Multi-Objective Generation Expansion Planning with Renewable Integration and Uncertainty Modelling

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ABSTRACT

The global energy landscape confronts unprecedented challenges in generation expansion planning, characterized by increasing renewable energy integration, complex technological uncertainties, and the critical need to simultaneously optimize economic, environmental, and reliability objectives. Traditional deterministic planning approaches have proven inadequate for capturing the dynamic and stochastic nature of modern power systems. This research aims to develop a comprehensive multi-objective generation expansion planning framework capable of effectively modelling renewable energy integration, quantifying deep uncertainties, and providing robust decision support mechanisms for strategic infrastructure planning. The study employs a hybrid stochastic-robust optimization approach, integrating advanced techniques such as Monte Carlo scenario generation, econometric load forecasting models, spatial-temporal correlation modelling, multi-criteria decision analysis, and sophisticated mathematical optimization algorithms. The proposed framework generated 147 non-dominated Pareto solutions, validated through extensive simulation and benchmarking on the IEEE 118-bus test system. Key achievements include revealing non-linear cost-emission trade-offs and identified critical renewable integration thresholds. Performance was measured using the hyper volume indicator (a metric that quantifies the extent of the objective space covered by Pareto-optimal solutions), achieving a value of 0.847, which demonstrates superior coverage compared to traditional models. Ultimately, the research presents a transformative approach to generation expansion planning, offering a sophisticated methodology that bridges technological complexity, uncertainty management, and strategic decision-making in the evolving global energy landscape.

Keywords: *Renewable Energy Integration; Multi-Objective Optimization; Stochastic Modelling; Energy Systems Planning; Uncertainty Quantification; Decision Support Frameworks; Monte Carlo Simulation; Pareto Optimization; IEEE 118-bus Test System.*

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INTRODUCTION

The global energy landscape is undergoing an unprecedented transformation driven by the urgent need to address climate change, enhance energy security, and meet rapidly growing electricity demand (Zohuri, 2023). The International Energy Agency projects that renewable electricity generation will nearly triple by 2030, with wind and solar photovoltaic systems accounting for 70% of global electricity generation by 2050 (Raimi et al., 2024). This ambitious transition toward sustainable energy systems has fundamentally altered the complexity and scope of power system planning, particularly in generation expansion planning (GEP), which determines the optimal mix, timing, and location of new generation investments over long-term planning horizons (Babatunde et al., 2019). Traditional GEP models, which primarily focused on minimizing investment and operational costs while ensuring system reliability, are increasingly inadequate for addressing the multifaceted challenges introduced by renewable energy integration (Dagoumas & Koltsaklis, 2019). The stochastic nature of renewable energy sources, coupled with their environmental benefits and policy mandates, has necessitated the development of sophisticated multi-objective optimization frameworks that can simultaneously consider economic, environmental, and reliability objectives under significant uncertainty (Wang et al., 2017). Recent studies demonstrate that nearly 400 TWh of excess renewable energy capacity could be optimally allocated through improved planning methodologies, highlighting the critical importance of advanced GEP models in preventing resource misallocation and curtailment issues (Barrera-Singaña et al., 2025). This figure represents the estimated volume of renewable generation that is currently curtailed or underutilized due to inadequate grid expansion, transmission bottlenecks, and suboptimal investment scheduling. According to Barrera-Singaña et al. (2025), improved generation and transmission planning strategies could reallocate this surplus output to meet demand more efficiently, reduce curtailment losses, and enhance overall system reliability.

