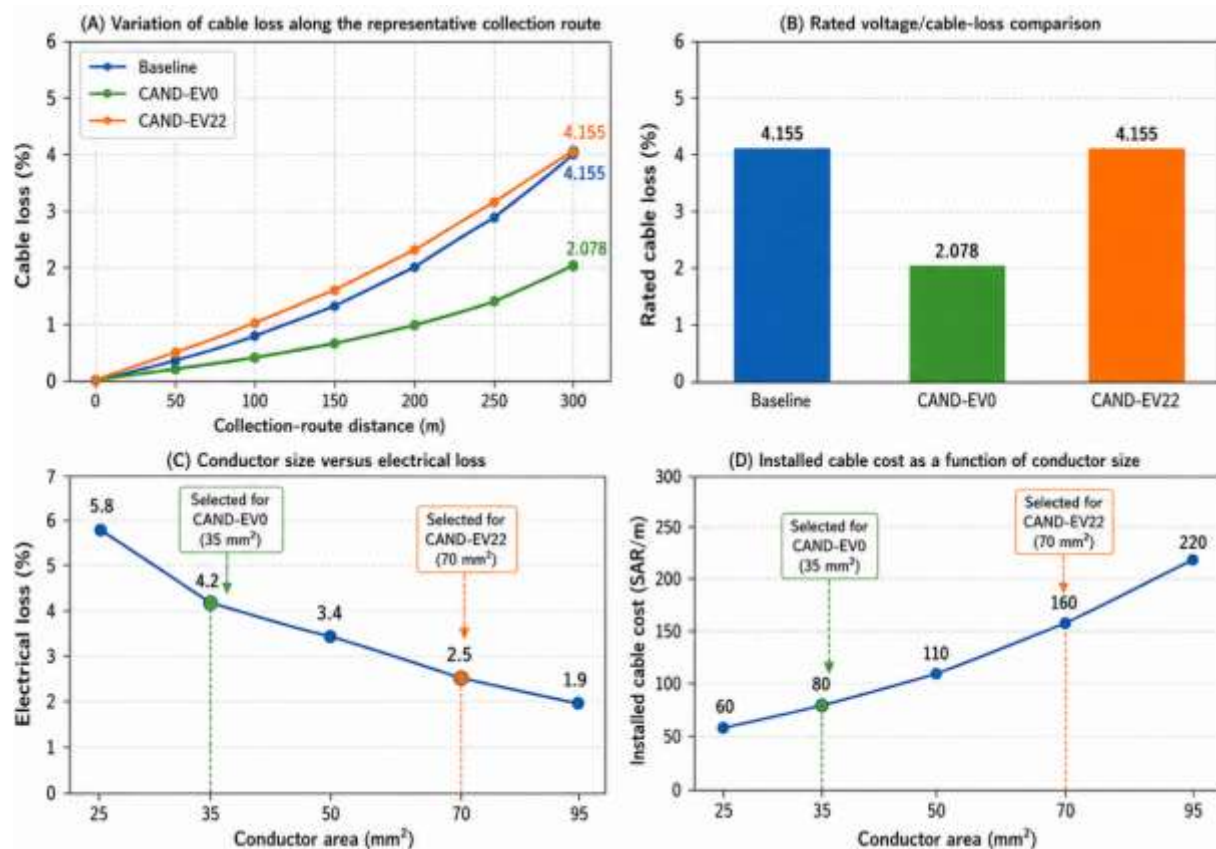


Figure 9. Electrical collection and cable-sizing results for the full-corridor configurations: (A) variation of cable loss along the representative collection route; (B) comparison of rated voltage/cable losses for the evaluated service tracks; (C) relationship between conductor cross-sectional area and electrical loss; and (D) installed cable cost as a function of conductor size.

4.4.3. Techno-Economic Assessment

The deterministic techno-economic analysis included the generation hardware, batteries and BMS units, local control and sensing equipment, DC/DC stages, collection cables, cluster cabinets, gateways, civil works, installation, annual O&M, and discounted battery replacements. Annual O&M was modeled as 3% of initial CAPEX and the battery/BMS replacement costs were discounted at years 10 and 20 over the 25-year study horizon.

Table 11 compares the deterministic economic results. CAND-EV0 achieved a lifecycle cost of 152.47 million SAR and the lowest LCOE, at 6.47 SAR/kWh served. CAND-EV22 required 3160 turbines and a lifecycle cost of 534.80 million SAR. This larger configuration supported the additional 22 kW charging service with a deterministic EV service ratio of 98.39%.

Table 11. Deterministic techno-economic comparison of the principal full-corridor service-track alternatives.

Economic indicator	Baseline	CAND-EV0	CAND-EV22
Initial CAPEX (M SAR)	185.78	106.03	369.86
Annual O&M (M SAR/year)	5.57	3.18	11.10
PV of battery/BMS replacements (M SAR)	8.66	5.77	23.10
Lifecycle cost (M SAR)	265.69	152.47	534.80
LCOE (SAR/kWh served)	9.17	6.47	7.76
Annual served energy (GWh/year)	2.267	1.842	5.388
Energy-based critical LLP (%)	0.000	0.518	0.000
EV service ratio (%)	N/A	N/A	98.39
LCC per corridor kilometer (M SAR/km)	0.673	0.386	1.354
LCC per turbine (kSAR/turbine)	168.2	193.0	169.2
Deterministic decision	Reference	Feasible EV0 optimum	Feasible EV22 optimum

Note: LLP denotes the ratio of annual unserved critical energy to annual critical energy demand. Values marked (%) express this ratio as a percentage. LLP does not represent the fraction of hours with supply shortfalls or the frequency of interruption events.

The two designs serve different objectives. CAND-EV0 reduces infrastructure scale and lifecycle cost for critical-only service. CAND-EV22 requires approximately four times as many turbines and battery units to support additional EV charging. Figure 10 compares their capital-cost structure, annual energy delivery, lifecycle-cost components, and normalized corridor costs.

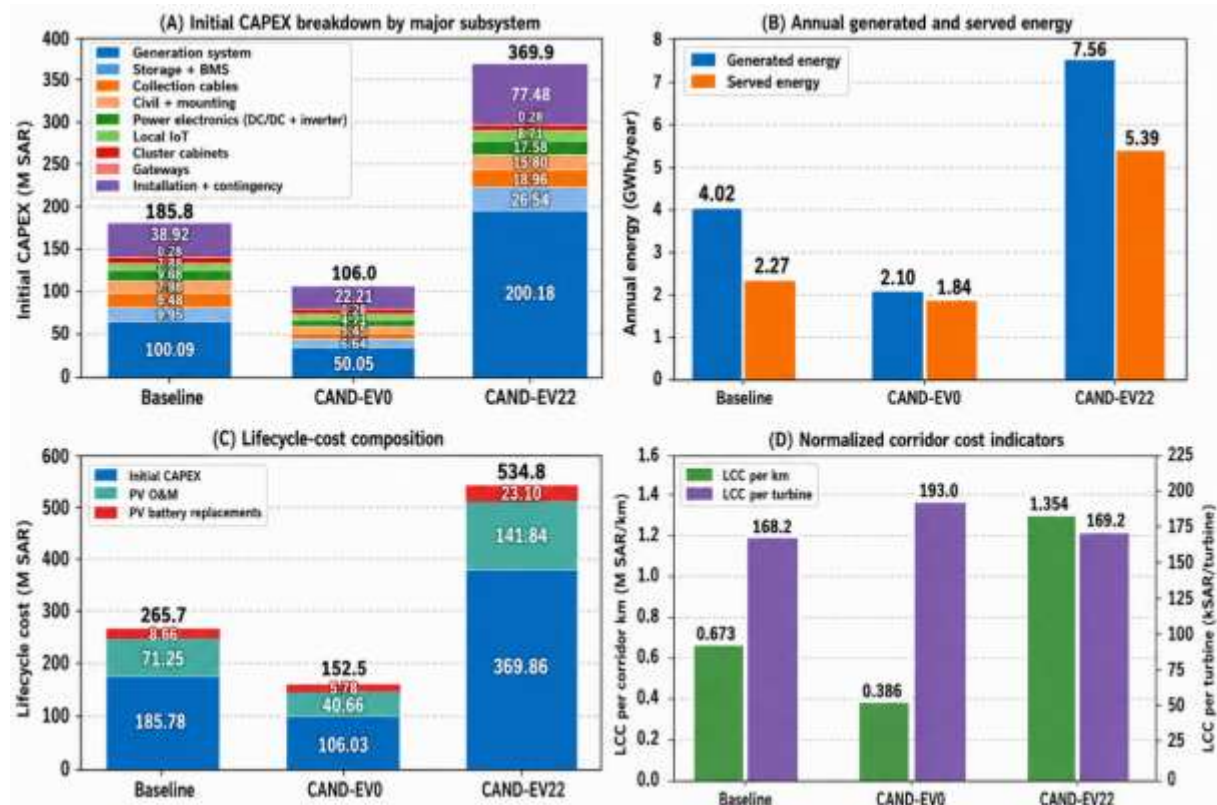


Figure 10. Road-level techno-economic assessment of the deterministic corridor configurations: **(A)** initial CAPEX breakdown by major subsystem; **(B)** annual generated and served energy for the evaluated service tracks; **(C)** lifecycle-cost composition including initial investment, present-value O&M, and battery replacements; and **(D)** lifecycle cost per corridor **kilometer** and per installed turbine.

The deterministic comparison retains CAND-EV0 and CAND-EV22 as nominal service-track candidates. Their selection is provisional: the next section tests whether the energy, EV-service, cable, storage, and communication requirements remain acceptable under correlated uncertainty. This transition is the central

decision point of the study because a low nominal lifecycle cost has engineering value only when the prescribed probabilistic constraints are also satisfied.

4.5. Monte Carlo Evidence for Probabilistic Acceptance and Redesign

This section presents the principal evidence that nominal acceptance can change when uncertain inputs are propagated through the complete corridor model. CAND-EV0 and CAND-EV22 are evaluated through output distributions and constraint-pass probabilities, followed by targeted redesign of the failed service and technical constraints. Tables 12–14 and Figures 11–14 connect the sampling configuration, feasibility diagnosis, sensitivity results, and cost of the resulting design changes.

4.5.1. Monte Carlo Convergence and Output Distributions

The robustness analysis used 10,000 correlated Latin-hypercube realizations, a fixed random seed of 42, and 54 active uncertain inputs. Spearman-rank correlation groups represented dependence among related inputs. Convergence was monitored every 500 realizations, and outputs were reported at P5, P10, P50, P90, and P95. The simulation met the prescribed convergence criterion: a final stability coefficient of variation within 1%.

Table 12. Monte Carlo configuration and principal uncertainty structure used in the robustness analysis.

Category	Parameter / uncertainty group	Implementation
Sampling	Monte Carlo realizations	10,000
Sampling	Method	Correlated Latin Hypercube
Reproducibility	Random seed	42
Correlation	Dependence model	Spearman-rank groups
Convergence	Evaluation interval	500 runs
Convergence	Final stability requirement	CV ≤ 1%
Reporting	Output percentiles	P5, P10, P50, P90, P95
Traffic	Demand, class and temporal variability	Uncertain
Wind resource	Ambient-wind energy and temporal variability	Uncertain
Vehicle wake	Vehicle-induced wind contribution	Uncertain
Components	Turbine, generator and converter performance	Uncertain
Storage	Battery capacity and performance	Uncertain
Electrical	Cable loss and electrical efficiency	Uncertain
Availability	Turbine/component operational availability	Uncertain
Communications	Gateway availability and PDR	Uncertain
Economics	CAPEX, O&M, installation, contingency and discount rate	Uncertain
Total active uncertain inputs	—	54

The output distributions provide the economic and service-risk context for the acceptance tests in Table 13. The nominal candidates have P90 lifecycle costs of 174.77 million SAR for CAND-EV0 and 613.58 million SAR for CAND-EV22; these values form the uncertainty-consistent cost baselines for the redesign comparison. Median performance alone cannot establish compliance because the decision also depends on the frequency of constraint violations and the relevant lower or upper tails of the output distributions.

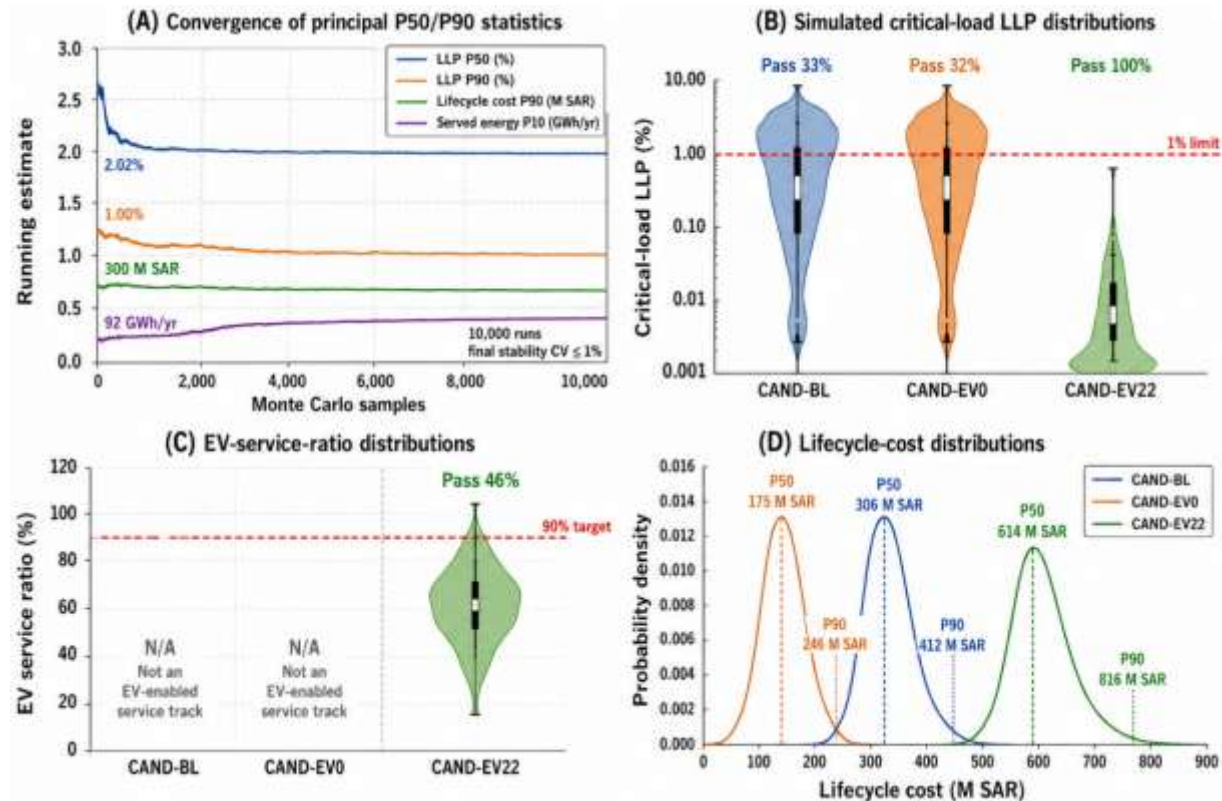


Figure 11. Monte Carlo robustness results for the deterministic corridor configurations: (A) convergence of the principal P50/P90 output statistics with increasing sample size; (B) **simulated annual unserved critical-energy fraction (LLP) distributions**; (C) EV-service-ratio distributions for the EV-enabled configurations; and (D) lifecycle-cost distributions showing median and upper-tail economic risk. **LLP in the graphic denotes the energy-based critical-load index defined in Equation (22).**

4.5.2. Robust Constraint Satisfaction

Robust feasibility was assessed using the probability of satisfying each operating limit across Monte Carlo realizations. The annual unserved critical-energy fraction was required to remain at or below 1% in at least 95% of realizations for both service tracks. EV-enabled configurations additionally required an EV service ratio of at least 90% in at least 90% of realizations. The SOC, cable-loss, gateway-availability, and PDR constraints each required at least 95% compliance.

Table 13 shows that both nominally feasible candidates fail probabilistic acceptance, for different reasons. CAND-EV0 satisfies the annual critical-energy deficit limit in only 31.99% of realizations and the PDR requirement in 4.87%, despite full cable-loss compliance. CAND-EV22 satisfies the critical-energy limit in all sampled realizations, but its EV-service, cable-loss, and PDR compliance probabilities are only 46.38%, 93.99%, and 4.87%, respectively. Thus, adequate critical-energy supply alone cannot establish the acceptability of an EV-enabled design, and nominal communication performance does not establish communication robustness. These failed constraints identify the specific requirements to address before either candidate can be retained.

Table 13. Robust constraint-pass probabilities for the deterministic service-track candidates.

Robust criterion	Required probability	CAND-EV0	CAND-EV22	Outcome
P(LLP ≤ 1%)	≥95%	31.99%	100.00%	EV0 fails
(P(EVSR ≥ 90%))	≥90%	N/A	46.38%	EV22 fails
Minimum SOC ≥ 20%	≥95%	Pass	Pass	Satisfied
Maximum SOC ≤ 95%	≥95%	Pass	Pass	Satisfied
Cable loss ≤ 5%	≥95%	100.00%	93.99%	EV22 marginally fails
Gateway availability ≥ 95%	≥95%	Pass	Pass	Satisfied
(P(PDR ≥ 98%))	≥95%	4.87%	4.87%	Both fail
Monte Carlo convergence	Required	Pass	Pass	Satisfied
Overall robust status	—	Fail	Fail	Redesign required

Note: The consolidated robustness report identifies LLP and PDR as the failed gates for CAND-EV0, and EV service, cable loss, and PDR as the failed gates for CAND-EV22. SOC and gateway-availability gates were therefore satisfied; their individual numerical probabilities are not repeated in the consolidated summary. **LLP denotes the annual unserved critical-energy fraction. $P(LLP \leq 1\%)$ is the estimated probability of satisfying the 1% annual critical-energy deficit limit across Monte Carlo realizations, reported here as a percentage.**

	Criteria	Required threshold	CAND-EV0	CAND-EV22	Interpretation
❗	$P(LLP \leq 1\%)$	$\geq 95\%$	31.99% ❌	100.00% ✅	EV0 fails; EV22 passes
📊	$P(EVSR \geq 90\%)$	$\geq 90\%$	N/A	46.38% ❌	EV22 fails
📁	Minimum SOC $\geq 20\%$	$\geq 95\%$	Pass ✅	Pass ✅	Satisfied
📁	Maximum SOC $\leq 95\%$	$\geq 95\%$	Pass ✅	Pass ✅	Satisfied
⚡	Cable loss $\leq 5\%$	$\geq 95\%$	100.00% ✅	93.99% ⚠️	EV22 marginally fails
📶	Gateway availability $\geq 95\%$	$\geq 95\%$	Pass ✅	Pass ✅	Satisfied
📶	$P(PDR \geq 98\%)$	$\geq 95\%$	4.87% ❌	4.87% ❌	Both fail
📈	Monte Carlo convergence	Required	Pass ✅	Pass ✅	Satisfied
🎯	Overall robust status	—	Fail ❌	Fail ❌	Redesign required

✅ Green = Pass / Satisfied ❌ Red = Fail
 ⚠️ Amber = Marginal fail 📁 Gray = Not applicable

Monte Carlo probability of satisfying each mandatory reliability, service, electrical, communications, and convergence requirement for the deterministic corridor candidates.

Figure 12. Robust feasibility matrix of the deterministic corridor candidates, showing the Monte Carlo probability of satisfying each mandatory reliability, EV-service, SOC, cable-loss, gateway-availability, communications, and convergence requirement; cells are classified as pass or fail relative to the prescribed probability thresholds. **LLP denotes the annual unserved critical-energy fraction; $P(LLP \leq 1\%)$ is the Monte Carlo probability of satisfying the 1% annual critical-energy deficit limit.**

4.5.3. Sensitivity Analyses

Spearman rank correlations were calculated between each uncertain input and the principal outputs: energy-based critical LLP, EV service ratio, total served energy, and lifecycle cost. Critical-energy adequacy showed strong rank associations with ambient-wind energy, interannual variability, seasonal wind amplitude, controller parasitic load, and auxiliary electrical demand. Lifecycle cost was primarily associated with turbine/drivetrain CAPEX, annual O&M, contingency allowance, installation allowance, real discount rate, battery replacement cost, gateway CAPEX, and cable CAPEX.