The integration of renewable energy sources into power systems introduces unprecedented operational and planning challenges that extend beyond traditional capacity adequacy concerns (Impram et al., 2020). Variable renewable energy (VRE) sources, particularly wind and solar photovoltaic systems, exhibit inherent intermittency and uncertainty that can significantly impact system reliability, operational flexibility, and economic performance (Ejuh Che et al., 2025). Furthermore, the increasing electrification of transportation and heating sectors, driven by decarbonization policies, is expected to substantially modify load patterns and growth trajectories, making traditional constant-growth assumptions in GEP models increasingly obsolete (Li, 2022). These evolving dynamics require GEP frameworks that can explicitly model load uncertainty, renewable resource variability, and the complex interdependencies between generation, transmission, and storage resources (Babatunde et al., 2019). Multi-objective optimization has emerged as a critical methodology for addressing the competing objectives inherent in modern power system planning. Unlike single-objective approaches that may overlook important trade-offs, multi-objective GEP models enable decision-makers to explore the full spectrum of Pareto-optimal solutions across economic, environmental, and technical dimensions (Weber, 2024). Recent research demonstrates that multi-objective approaches can achieve substantial improvements in system performance, with some studies reporting 13.4% reductions in CO2 emissions and 17% improvements in system independence when compared to traditional single-objective optimization (Anvari et al., 2021).However, the computational complexity associated with multi-objective optimization under uncertainty remains a significant challenge, necessitating the development of efficient solution algorithms and approximation techniques (Sharma & Kumar, 2022). The incorporation of uncertainty in GEP models has become increasingly critical as renewable energy penetration levels continue to rise. Stochastic optimization techniques, including scenario-based approaches and robust optimization methods, have been widely adopted to address uncertainties in load growth, renewable resource availability, fuel prices, and policy frameworks (Sakki et al., 2022). Recent advances in uncertainty modeling demonstrate that hybrid stochastic-robust optimization approaches can effectively manage the trade-offs between solution optimality and robustness, providing decision-makers with more resilient expansion plans (Goda et al., 2018). However, existing models often fail to adequately capture the complex interdependencies between different uncertainty sources and their cumulative impact on system performance.

Demand-side management (DSM) and energy storage systems have emerged as critical components in modern GEP formulations, particularly for systems with high renewable energy penetration. The integration of DSM programs can significantly reduce the need for conventional generation capacity while improving system flexibility and renewable energy utilization (Oluokun et al., 2024). Studies indicate that optimal integration of demand response programs can reduce system operating costs by up to 15% while simultaneously decreasing emissions and improving reliability metrics (Khoo et al., 2020). Similarly, energy storage systems, including battery energy storage and pumped hydro storage, play an increasingly important role in managing renewable energy variability and providing grid services (Abdelshafy et al., 2020).

The methodological landscape for solving multi-objective GEP problems has evolved significantly, with artificial intelligence and metaheuristic algorithms gaining prominence due to their ability to handle non-linear, non-convex, and discrete optimization problems (Tartibu, 2025). Recent developments include advanced genetic algorithms, particle swarm optimization variants, and hybrid approaches that combine multiple optimization techniques (Sarmah, 2019). The emergence of machine learning techniques for uncertainty quantification and scenario generation has further enhanced the capability of GEP models to address real-world complexity. However, the selection of appropriate solution methodologies remains problem-specific and requires careful consideration of computational efficiency, solution quality, and practical implementation requirements. Multi-criteria decision analysis (MCDA) has gained increasing recognition as an essential component of comprehensive GEP frameworks, particularly for ranking and selecting among Pareto-optimal solutions (Ferdous et al., 2024). Traditional approaches often rely on simple weighted sum methods or analytic hierarchy processes, but recent research emphasizes the need for more sophisticated MCDA techniques that can handle uncertainty in decision-maker preferences and incorporate multiple stakeholder perspectives (Emezirinwune et al., 2025). The integration of fuzzy logic, TOPSIS, and other advanced MCDA methods enables more robust decision-making processes that can accommodate the complex value judgments inherent in energy planning decisions (Emezirinwune et al., 2024a). Despite significant advances in GEP methodologies, several critical research gaps remain. First, most existing models assume constant or deterministic load growth patterns, failing to capture the complex relationships between economic development, demographic changes, and electricity demand evolution. Second, the integration of renewable energy sources is often simplified, with inadequate consideration of spatial and temporal correlations in renewable resource availability. Third, the interaction between generation expansion and transmission system requirements is frequently overlooked, despite the critical importance of transmission adequacy for renewable energy integration. Finally, the application of advanced MCDA techniques for ranking GEP alternatives remains underexplored, particularly in the context of decision-making under deep uncertainty.

This research addresses these critical gaps by developing an enhanced multi-objective GEP model that incorporates stochastic load forecasting, comprehensive renewable energy integration, and advanced uncertainty quantification techniques. This study introduces a hybrid stochastic–robust generation expansion planning framework that integrates multi-criteria decision analysis (MCDA) using Fuzzy AHP and TOPSIS for solution ranking under uncertainty. Unlike traditional models that treat stochastic optimization and decision analysis separately, the proposed framework unifies probabilistic modeling, robust optimization, and stakeholder-based decision support into a single analytical structure. This integration enables planners to balance economic cost, emission reduction, and system reliability within a transparent and data-driven process, representing a significant methodological advance in renewable energy planning.