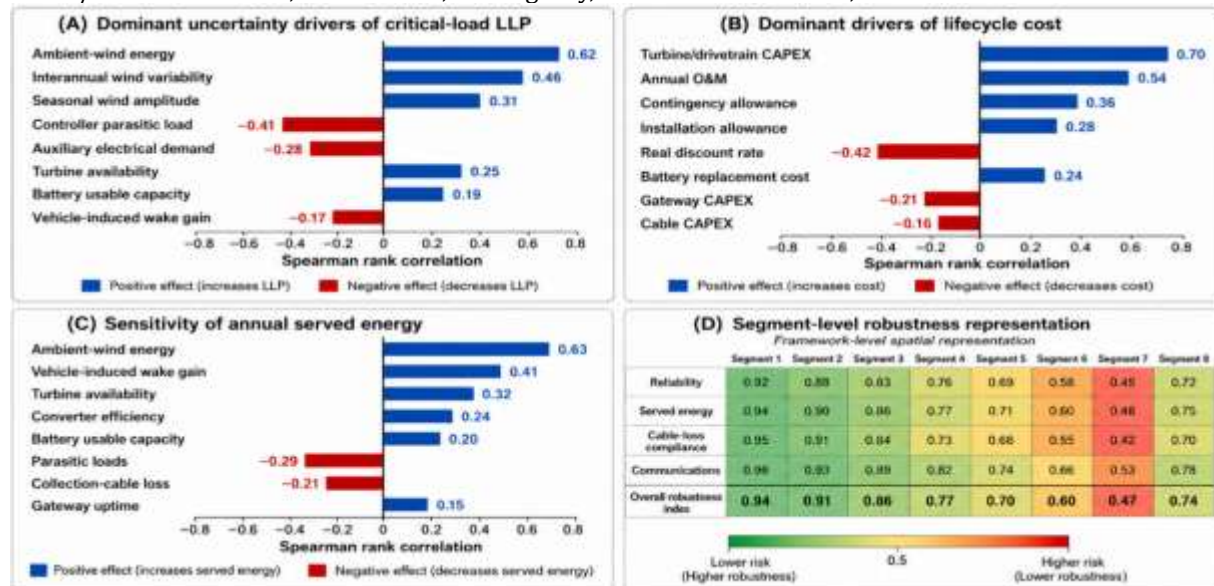


Figure 13. Sensitivity and spatial-risk analysis of the corridor robustness model: **(A) dominant uncertainty drivers of energy-based critical-load LLP; (B) dominant drivers of lifecycle cost; (C) sensitivity of annual served energy to the principal uncertain energy and component parameters; and (D) segment-level robustness representation across the eight Riyadh–Dammam macro-segments. LLP in the graphic denotes the energy-based critical-load index defined in Equation (22).**

Figure 13(D) requires a specific qualification. Segment-level traffic, ambient-wind, vehicle-wake, critical-load, and availability multipliers were held at their reference placeholder values. The heatmap therefore illustrates the spatial assessment framework; it does not demonstrate geographic differences in corridor risk.

PDR was assessed as a probabilistic constraint and was not included among the formal Spearman sensitivity outputs. The sensitivity results therefore describe LLP, energy, and economic responses. Communication uncertainty remains part of the robust-feasibility assessment.

4.5.4. Targeted Redesign and the Cost of Probabilistic Acceptance

Redesign addressed the failed probabilistic constraints for each service. For the critical-only track, CAND-EV0 became EV0-R1 by increasing both turbine and battery counts from 790 to 948, gateway count from 79 to 158, and conductor area from 35 to 50 mm². For the EV-enabled track, CAND-EV22 became EV22-R1. Both turbine and battery counts increased from 3160 to 3555, gateway count from 79 to 158, and conductor area from 70 to 95 mm².

Table 14. Monte Carlo evidence linking nominal-candidate failure, service-specific redesign, compliance improvement, and P90 lifecycle-cost increments.

Indicator	CAND-EV0	EV0-R1	CAND-EV22	EV22-R1
Service track	Critical-only	Critical-only	EV22-enabled	EV22-enabled
Turbines	790	948	3160	3555
Battery units	790	948	3160	3555
Gateways	79	158	79	158
Conductor area (mm ²)	35	50	70	95
(P(LLP≤1%))	31.99%	95.83%	100.00%	100.00%
(P(EVSR≥90%))	N/A	N/A	46.38%	94.07%
(P(PDR≥98%))	4.87%	100.00%	4.87%	100.00%
P90 LCC (M SAR)	174.77	191.98	613.58	636.68
Incremental P90 LCC (M SAR)	—	+17.22	—	+23.11
P90 LCC increase (%)	—	+9.85%	—	+3.77%
Robust engineering status	Fail/HOLD	Conditional Pass	Fail/HOLD	Conditional Pass

Note: LLP denotes the annual unserved critical-energy fraction. P(LLP ≤ 1%) is the estimated probability of satisfying the 1% annual critical-energy deficit limit across Monte Carlo realizations, reported here as a percentage.

Table 14 quantifies how probabilistic diagnosis changes the design decision. For EV0-R1, critical-energy compliance increases from 31.99% to 95.83% and PDR compliance from 4.87% to 100%, while P90 lifecycle cost increases by 9.85% to 191.98 million SAR. For EV22-R1, EV-service compliance increases from 46.38% to 94.07%, critical-energy compliance remains 100%, and PDR compliance reaches 100%; the corresponding P90 cost increase is 3.77%, to 636.68 million SAR. These comparisons express the incremental cost of the evaluated redesigns relative to their respective nominal candidates under uncertainty. They support targeted investment to meet service constraints, without establishing that the reported redesigns are globally minimum-cost robust solutions.

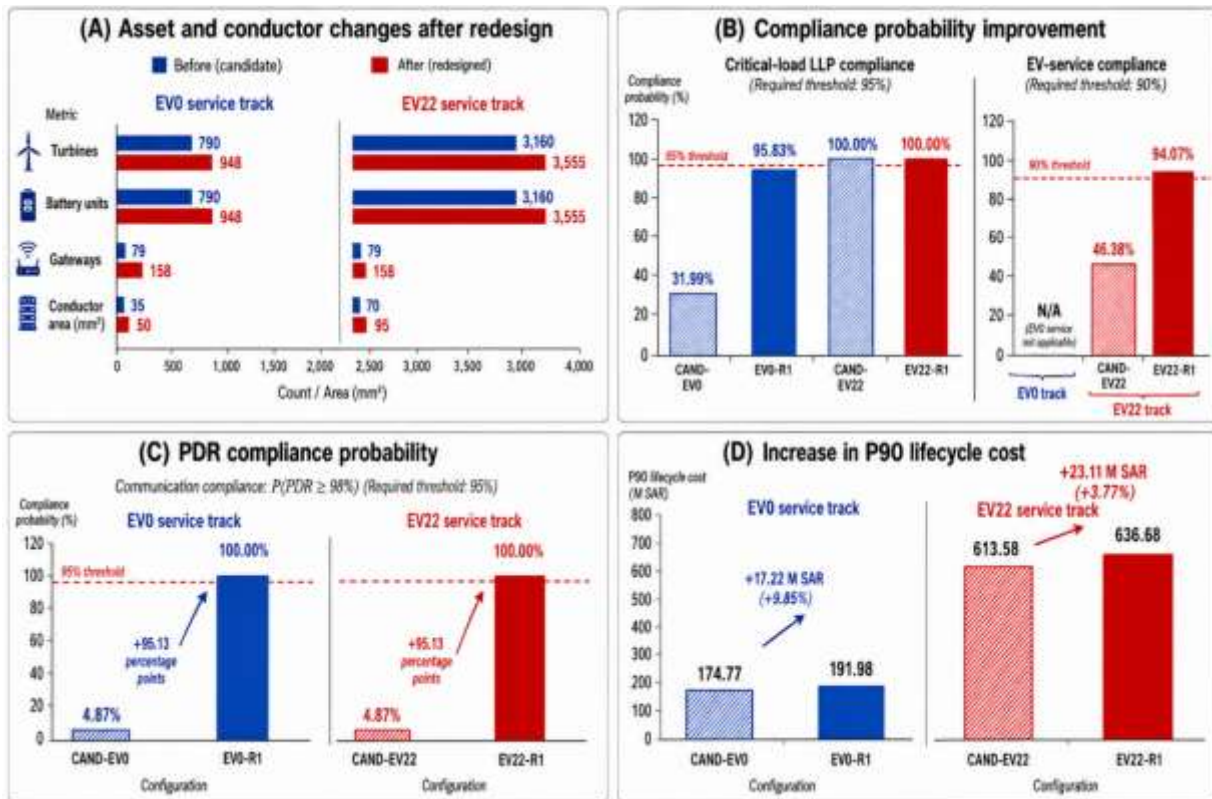


Figure 14. Reliability improvement resulting from the service-specific redesign: **(A)** turbine, battery, gateway, and conductor changes from CAND-EV0 to EV0-R1 and from CAND-EV22 to EV22-R1; **(B)** improvement in compliance probabilities for the annual critical-energy deficit limit and EV-service requirement; **(C)** increase in PDR compliance probability; and **(D)** corresponding increase in P90 lifecycle cost. LLP denotes the annual critical-energy deficit fraction; the displayed compliance probabilities are estimated across Monte Carlo realizations.

The resulting decision is to retain EV0-R1 and EV22-R1 for further evaluation, with conditional engineering status. Monte Carlo assessment changes which designs are acceptable and quantifies the associated investment increment; it therefore directly determines the study's final recommendations. The reported 100% compliance values mean that no violations occurred in the evaluated realizations for those constraints, not that failure is impossible outside the sampled model. The requirements are assessed as individual constraint-pass probabilities; these values should not be interpreted as a separately estimated joint probability that all constraints are satisfied simultaneously.

4.6. Digital Twin, EMS, and IoT Results

The redesigned EV0-R1 and EV22-R1 configurations were evaluated in the multi-resolution digital-twin environment. EMS-BASE, EMS-PRED, and EMS-RES were compared using the same physical configurations and operating disturbances. Three temporal scales were used: 86,400 one-second records for a diagnostic day, 10,080 one-minute records for a representative week, and 8,760 hourly records for annual energy and reliability assessment.

4.6.1. Comparison of EMS Policies

EMS-BASE used reactive priority dispatch. EMS-PRED added a 60-min forecast horizon and a 25% reserve-SOC target. EMS-RES extended the horizon to 120 min and the reserve-SOC target to 30%, adding fault-aware dispatch and store-and-forward communication. Policies were evaluated against reliability, energy-service, communication, maintenance, cost, and complexity criteria.

Selection used the complete three-policy scorecard. Table 15 reports the selected policy for each service to keep the main results concise. EMS-PRED was selected for EV0-R1 with a weighted score of 0.629, while EMS-RES was selected for EV22-R1 with a score of 0.865. EMS-PRED provided adequate forecast-based reserve control at lower complexity. EMS-RES supported the greater EV-service and communication-resilience requirements of EV22-R1.

Table 15. Selected EMS-policy performance for the reliability-redesigned corridor configurations.

Indicator	EV0-R1 / EMS-PRED	EV22-R1 / EMS-RES
Energy-based critical-load LLP (%)	0.5992	0.0000
EV service ratio (%)	N/A	98.28
Minimum SOC (%)	20.0	30.0
Maximum SOC (%)	95.0	95.0
PDR (%)	99.607	99.951
Gateway availability (%)	99.496	99.906
Latency P95 (s)	3.12	1.85
Fault-detection recall (%)	92.06	98.08
MTTR (h)	3.39	3.08
Weighted operational score	0.629	0.865
Operational result	Conditional Pass	Conditional Pass

Note: LLP denotes the ratio of annual unserved critical energy to annual critical energy demand. Values marked (%) express this ratio as a percentage. LLP does not represent the fraction of hours with supply shortfalls or the frequency of interruption events.

The two policy-design pairs satisfied their applicable operational KPI limits within the reference-synthetic digital twin. The higher EV22-R1 score should not, however, be interpreted as universal superiority because the two configurations provide different service levels and are evaluated using service-specific priorities.

4.6.2. Digital-Twin Energy and SOC Performance

The annual digital-twin simulation showed that the selected policies satisfied the energy and storage constraints under the modeled conditions. EV0-R1 generated approximately 2.524 GWh/year and maintained battery SOC between 20% and 95%. Unserved critical energy was 0.5992% of annual critical demand. EV22-R1 generated approximately 8.594 GWh/year, maintained a minimum SOC of 30%, and supplied all critical energy in the evaluated simulation. It also supplied 98.28% of requested EV charging energy. These results describe simulated energy adequacy and do not establish field-observed interruption probabilities.

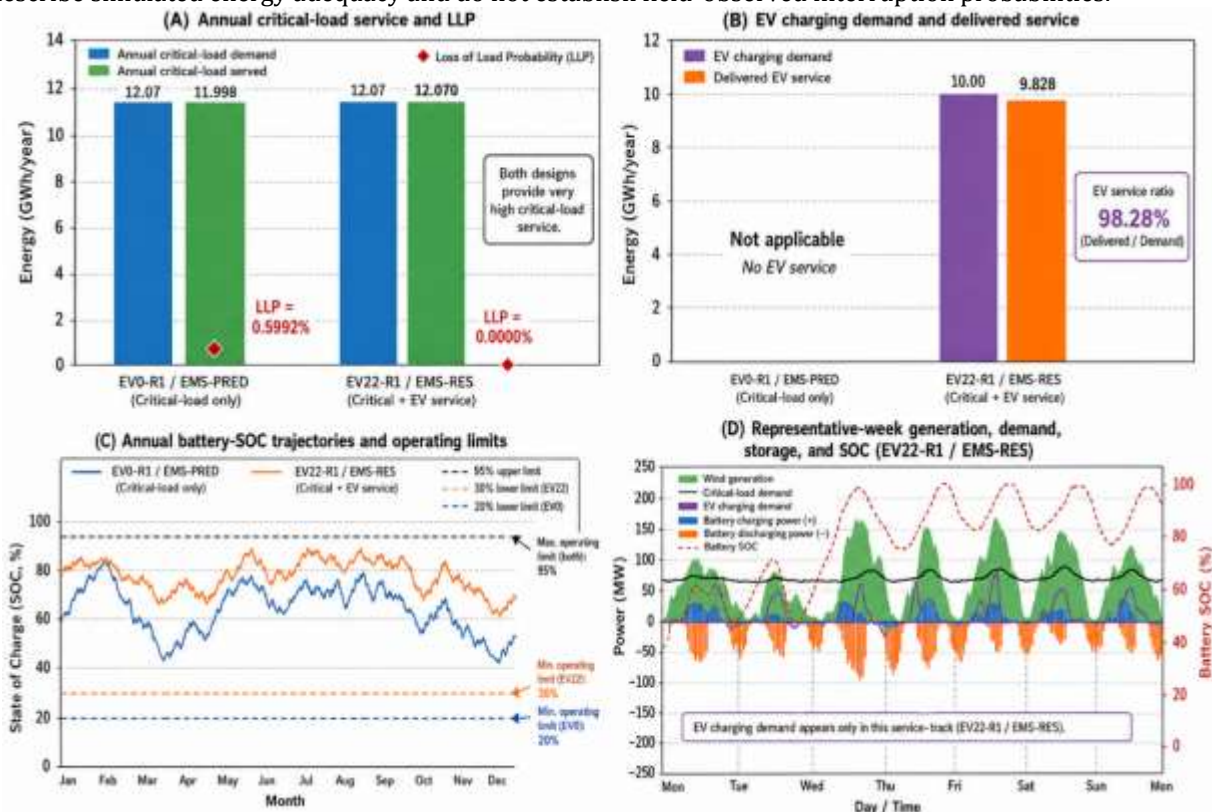


Figure 15. Digital-twin energy and storage performance of the selected service-track configurations: **(A)** annual critical-energy service and corresponding energy-based LLP; **(B)** EV charging demand and delivered service for EV22-R1, with EV0-R1 treated as not applicable; **(C)** annual battery-SOC trajectories and operating limits; and **(D)** representative-week generation, critical demand, EV demand, battery

charging/discharging, and SOC behavior under the selected EMS policies. **LLP in the graphic denotes the energy-based critical-load index defined in Equation (22).**

The representative-week results explain the operating behavior underlying the annual indicators. They show how the EMS redistributes surplus generation, maintains battery reserves, and prioritizes critical demand over discretionary EV charging.

4.6.3. IoT Communication Performance

The communication layer used 158 dual-SIM gateways, each serving approximately 2–3 one-kilometer clusters. Nominal gateway coverage was 2.5 km, with 512 MB of local buffering. The digital-twin model evaluated PDR, gateway availability, P95 latency, telemetry volume, and retransmissions for each EMS policy. Both selected policies met the minimum requirements of 98% PDR and 95% gateway availability (Table 16). The 158-gateway network generated approximately 1.384 million modeled telemetry transactions per design-policy case at annual hourly resolution. Improved communication logic reduced estimated retries to approximately 5440 messages for EMS-PRED and fewer than 700 for EMS-RES. These values represent simulated communication loads and require validation against measured cellular-network traffic.

Table 16. IoT communication and gateway KPIs for the selected digital-twin policies.

Communication KPI	EV0-R1 / EMS-PRED	EV22-R1 / EMS-RES
Gateway count	158	158
Redundancy	Dual-SIM	Dual-SIM
Nominal gateway coverage (km)	2.5	2.5
Annual-scale telemetry messages	1,384,080	1,384,080
Estimated retries	≈5,440	≈680
PDR (%)	99.607	99.951
Gateway availability (%)	99.496	99.906
Latency P95 (s)	3.12	1.85
Buffer capacity per gateway (MB)	512	512

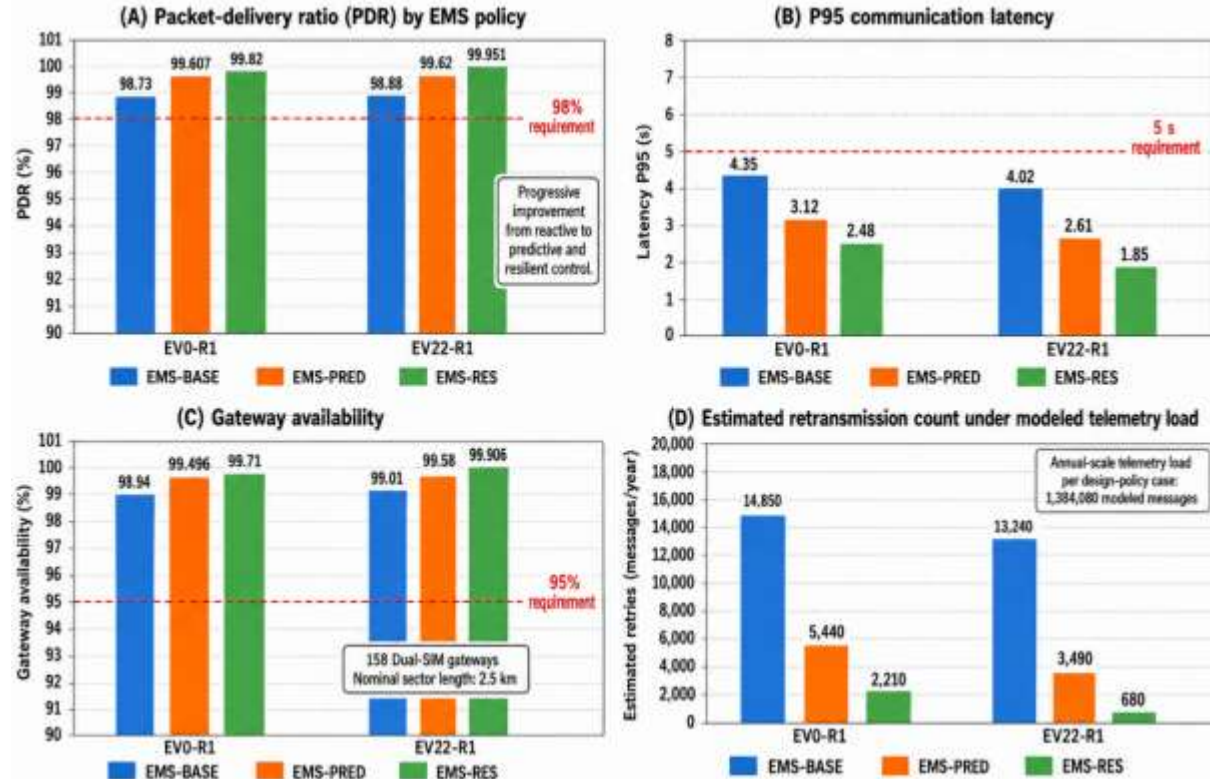


Figure 16. IoT communication performance of the digital-twin configurations: **(A)** packet-delivery ratio under EMS-BASE, EMS-PRED, and EMS-RES; **(B)** P95 communication latency; **(C)** gateway availability; and **(D)** estimated retransmission count under the modeled telemetry load.

The communication results show a progressive improvement from reactive to predictive and resilient supervisory strategies, with EMS-RES providing the highest modeled PDR and gateway availability and the lowest P95 latency.