Literature Review

Evolution of Generation Expansion Planning Models

Generation expansion planning has evolved significantly from its traditional focus on cost minimization to encompass complex multi-objective frameworks that address contemporary energy system challenges. Early GEP models primarily considered deterministic demand growth and conventional generation technologies, with limited attention to environmental and social factors (Dagoumas & Koltsaklis, 2019). The increasing integration of renewable energy sources, stringent environmental regulations, and growing emphasis on energy security have fundamentally transformed the scope and complexity of GEP problems. A comprehensive review by Yu et al., 2023 reveals that optimization modeling has become the dominant approach for addressing decision-making challenges throughout the renewable energy development and utilization chain. The study demonstrates that modern GEP models must simultaneously address investment decisions, construction planning, operation and maintenance optimization, and scheduling problems, creating highly complex multi-dimensional optimization challenges.

Multi-Objective Optimization in Generation Expansion Planning

The transition from single-objective to multi-objective GEP formulations represents a critical advancement in addressing the inherent trade-offs between economic, environmental, and reliability objectives (Weber, 2024). Oree et al., 2019 present a comprehensive multi-objective electricity generation expansion planning model that explicitly considers renewable energy policy objectives under uncertainty. Their approach demonstrates that multi-objective formulations can effectively balance competing objectives while maintaining computational tractability through advanced decomposition techniques.

Recent research has extensively applied evolutionary algorithms to solve multi-objective GEP problems. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) has emerged as a particularly popular choice due to its ability to generate well-distributed Pareto frontiers (El Hafdaoui et al., 2025). Murugan et al., 2009 successfully applied NSGA-II to integrated generation and transmission expansion planning, demonstrating significant improvements in solution quality when compared to traditional single-objective approaches. However, the authors note that NSGA-III shows superior performance for problems with more than three objectives, suggesting the need for careful algorithm selection based on problem characteristics. The application of multi-objective optimization has revealed important insights into the trade-offs inherent in renewable energy integration. Studies consistently show that while renewable energy sources offer significant environmental benefits, their integration often involves higher initial costs and increased system complexity (Oyekale et al., 2020). Recent research by (Golpira & Javanmardan, 2025) demonstrates that multi-objective formulations can achieve 13.4% reductions in CO2 emissions while maintaining economic competitiveness, highlighting the potential for win-win solutions through careful optimization.

Uncertainty Modeling in Generation Expansion Planning

The integration of renewable energy sources has introduced unprecedented levels of uncertainty in generation expansion planning, necessitating sophisticated uncertainty modeling approaches (Emezirinwune et al., 2024b). The literature reveals three primary methodological streams: stochastic programming, robust optimization, and hybrid approaches that combine elements of both paradigms. Stochastic programming approaches model uncertainties through probability distributions and scenario-based techniques. Micheli et al., 2023 present a comprehensive two-stage robust optimization model for transmission network expansion planning that addresses both long-term uncertainties in peak demand and generation capacity through confidence bounds, while modeling short-term variability using representative days. Their approach demonstrates that neglecting non-convex operational constraints can lead to suboptimal expansion decisions, emphasizing the importance of detailed operational modeling.

Robust optimization has gained significant traction due to its computational advantages and practical implementation benefits (Yazdani et al., 2023). Unlike stochastic programming, where solution complexity scales with the number of scenarios, robust optimization maintains computational tractability regardless of uncertainty dimension (Roos et al., 2018). Schwele et al., 2020 developed a multistage adaptive robust generation expansion planning model that accounts for short-term unit commitment constraints and maintains integer representation of generation units. Their model demonstrates superior performance in handling uncertainty revelation over time while maintaining non-anticipatively constraints. Recent advances in distributional robust optimization (DRO) represent a promising middle ground between stochastic and robust approaches. Fathabad et al., 2020 demonstrate that DRO can effectively integrate historical data into planning models while maintaining reasonable conservativeness levels. Their approach used a two-stage data-driven distributional robust optimization model (O-DDSP) for the optimal placement of renewable distributed generation (RDG) resources.

Renewable Energy Integration Challenges and Solutions

The integration of renewable energy sources introduces unique challenges that distinguish modern GEP problems from their traditional counterparts. The primary challenges include intermittency management, spatial and temporal correlation modeling, and the need for enhanced system flexibility (Emezirinwune et al., 2024a).