4.6.4. IoT Monitoring and Data-Visualization Dashboard

Digital-twin outputs were integrated with a server-based IoT monitoring interface for the 395 km Riyadh–Dammam corridor, covering 395 clusters and 158 gateways. The interface displayed generation, critical and EV demand, battery SOC, the selected EMS policy, connectivity, communication KPIs, alarms, and asset-health information. Users could navigate from the corridor overview to individual gateways and one-kilometer clusters. Evaluation used one-second, one-minute, and hourly resolutions.

Figure 17 shows four dashboard views: corridor status, energy and storage, IoT communications, and alarms and maintenance. These views link abnormal energy, communication, or asset-health conditions to their corridor locations. They also support visualization of the maintenance assessment described below. The interface belongs to the reference-synthetic digital-twin environment and has not been commissioned as a field monitoring system.



Figure 17. IoT server and data-visualization interface of the proposed roadside wind-energy digital twin: **(A)** corridor-level overview showing the 395 km Riyadh–Dammam corridor, cluster and gateway status, service-track configuration, generation, **energy-based critical-load LLP**, **EV service**, and battery SOC; **(B)** energy and storage monitoring showing wind generation, critical and EV demand, battery charging/discharging, SOC, and the active EMS policy; **(C)** IoT communication view showing gateway status, PDR, availability, P95 latency, retransmissions, and online/offline clusters; and **(D)** alarm and predictive-maintenance view showing active faults, severity, asset-health index, corridor location, risk class, and maintenance priority. **LLP in the graphic denotes the energy-based critical-load index defined in Equation (22).**

4.6.5. Fault Detection and Maintenance Assessment

Faults were injected into the turbine, battery, power-electronics, sensing, control, and communication subsystems in the representative-week digital twin. Events were classified by severity and assessed using detection recall, repair duration, and estimated energy loss. Detection recall was 92.06% for EV0-R1/EMS-PRED and 98.08% for EV22-R1/EMS-RES. The corresponding mean times to repair were 3.39 h and 3.08 h.

Cluster-level maintenance risk was calculated from simulated fault frequency and corridor exposure factors. Each cluster received a health index and risk score. High-risk clusters were prioritized for inspection within 24 h. Medium-risk clusters were assigned to the next maintenance route, while low-risk clusters remained under routine monitoring.

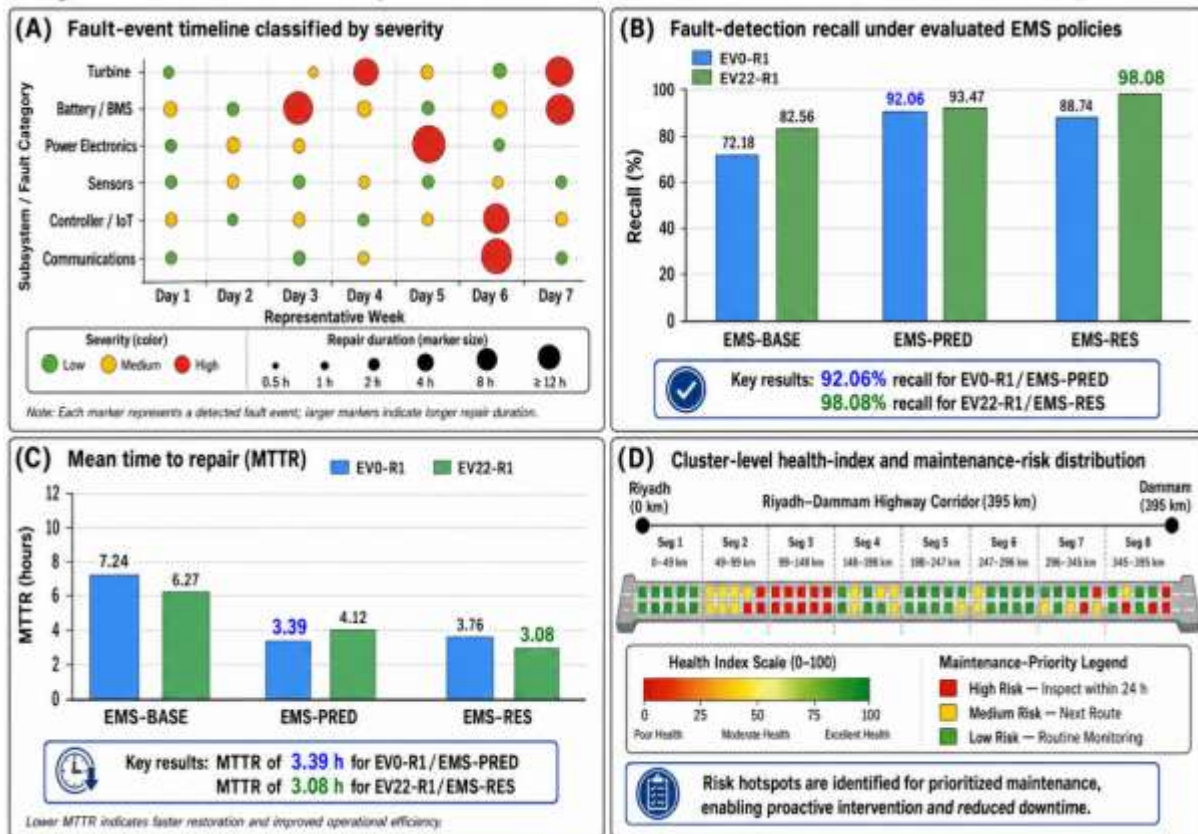


Figure 18. Fault-detection and predictive-maintenance results from the representative-week digital twin: (A) fault-event timeline classified by severity, with marker size representing repair duration; (B) fault-detection recall under the evaluated EMS policies; (C) mean time to repair; and (D) cluster-level health-index and maintenance-risk distribution along the 395 km Riyadh–Dammam corridor.

The combined energy, communication, and maintenance results support retaining EV0-R1/EMS-PRED and EV22-R1/EMS-RES for their respective services within the reference-synthetic evaluation. Both pairings met the applicable modeled operating criteria. Field and HIL validation remain necessary.

4.7. Final Design Selection and Integrated Comparison

The analysis retained two corridor configurations with distinct service objectives. EV0-R1 supplies critical roadside loads, while EV22-R1 adds EV charging. Table 17 brings together the probabilistic design, economic, communication, and digital-twin results to support service-specific selection.

Table 17. Final integrated comparison of the selected EV0-R1 and EV22-R1 corridor configurations.

Indicator	EV0-R1	EV22-R1
Service scope	Critical roadside loads	Critical + EV22 charging
Turbines	948	3555
Battery units	948	3555
Gateways	158	158
Conductor area	50 mm ²	95 mm ²
Robust (P(LLP≤1%))	95.83%	100.00%
Robust (P(EVSR≥90%))	N/A	94.07%
P90 lifecycle cost	191.98 M SAR	636.68 M SAR
Selected EMS	EMS-PRED	EMS-RES
Digital-twin energy-based critical LLP	0.5992%	0.0000%
Digital-twin EV service	N/A	98.28%
PDR	99.607%	99.951%
Gateway availability	99.496%	99.906%
Latency P95	3.12 s	1.85 s
Fault-detection recall	92.06%	98.08%
MTTR	3.39 h	3.08 h

Indicator	EV0-R1	EV22-R1
Digital-twin weighted score	0.629	0.865
Engineering result	Conditional Pass	Conditional Pass

Note: Energy-based LLP is the annual unserved critical-energy fraction, expressed as a percentage in the digital-twin results. Robust $P(LLP \leq 1\%)$ is the estimated probability of satisfying the 1% annual critical-energy deficit limit across Monte Carlo realizations. These quantities describe energy adequacy and constraint compliance, respectively; neither is an hourly interruption probability.

The comparison quantifies the trade-off between infrastructure scale and service capability. EV0-R1 supports critical-load service with fewer turbines and batteries and a P90 lifecycle cost of 191.98 million SAR. EV22-R1 requires a larger conductor and approximately 3.75 times as many turbines and battery units, with a P90 lifecycle cost of 636.68 million SAR. It also meets the probabilistic EV22-service requirement and supplies all critical energy in the evaluated digital-twin simulation.

The digital-twin results reinforce this service distinction. EV0-R1 with EMS-PRED achieved an annual unserved critical-energy fraction of 0.5992%, a PDR of 99.607%, and a weighted operational score of 0.629. EV22-R1 with EMS-RES supplied all critical energy and 98.28% of requested EV energy, with a PDR of 99.951% and a weighted score of 0.865. Figure 19 summarizes these differences.

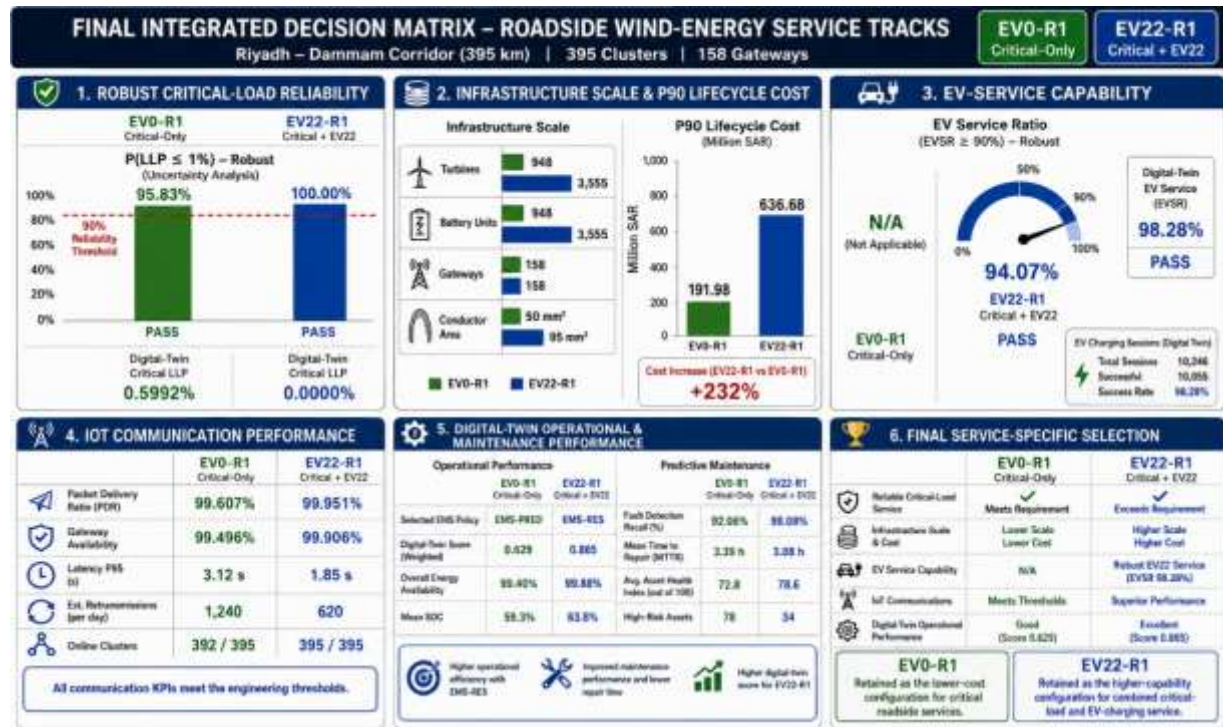


Figure 19. Final integrated decision matrix for the selected roadside wind-energy service tracks: (A) Monte Carlo compliance probability for the annual critical-energy deficit limit; (B) infrastructure scale and P90 lifecycle cost; (C) EV-service capability; (D) IoT communication performance; (E) digital-twin operational and maintenance performance; and (F) final service-specific engineering selection of EV0-R1 and EV22-R1. LLP denotes the annual critical-energy deficit fraction. In panel (A), the required Monte Carlo compliance probability is 95%, as specified in Equation (41); this supersedes the 90% threshold annotation in the graphic.