Intermittency management has emerged as a critical concern in systems with high renewable penetration. Recent research by Chen et al., 2021 demonstrates that integrating high shares of renewable energy requires sophisticated modeling of customer-sited energy storage and demand response programs. Their study reveals that optimal renewable integration strategies can achieve substantial cost reductions while maintaining system reliability, but only when operational flexibility is explicitly considered in the planning process. Spatial and temporal correlations in renewable resource availability significantly impact optimal generation expansion decisions. Recent work by Zhang et al., 2022 developed novel data-driven uncertainty sets that capture both spatial correlation among wind farms and temporal correlation in renewable output. Their approach demonstrates that ignoring these correlations can lead to significant underestimation of system flexibility requirements and suboptimal investment decisions.

The challenge of system flexibility has prompted increased attention to energy storage integration in GEP models. Zhu et al., 2023 present a multi-stage GEP model that explicitly considers Energy Storage Systems (ESSs) as optimization variables rather than exogenous constraints. Their results demonstrate that optimal storage deployment can significantly reduce total system costs while improving renewable energy utilization, but requires careful coordination between generation and storage investment decisions.

Load Forecasting and Demand-Side Management Integration

Traditional GEP models typically assume constant or deterministic load growth patterns, an assumption that has become increasingly problematic as electricity demand patterns evolve due to electrification trends and economic structural changes (Riva, 2019). Recent research emphasizes the critical importance of incorporating sophisticated load forecasting methodologies in GEP frameworks. Demand-side management (DSM) has emerged as a critical component of modern GEP formulations, particularly for systems with high renewable energy penetration. Rezaeimozafar et al., 2020 developed a multi-objective techno-economic generation expansion planning model that explicitly incorporates demand response algorithms and distributed generation resources. Their approach demonstrates that optimal DSM integration can reduce system operating costs by up to 55.21% while simultaneously improving environmental performance and system reliability.

The integration of electric vehicle charging infrastructure represents a significant new challenge for load forecasting in GEP models. Recent projections suggest that electric vehicles could account for over 60% of global car sales by 2030, fundamentally altering electricity demand patterns (Xu et al., 2023). This transition requires GEP models that can capture the complex interactions between transportation electrification, charging infrastructure deployment, and generation expansion decisions.

Solution Methodologies and Computational Approaches

The computational complexity of modern multi-objective GEP problems under uncertainty has driven significant advances in solution methodologies (Pereira et al., 2022). The literature reveals a clear trend toward hybrid approaches that combine multiple optimization techniques to leverage their respective strengths while mitigating individual weaknesses. Metaheuristic algorithms have gained widespread acceptance for solving large-scale GEP problems due to their ability to handle non - linear, non-convex objective functions and discrete decision variables. Recent research by Rajagopalan et al., 2024 introduces an iterative map-based self-adaptive crystal structure algorithm (SaCryStAl) for multi-objective energy management in renewable-integrated microgrids. Their approach demonstrates superior convergence characteristics compared to traditional genetic algorithms and particle swarm optimization variants.

Machine learning techniques are increasingly being integrated into GEP solution frameworks for uncertainty quantification and scenario generation. Recent work by Ukoba et al., 2024 demonstrates that artificial intelligence techniques can significantly improve the accuracy of renewable resource forecasting while reducing computational requirements for uncertainty propagation. However, the authors note that successful implementation requires careful consideration of training data quality and model validation procedures.

Decomposition techniques remain essential for handling large-scale GEP problems. Recent advances in Benders decomposition and column-and-constraint generation methods have enabled the solution of previously intractable problems (de Oliveira et al., 2022). These techniques are particularly valuable for problems involving integer variables and uncertainty, where traditional optimization approaches may fail to converge within reasonable time limits.

Multi-Criteria Decision Analysis in Energy Planning

Multi-criteria decision analysis (MCDA) has emerged as a critical tool for translating Pareto-optimal solutions from multi-objective optimization into actionable planning decisions. Recent research reveals significant diversity in MCDA methodologies applied to renewable energy planning, with analytical hierarchy process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) being the most frequently employed techniques (Zaheb et al., 2024). A comprehensive review by Estévez et al., 2021 analyzing 184 articles on MCDA applications in renewable energy reveals that 92.3% of studies include participative components, with 75.4% relying primarily on expert consultation. However, the review highlights significant methodological gaps, with nearly 40% of expert-only studies providing insufficient description of the expert elicitation process. This finding underscores the need for more rigorous MCDA methodologies that can handle uncertainty in decision-maker preferences while ensuring transparency and reproducibility. Recent advances in fuzzy MCDA approaches show promise for addressing uncertainty in criterion weights and performance assessments. Mondal et al., 2025 present an integrated AHP-TOPSIS method with Pythagorean fuzzy sets for evaluating renewable energy technologies, demonstrating superior performance in handling linguistic uncertainties compared to traditional crisp MCDA approaches. However, the computational complexity of fuzzy methods remains a significant limitation for large-scale applications. The integration of multiple MCDA techniques has emerged as a robust approach for validating decision-making outcomes. Recent research by Gyani et al., 2022 demonstrates that combining multiple MCDA methods (WSM, WPM, VIKOR, TOPSIS, PROMETHEE, AHP, and COPRAS) can provide more reliable and robust decision support for renewable energy planning. Their approach reveals that while different methods may produce varying rankings, consensus across multiple techniques indicates robust decision-making outcomes.