EV0-R1 is the lower-cost configuration for critical roadside service. EV22-R1 supports the additional EV-charging service with greater infrastructure capacity. Selection therefore depends on the required service scope. Both designs received a conditional engineering pass in the reference probabilistic and digital-twin evaluations.

5. Discussion

The principal contribution is the demonstration that nominally feasible roadside wind-battery designs can fail probabilistic service requirements. Diagnosing these failures guides specific infrastructure changes and quantifies their lifecycle-cost implications. Tables 13 and 14 show how acceptance changes from CAND-

EV0/CAND-EV22 to EV0-R1/EV22-R1. The resource, storage, electrical, communication, and control models provide the engineering basis for this comparison. Monte Carlo assessment connects their uncertain outputs to the final design decision.

5.1. Deterministic Feasibility and Probabilistic Robustness

The strongest evidence is the reversal of the nominal design decision. CAND-EV0 is feasible in the deterministic corridor assessment, yet it meets the annual critical-energy deficit limit in only 31.99% of realizations and the PDR requirement in 4.87%. The EV0-R1 redesign raises these probabilities to 95.83% and 100%, respectively. The EV-enabled case reinforces the finding: CAND-EV22 already meets the critical-energy constraint in all sampled realizations, but its EV-service compliance is only 46.38%; redesign raises this to 94.07%. Accordingly, the framework tests the adequacy of each required service explicitly. A favorable annual energy balance or a passing nominal simulation cannot substitute for these separate probability thresholds (Table 13 and Figure 12).

The methodological contribution is the use of the uncertainty results to govern acceptance, redesign, and reassessment in the integrated corridor problem. Latin-hypercube sampling, 54 active uncertain inputs, and Spearman-rank dependence represent the adopted input variability; convergence monitoring every 500 realizations checks the stability of the reported statistics. P5/P10 and P90/P95 reveal the relevant lower and upper tails, with P50 describing the median. Together with the constraint-pass probabilities, these summaries connect uncertainty to an engineering decision. The number of realizations and numerical convergence support the simulation analysis but do not independently validate the physical model or its input distributions.

This decision sequence builds on the reliability and storage-design literature [33, 34, 41]. Krishna et al. [41] optimize capacity against worst-case uncertainty, whereas the present analysis estimates compliance frequencies under specified distributions and dependence, then reassesses targeted candidate changes. Qiu et al. [42] focus on robust network operation, while the current decision includes installed generation, storage, conductors, and gateways. Thus, probabilistic candidate acceptance here should not be interpreted as a distribution-free guarantee or as a new robust-optimization algorithm. The added evidence is how separate service and technical constraints alter the retained highway design.

5.2. Vehicle-Induced Wind within the Probabilistic Design Framework

Within the adopted model, ambient wind provides the dominant energy contribution, while vehicle-induced airflow adds intermittent energy whose magnitude depends on vehicle class and turbine offset. This interpretation is consistent with the placement and vehicle-class dependence measured by Bakırcı and Kazal [28] and with the transient aerodynamic focus of recent highway VAWT studies [30–32]. Singh et al. [29] demonstrate a related connection between highway wind, PV, storage, and charging at the hybrid-system level. However, neither those measurements nor reported hybrid-system yields directly calibrate the present wake coefficients: vehicle geometry, speed, sensor height, offset definition, rotor characteristics, and time resolution must be matched. Accordingly, the modeled HGV contribution and lateral attenuation are conditional predictions, and the reviewed evidence strengthens the rationale for the model variables without converting baseline coefficients into measured values.

5.3. Reliability, Cost, and Infrastructure Trade-Off

The redesign comparisons quantify the infrastructure cost of reaching the prescribed probabilistic acceptance thresholds within the evaluated candidate set. EV0-R1 increases P90 lifecycle cost by 9.85%, from 174.77 to 191.98 million SAR, while EV22-R1 increases it by 3.77%, from 613.58 to 636.68 million SAR (Table 14 and Figure 14). Both comparisons use P90 costs, avoiding a comparison between nominal costs and uncertain upper-tail costs. Increased generation and storage, additional gateways, and larger conductors address different service and technical margins. These results support evaluating the cost of meeting the required probabilities before ranking acceptable designs. The two increments apply to different service scopes and baseline asset populations; they do not establish a universal cost of robustness or an economic optimum beyond the configurations examined.

The comparison with Singh et al. [29] and Hammood et al. [46] locates these results within existing highway renewable-system research. Their work already connects generation with downstream energy services or corridor-scale planning. The present extension is to report how uncertain compliance changes the accepted wind-battery configuration and its P90 cost for each service track. Direct numerical comparisons of energy yield or cost would be inappropriate without harmonizing resource data, technology mix, load definitions, road geometry, economic assumptions, and validation level.

5.4. Service-Specific Design for EV0 and EV22

EV0-R1 and EV22-R1 address different service requirements. EV0-R1 supplies critical roadside loads with a smaller infrastructure footprint. EV22-R1 adds EV charging and requires substantially greater generation, storage, and conductor capacity. EV0-R1 is therefore appropriate when the objective is critical-only service; the

additional investment in EV22-R1 is justified by the requirement to provide charging. Their comparison should be interpreted against these distinct objectives.

5.5. Operational Implications of Digital Twin, EMS, and IoT

The digital twin extends the designs selected through probabilistic assessment to supervisory operation. EMS-PRED was selected for EV0-R1, while EMS-RES was selected for EV22-R1, reflecting the different reserve, EV-service, communication, and fault-management requirements. The reported operational results support the consistency of these design-policy pairings within the reference-synthetic evaluation. They remain distinct from the Monte Carlo compliance probabilities: a digital-twin annual energy-deficit value describes the evaluated operating case, whereas probabilistic compliance summarizes outcomes across uncertain realizations. Digital-twin results therefore complement the probabilistic design decision and identify operational requirements for subsequent experimental validation.

The evidence boundary is consequential when comparing digital systems. Jiang et al. [48] compared real-time microgrid simulations with physical assets, and Marykovskiy et al. [52] implemented an instrumented blade-monitoring architecture. The present supervisory assessment has not reached those validation stages. Likewise, the security measures studied by Rekeraho et al. [50] and the metering approach of Bonavolontà et al. [51] identify tests beyond modeled PDR and latency. The fault-detection and repair indicators reported here should therefore be read as outcomes of the stated supervisory scenarios, not as field-verified diagnostic or predictive-maintenance performance.

5.6. Sensitivity and Key Drivers of Uncertainty

The uncertainty analysis also identifies where improved evidence could most usefully refine design decisions. Spearman sensitivity results associate critical-energy adequacy with ambient-wind energy, interannual and seasonal variability, and parasitic and auxiliary demand, while lifecycle cost is associated with turbine/drivetrain CAPEX, O&M, contingency, installation, and discount-rate assumptions (Figure 13). These rankings support prioritizing long-duration wind records, auxiliary-load measurements, matched turbine performance data, and supplier quotations. They describe rank associations within the adopted uncertainty model and do not establish causal effects. PDR was evaluated as a probabilistic constraint rather than a formal Spearman output, so its redesign rationale follows the failed communication gate and subsequent reassessment. This distinction keeps the sensitivity interpretation consistent with the reported analysis.

5.7. Practical Implications

A practical implication is to retain deterministic sizing as an initial screening step and require probabilistic acceptance before committing to a service-track design. The modular one-kilometer cluster architecture allows generation, storage, communications, and conductor choices to be reconsidered in response to failed constraints. The study provides an example of this decision sequence for both critical-only and EV-enabled services, with explicit service thresholds and P90 budget implications. Applying the framework to another corridor requires replacing the reference inputs with site-specific evidence and reassessing the relevant uncertainty distributions and dependence assumptions. The present results support conditional engineering decisions and a structured validation program.

5.8. Limitations and Path to Experimental Validation

The study uses a reference-synthetic dataset. The literature basis of the vehicle-wake model supports its principal variables and transient treatment, while the adopted peak-speed fractions, lateral attenuation exponent, and decay time constants remain uncalibrated baseline assumptions. Representative corridor traffic and wind measurements, or compatible CFD-derived velocity data, are required to estimate these coefficients and assess their uncertainty. The surrogate turbine-generator-rectifier-MPPT chain also requires verification against a matched 5 kW manufacturer package. Battery thermal and degradation characteristics, economic inputs, and supplier quotations require independent confirmation. RF drive and soak tests are needed to assess communication performance, and proposed installations require GIS, structural, electrical, road-safety, and authority review.

The reported probabilities are conditional on the selected distributions, correlation structure, and fixed model formulation. The convergence criterion addresses numerical stability of the monitored statistics; it does not establish that unmodeled conditions or structural model errors have been captured. In particular, increasing the number of Monte Carlo realizations cannot calibrate the baseline wake coefficients. The near-threshold 95.83% critical-energy compliance of EV0-R1 should therefore be reassessed when field evidence updates the uncertain inputs. This limitation defines the scope of the central contribution: a demonstrated probabilistic decision process and conditional redesign outcome within the stated reference case.