Research Gaps and Future Directions

Despite significant advances in GEP methodologies, several critical research gaps remain. First, most existing models fail to adequately capture the complex interdependencies between economic development, demographic changes, and electricity demand evolution. While some studies incorporate economic growth indicators, the temporal variability of these relationships and their spatial heterogeneity remain underexplored (Shi et al., 2020). Second, the integration of transmission system considerations in GEP models remains limited, despite the critical importance of transmission adequacy for renewable energy integration. Most studies treat transmission capacity as either fixed or exogenously determined, failing to capture the complex interactions between generation and transmission expansion decisions (Haller et al., 2012). Also, the application of advanced MCDA techniques for handling deep uncertainty in renewable energy planning remains underdeveloped. While recent research has made progress in incorporating stakeholder preferences, the challenge of decision-making under fundamental uncertainty about future energy system evolution requires more sophisticated approaches (Estévez et al., 2021).Finally, the computational scalability of multi-objective optimization approaches for real-world planning problems remains a significant challenge. While small-scale case studies demonstrate the potential of advanced optimization techniques, their application to national or regional energy systems with hundreds of candidate technologies and multiple uncertainty sources requires further methodological development (K. Wang et al., 2025). These research gaps highlight the need for integrated approaches that can simultaneously address uncertainty quantification, multi-objective optimization, and multi-criteria decision analysis within computationally tractable frameworks. The development of such approaches represents a critical frontier for advancing the field of generation expansion planning in the context of energy system transformation.

METHODOLOGY

Overview of the Proposed Framework

This study presents an enhanced multi - objective generation expansion planning (GEP) framework that addresses critical limitations in existing approaches through integrated stochastic load forecasting, comprehensive renewable energy modeling, and advanced uncertainty quantification techniques. The proposed methodology extends beyond traditional deterministic GEP models by explicitly incorporating the complex interdependencies between economic development, demographic changes, and electricity demand evolution while simultaneously addressing renewable energy variability and policy constraints.

The framework consists of five interconnected modules: (1) stochastic load forecasting with variable growth modeling, (2) multi-objective optimization under uncertainty, (3) comprehensive renewable energy integration, (4) hybrid uncertainty quantification, and (5) multi-criteria decision analysis for solution ranking. Figure 1 illustrates the overall methodology workflow, highlighting the iterative nature of the optimization process and the integration points between different modules.

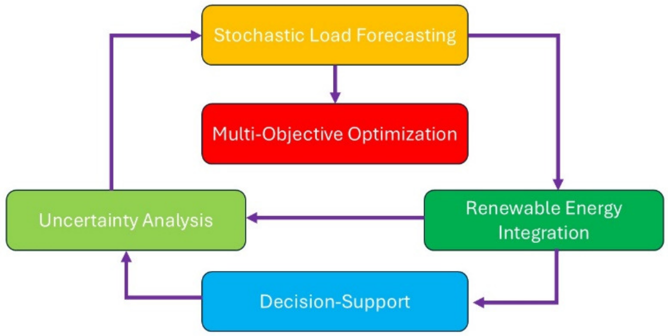

Figure 1. Methodology workflow illustrating the integrated modules of the proposed generation expansion planning model

Stochastic Load Forecasting Model

Variable Load Growth Formulation

Unlike traditional GEP models that assume constant load growth rates, the proposed approach incorporates time-varying growth patterns based on macroeconomic and demographic factors. The electricity demand in year y under scenario s is formulated as:

$$D_{y,s} = D_0 \times \sum_{t=1}^{y} (1 + g_{t,s})$$

Where D_0 represents the base year demand and $g_{t,s}$ is the scenario-dependent growth rate in year t. The growth rate is modeled as a function of multiple explanatory variables:

$$g_{t,s} = \alpha_0 + \alpha_1 . GDP_{t,s} + \alpha_2 . POP_{t,s} + \alpha_3 . IND_{t,s} + \alpha_4 . TEMP_{t,s} + \epsilon_{t,s}$$