The maintenance literature further specifies the required evidence. The outdoor damage measurements of Mostafavi and Friedmann [53] illustrate the type of labeled, multisensor data needed to test diagnostics, while the review by Maldonado-Correa et al. [54] identifies benchmarking and component-to-system integration as

continuing challenges. For this corridor, subsequent validation should align asset-level fault measurements with downtime, repair actions, and lost critical or EV energy. Until such data are available, maintenance benefits remain conditional on the assumed fault and repair scenarios.

Validation should proceed through field-data calibration, matched-component verification, HIL testing, a controlled small-scale pilot, and long-duration corridor evaluation. HIL and pilot studies are proposed future activities; they do not constitute evidence for the current simulation results. EV0-R1 and EV22-R1 should retain conditional engineering status until these validation stages are completed.

6. Conclusions

The central finding is that deterministic feasibility does not establish probabilistic robustness for roadside wind-battery systems. In the 395 km Riyadh–Dammam case, correlated Latin-hypercube Monte Carlo analysis evaluated 10,000 realizations across 54 uncertain inputs. The results changed the acceptance of nominal designs and guided service-specific redesign. Convergence monitoring, Spearman sensitivity analysis, and percentile reporting supported interpretation of service risk and lifecycle cost.

For the critical-only track, redesign increased the probability of limiting annual unserved critical energy to 1% of demand from 31.99% to 95.83%. PDR compliance increased from 4.87% to 100%. P90 lifecycle cost increased by 9.85% to 191.98 million SAR. For the EV-enabled track, the probability of supplying at least 90% of requested charging energy increased from 46.38% to 94.07%. Critical-energy compliance remained 100%, and PDR compliance reached 100%. P90 lifecycle cost increased by 3.77% to 636.68 million SAR. These results make probabilistic acceptance and the cost of targeted redesign the principal basis for retaining EV0-R1 and EV22-R1 for their respective services.

Subsequent digital-twin evaluation selected EMS-PRED for EV0-R1 and EMS-RES for EV22-R1, linking design selection to supervisory operation. The recommendations remain conditional on the reference-synthetic inputs, model structure, and assumed dependence. Reported 100% compliance applies only to the evaluated sample. Field calibration, matched-component verification, communication testing, HIL evaluation, and pilot operation are required before deployment claims can be made.

References

- [1] A. Tummalala, R. K. Velamati, D. K. Sinha, V. Indrajha, and V. H. Krishna, "A review on small scale wind turbines," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 1351–1371, Apr. 2016, doi: 10.1016/j.rser.2015.12.027.
- [2] C. Simão Ferreira, G. van Kuik, G. van Bussel, and F. Scarano, "Visualization by PIV of dynamic stall on a vertical axis wind turbine," *Experiments in Fluids*, vol. 46, pp. 97–108, Jan. 2009, doi: 10.1007/s00348-008-0543-z.
- [3] R. Howell, N. Qin, J. Edwards, and N. Durrani, "Wind tunnel and numerical study of a small vertical axis wind turbine," *Renewable Energy*, vol. 35, no. 2, pp. 412–422, Feb. 2010, doi: 10.1016/j.renene.2009.07.025.
- [4] D. W. Wekesa, C. Wang, Y. Wei, and W. Zhu, "Experimental and numerical study of turbulence effect on aerodynamic performance of a small-scale vertical axis wind turbine," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 157, pp. 1–14, Oct. 2016, doi: 10.1016/j.jweia.2016.07.018.
- [5] M. A. Miller, S. Duvvuri, and M. Hultmark, "Solidity effects on the performance of vertical-axis wind turbines," *Flow*, vol. 1, Art. no. E9, 2021, doi: 10.1017/flo.2021.9.
- [6] L. Chahla, A. Saadane, and A. Rachid, "Unified environment for real time control of hybrid energy system using Digital Twin and IoT approach," *Sensors*, vol. 23, no. 12, Art. no. 5646, Jun. 2023, doi: 10.3390/s23125646.
- [7] M. U. Saleem, M. Shakir, M. R. Usman, M. H. T. Bajwa, N. Shabbir, P. Shams Ghahfarokhi, and K. Daniel, "Integrating smart energy management system with Internet of Things and cloud computing for efficient demand side management in smart grids," *Energies*, vol. 16, no. 12, Art. no. 4835, Jun. 2023, doi: 10.3390/en16124835.
- [8] K. A. Al Sumarmad, N. Sulaiman, N. I. A. Wahab, and H. Hizam, "Microgrid energy management system based on fuzzy logic and monitoring platform for data analysis," *Energies*, vol. 15, no. 11, Art. no. 4125, Jun. 2022, doi: 10.3390/en15114125.
- [9] P. García, P. Arboleya, B. Mohamed, and A. A. C. Vega, "Implementation of a hybrid distributed/centralized real-time monitoring system for a DC/AC microgrid with energy storage capabilities," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 5, pp. 1900–1909, Oct. 2016, doi: 10.1109/TII.2016.2574999.
- [10] E.-K. Lee, W. Shi, R. Gadh, and W. Kim, "Design and implementation of a microgrid energy management system," *Sustainability*, vol. 8, no. 11, Art. no. 1143, Nov. 2016, doi: 10.3390/su8111143.

- [11] M. N. Musa, K. Osman, and A. M. A. Hamat, "Renewable energy from induced airflow generated by cruising ground vehicles in tandem using RANS," *Energy Procedia*, vol. 14, pp. 1877–1882, 2012, doi: 10.1016/j.egypro.2011.12.1182.
- [12] T. Morbiato, C. Borri, and R. Vitaliani, "Wind energy harvesting from transport systems: A resource estimation assessment," *Applied Energy*, vol. 133, pp. 152–168, Nov. 2014, doi: 10.1016/j.apenergy.2014.07.055.
- [13] S. Santhakumar, I. Palanivel, and K. Venkatasubramanian, "A study on the rotational behaviour of a Savonius wind turbine in low rise highways during different monsoons," *Energy for Sustainable Development*, vol. 40, pp. 1–10, Oct. 2017, doi: 10.1016/j.esd.2017.05.002.
- [14] W. Tian, Z. Mao, X. An, B. Zhang, and H. Wen, "Numerical study of energy recovery from the wakes of moving vehicles on highways by using a vertical axis wind turbine," *Energy*, vol. 141, pp. 715–728, Dec. 2017, doi: 10.1016/j.energy.2017.07.172.
- [15] W. Hu, J. E. Y. Deng, L. Li, D. Han, X. Zhao, Z. Zhang, and Q. Peng, "Effect analysis on power coefficient enhancement of a convective wind energy collecting device in the expressway," *Energy Conversion and Management*, vol. 171, pp. 249–271, Sep. 2018, doi: 10.1016/j.enconman.2018.05.101.
- [16] W. Tian, B. Song, and Z. Mao, "Numerical investigation of wind turbines and turbine arrays on highways," *Renewable Energy*, vol. 147, pt. 1, pp. 384–398, Mar. 2020, doi: 10.1016/j.renene.2019.08.123.
- [17] L. C. Kunkel and D. M. Hall, "Improving site assessment tools in emerging technologies: The case of highway vertical-axis wind turbines in the United States," *Energy Research & Social Science*, vol. 64, Art. no. 101456, Jun. 2020, doi: 10.1016/j.erss.2020.101456.
- [18] D. H. Kumar, R. Krishna, M. D. Kumar, R. Pradhan, and M. Sreenivasan, "Harvesting energy from moving vehicles with single-axis solar tracking assisted hybrid wind turbine," *Materials Today: Proceedings*, vol. 33, pt. 1, pp. 326–332, 2020, doi: 10.1016/j.matpr.2020.04.116.
- [19] L. Qi, P. Zheng, X. Wu, W. Duan, L. Li, and Z. Zhang, "A hybrid wind-photovoltaic power generation system based on the foldable umbrella mechanism for applications on highways," *Solar Energy*, vol. 208, pp. 368–378, Sep. 2020, doi: 10.1016/j.solener.2020.07.082.
- [20] M. K. Rathore, M. Agrawal, and P. Baredar, "Energy production potential from the wake of moving traffic vehicles on a highway by the array of low economic VAWT," *Materials Today: Proceedings*, vol. 46, pt. 11, pp. 5272–5277, 2021, doi: 10.1016/j.matpr.2020.08.638.
- [21] S. Toudarbari, M. J. Maghrebi, and A. Hashemzadeh, "Evaluation of Darrieus wind turbine for different highway settings using CFD simulation," *Sustainable Energy Technologies and Assessments*, vol. 45, Art. no. 101077, Jun. 2021, doi: 10.1016/j.seta.2021.101077.
- [22] A. Yadav, S. R. Pillai, V. K. Vashistha, and A. Kumar, "Feasibility study of vertical axis wind turbine on UAE highways," *Materials Today: Proceedings*, vol. 64, pt. 3, pp. 1392–1397, 2022, doi: 10.1016/j.matpr.2022.04.523.
- [23] W. Hu, J. E. Y. Tan, F. Zhang, and G. Liao, "Modified wind energy collection devices for harvesting convective wind energy from cars and trucks moving in the highway," *Energy*, vol. 247, Art. no. 123454, May 2022, doi: 10.1016/j.energy.2022.123454.
- [24] W. Hu, J. E. F. Zhang, J. Chen, Y. Ma, and E. Leng, "Investigation on cooperative mechanism between convective wind energy harvesting and dust collection during vehicle driving on the highway," *Energy*, vol. 260, Art. no. 124923, Dec. 2022, doi: 10.1016/j.energy.2022.124923.
- [25] W. Hu, J. E. E. Leng, F. Zhang, J. Chen, and Y. Ma, "Investigation on harvesting characteristics of convective wind energy from vehicle driving on multi-lane highway," *Energy*, vol. 263, pt. E, Art. no. 126062, Jan. 2023, doi: 10.1016/j.energy.2022.126062.
- [26] W. Hu, J. E. D. Han, C. Feng, and X. Luo, "Investigation on distribution characteristics of convective wind energy from vehicle driving on multi-lane highway," *Energy*, vol. 271, Art. no. 127024, May 2023, doi: 10.1016/j.energy.2023.127024.
- [27] F. Gallorini and L. Barelli, "Design and prototyping of miniature wind turbine and power generation section for the exploitation of wind generated by vehicle movement in road tunnels," *Energy*, vol. 305, Art. no. 132308, Oct. 2024, doi: 10.1016/j.energy.2024.132308.
- [28] M. Bakirci and O. A. Kazal, "Highway wind energy conversion with a savonius-darrieus hybrid turbine," *International Journal of Energy Studies*, vol. 9, no. 4, pp. 867–904, 2024, doi: 10.58559/ijes.1527975.
- [29] S. P. Singh, P. Tiwari, S. N. Singh, and P. P. Singh, "Estimation of hybrid energy generation of solar-wind tower for electric vehicle charging: A case study of Indian highway," *Energy Storage*, vol. 6, no. 5, Art. no. e70004, 2024, doi: 10.1002/est2.70004.
- [30] A. Ulus and S. I. Moldovan, "Optimization of vertical axis wind turbine systems to capture vehicle-induced highway winds," *Energies*, vol. 18, no. 12, Art. no. 3139, Jun. 2025, doi: 10.3390/en18123139.

- [31] Z. Toor, H. M. Bahaidarah, M. E. Zayed, and S. Rehman, "Research on aerodynamic performances of the vertical-axis wind turbines under different wind gust configurations: Comparative numerical modeling," *Multiscale and Multidisciplinary Modeling, Experiments and Design*, vol. 9, Art. no. 99, 2026, doi: 10.1007/s41939-025-01152-z.
- [32] X. Guo, Z. Zou, L. Nie, W. Chen, and Y. Yu, "Performance improvement for Bach-type vertical-axis wind turbines in dynamic highway airflow environments," *Energy*, vol. 352, Art. no. 140956, Jun. 2026, doi: 10.1016/j.energy.2026.140956.
- [33] Z. Weng, J. Zhou, and Z. Zhan, "Reliability evaluation of standalone microgrid based on sequential Monte Carlo simulation method," *Energies*, vol. 15, no. 18, Art. no. 6706, Sep. 2022, doi: 10.3390/en15186706.
- [34] D. Huo, M. Santos, I. Sarantakos, M. Resch, N. Wade, and D. Greenwood, "A reliability-aware chance-constrained battery sizing method for island microgrid," *Energy*, vol. 251, Art. no. 123978, Jul. 2022, doi: 10.1016/j.energy.2022.123978.
- [35] M. Gholami, S. M. Muyeen, and S. Abokhamis Mousavi, "Development of new reliability metrics for microgrids: Integrating renewable energy sources and battery energy storage system," *Energy Reports*, vol. 10, pp. 2251–2259, Nov. 2023, doi: 10.1016/j.egyr.2023.09.047.
- [36] K. P. Kumar and B. Saravanan, "Recent techniques to model uncertainties in power generation from renewable energy sources and loads in microgrids—A review," *Renewable and Sustainable Energy Reviews*, vol. 71, pp. 348–358, May 2017, doi: 10.1016/j.rser.2016.12.063.
- [37] A. Heydari, M. Majidi Nezhad, F. Keynia, A. Fekih, N. Shahsavari-Pour, D. Astiaso Garcia, and G. Piras, "A combined multi-objective intelligent optimization approach considering techno-economic and reliability factors for hybrid-renewable microgrid systems," *Journal of Cleaner Production*, vol. 383, Art. no. 135249, Jan. 2023, doi: 10.1016/j.jclepro.2022.135249.
- [38] S. Mohseni and A. C. Brent, "Quantifying the effects of forecast uncertainty on the role of different battery technologies in grid-connected solar photovoltaic/wind/micro-hydro micro-grids: An optimal planning study," *Journal of Energy Storage*, vol. 51, Art. no. 104412, Jul. 2022, doi: 10.1016/j.est.2022.104412.
- [39] H. Mehrjerdi and R. Hemmati, "Stochastic model for electric vehicle charging station integrated with wind energy," *Sustainable Energy Technologies and Assessments*, vol. 37, Art. no. 100577, Feb. 2020, doi: 10.1016/j.seta.2019.100577.
- [40] S. Geng, M. Vrakopoulou, and I. A. Hiskens, "Chance-constrained optimal capacity design for a renewable-only islanded microgrid," *Electric Power Systems Research*, vol. 189, Art. no. 106564, Dec. 2020, doi: 10.1016/j.epsr.2020.106564.
- [41] P. V. N. M. Krishna, P. C. Sekhar, and T. R. Behera, "A robust optimal sizing of renewable-rich multi-source microgrid under uncertainties with multi-storage options," *Electrical Engineering*, vol. 106, no. 5, pp. 6547–6563, 2024, doi: 10.1007/s00202-024-02331-w.
- [42] Z. Qiu, Z. Zhu, L. Yu, Z. Han, W. Shao, K. Zhang, and Y. Ma, "Robust Optimal Operation of Smart Microgrid Considering Source-Load Uncertainty," *Processes*, vol. 13, no. 8, Art. no. 2458, 2025, doi: 10.3390/pr13082458.
- [43] H. Fathabadi, "Novel wind powered electric vehicle charging station with vehicle-to-grid (V2G) connection capability," *Energy Conversion and Management*, vol. 136, pp. 229–239, Mar. 2017, doi: 10.1016/j.enconman.2016.12.045.
- [44] H. Fathabadi, "Novel grid-connected solar/wind powered electric vehicle charging station with vehicle-to-grid technology," *Energy*, vol. 132, pp. 1–11, Aug. 2017, doi: 10.1016/j.energy.2017.04.161.
- [45] S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, "Review of electric vehicle charging technologies, standards, architectures, and converter configurations," *IEEE Access*, vol. 11, pp. 41218–41255, 2023, doi: 10.1109/ACCESS.2023.3267164.
- [46] M. M. Hammood, A. Elmitwally, and M. Zaki, "Techno-economic optimization of a PV-battery solar highway lighting system with IoT-based monitoring: A case study in Egypt," *Applied System Innovation*, vol. 9, no. 7, Art. no. 153, Jul. 2026, doi: 10.3390/asi9070153.
- [47] P. A. Gbadega and K. Loji, "Toward a digital twin framework for small-scale renewable energy microgrids with integrated energy management control," *Sustainability*, vol. 18, no. 13, Art. no. 6732, Jul. 2026, doi: 10.3390/su18136732.
- [48] H. Jiang, R. Tjandra, C. B. Soh, S. Cao, D. C. L. Soh, K. T. Tan, K. J. Tseng, and S. B. Krishnan, "Digital Twin of Microgrid for Predictive Power Control to Buildings," *Sustainability*, vol. 16, no. 2, Art. no. 482, 2024, doi: 10.3390/su16020482.
- [49] S. Li, S. Patnaik, and J. Li, "IoT-based technologies for wind energy microgrids management and control," *Electronics*, vol. 12, no. 7, Art. no. 1540, Mar. 2023, doi: 10.3390/electronics12071540.

- [50] A. Rekeraho, D. T. Cotfas, P. A. Cotfas, E. Tuyishime, T. C. Balan, and R. Acheampong, "Enhancing Security for IoT-Based Smart Renewable Energy Remote Monitoring Systems," *Electronics*, vol. 13, no. 4, Art. no. 756, 2024, doi: 10.3390/electronics13040756.
- [51] F. Bonavolontà, A. Liccardo, F. Mottola, and D. Proto, "Real-Time Monitoring of Energy Contributions in Renewable Energy Communities Through an IoT Measurement System," *Sensors*, vol. 25, no. 5, Art. no. 1402, 2025, doi: 10.3390/s25051402.
- [52] Y. Marykovskiy, T. Clark, J. Deparday, E. Chatzi, and S. Barber, "Architecting a digital twin for wind turbine rotor blade aerodynamic monitoring," *Frontiers in Energy Research*, vol. 12, Art. no. 1428387, 2024, doi: 10.3389/fenrg.2024.1428387.
- [53] A. Mostafavi and A. Friedmann, "Wind turbine condition monitoring dataset of Fraunhofer LBF," *Scientific Data*, vol. 11, no. 1, Art. no. 1108, 2024, doi: 10.1038/s41597-024-03934-5.
- [54] J. Maldonado-Correa, J. Cuenca-Granda, J. Torres-Cabrera, G. Cerda Mejía, W. D. Bastidas Barragan, R. Guapulema, E. Paccha-Herrera, J. C. Solano, D. Tapia-Peralta, J. Benavides, and C. Laverde-Albarracín, "Digital Twin Technology in Wind Turbine Condition Monitoring, Predictive Maintenance, and RUL Estimation: A Systematic Literature Review," *Energies*, vol. 19, no. 6, Art. no. 1477, 2026, doi: 10.3390/en19061477.
- [55] W. Tian, Z. Mao, and Y. Li, "Numerical Simulations of a VAWT in the Wake of a Moving Car," *Energies*, vol. 10, no. 4, Art. no. 478, 2017, doi: 10.3390/en10040478.
- [56] E. H. Bani-Hani, A. Sedaghat, M. AL-Shemmary, A. Hussain, A. Alshaieb, and H. Kakoli, "Feasibility of Highway Energy Harvesting Using a Vertical Axis Wind Turbine," *Energy Engineering*, vol. 115, no. 2, pp. 61–74, 2018, doi: 10.1080/01998595.2018.11969276.
- [57] S. J. Miller, M. Gordon, R. M. Staebler, and P. A. Taylor, "A Study of the Spatial Variation of Vehicle-Induced Turbulence on Highways Using Measurements from a Mobile Platform," *Boundary-Layer Meteorology*, vol. 171, no. 1, pp. 1–29, 2019, doi: 10.1007/s10546-018-0416-9.
- [58] R. M. A. Bakir, M. S. Soliman, M. S. M. Elksasy, M. S. Saraya and M. M. Abdelsalam, "PRO-MATE IOT-Based Cost-Effective Ground Motion Monitoring Acceleration Sensor Node: Hardware and Software Description," in *IEEE Sensors Letters*, vol. 7, no. 11, pp. 1-4, Nov. 2023, Art no. 6008704, doi: 10.1109/LSENS.2023.3327595.
- [59] Ali Bakir, Ramadan Madi, et al. "Low Cost MEMS accelerograph: structure, operation and application to seismology." *Delta University Scientific Journal* 6.1 (2023): 193-204.
- [60] M. Al shareef, M. M. El-Halwany, I. ismael, A. Ghanem, and R. M. Ali Bakir, "A Spatially Validated AI Framework for Predicting Optimal Solar-PV Tilt Angles Across Egypt," *International Journal of Artificial Intelligence and Machine Learning*, vol. 6, no. 10s, pp. 298–315, 2026, doi: 10.51483/ijaiml.6.10s.2026.298-315.
- [61] El-Halwany, M. M., et al. "A Multiprocessing-Based GPS Solar Tracking System with Dual-Axis Control for Remote EnergyAware Stations." *International Journal of Special Education* 41 (2026): 43.