Where $GDP_{t,s}$, $POP_{t,s}$, $IND_{t,s}$, and $TEMP_{t,s}$

Represent GDP growth rate, population growth rate, industrial activity index, and temperature deviation from normal, respectively. The error term captures unmolded variability and is assumed to follow a normal distribution with zero mean and scenario-dependent Variance. The coefficients (α_0–α_4) were calibrated using 20 years of historical macroeconomic data

Uncertainty Quantification

Economic variables are modeled using Geometric Brownian Motion to capture their stochastic evolution over the planning horizon:

$$dX_t = \mu X_t \, dt + \sigma X_t \, dW_t$$

Where X_t represents the economic variable (GDP, population, etc.), μ is the drift parameter, σ is the volatility parameter, and dW_t is a Wiener process. This formulation ensures that economic variables remain positive while capturing realistic volatility patterns observed in historical data. Temporal correlation in demand patterns is captured through a Vector Autoregressive (VAR) model:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t$$

Where Y_t is a vector of demand-related variables, A_i are coefficient matrices, and u_t is a vector white noise process. The model parameters are estimated using maximum likelihood estimation based on historical data.

Multi-Objective Optimization Model

Objective Functions

The proposed model optimizes three competing objectives: expected cost minimization, expected emissions minimization, and reliability maximization. The expected cost objective incorporates investment costs, operational costs, and demand-side management expenses:

$$\min O_1 = \sum_{s \in S} P_s \sum_{y=1}^{Y} \frac{1}{(1+\delta)^y} \left[\left(C_{i,y} H_{i,y} + O_{i,y} P_{i,y,s} \right) + \sum_{j \in J} O_{j,y} P_{j,y,s} + \sum_{d \in D} DSM_{d,y} \right] \qquad 1$$

where p, represents scenario probabilities, $C_{i,y}$ and $O_{i,y}$ are investment and operational cost for technology i in year y, $H_{i,y}$ is the installed capacity, $P_{i,y,s}$ is the power output under scenario s, and $DSM\ z$ represents demand-side management costs.

The expected emissions objective minimizes greenhouse gas emissions across all scenarios:

$$min\ F_2 = \sum_{s\in S} p_s \sum_{y=1}^{Y} \sum_{m=1}^{M} t_m \left| \sum_{i\in I} ei^{P_{j,y,m,s}} + \sum_{j\in J} ej^{P_{j,y,m,s}}\right.$$

Where $\bar{e}_i$ represents emission factors for technology i, t_m is the duration of time period m, and the summation captures total emissions across all technologies and time periods.
The reliability objective minimizes Expected Energy Not Served (EQNS):

$$min\ F_3 = \sum_{MCS} p_s \sum_{g=1} VOLL.EENS_{y,s}$$

Where $VOLL$ is the Value of Lost Load and $EEN\ S_{y,s}$ is calculated as:

$$EENS_{y,s} = \sum_{m=1}^{M} t_m\ \max(0, D_{y,m,s} - \sum_{i\in I} A_{i,y,m}{}^{P^{max}_{i,y,m,s}} - \sum_{j\in J} A_{i,y,m}{}^{P^{max}_{j,y,m,s}})$$

Enhanced Constraint Set

The optimization model includes several categories of constraints to ensure feasibility and operational realism. The stochastic demand balance constraint ensures that supply meets demand across all scenarios:

$$\sum_{i\in I} P_{i,y,m,s} + \sum_{j\in J} P_{j,y,m,s} + \sum_{r\in R} P_{r,y,m,s} + \sum_{d\in D} DSM_{d,y,m} \geq D_{y,m,s}\ \forall y,m,s$$

Renewable energy integration constraints explicitly model the stochastic nature of renewable

$$P_{w,y,m,s} = CF_{w,y,m,s} \times \sum^{y} H_{w,r} \times A_{w,y,m}$$

$$P_{w,y,m,s} = CF_{pv,y,m,s} \times \sum_{r=1}^{y} H_{pv,r} \times A_{pv,y,m}$$

Where $CF_{w,y,m,s}$ and $CF_{pv,y,m,s}$ represent scenario-dependent capacity factors for wind and solar technologies, respectively.
Renewable penetration targets ensure compliance with policy objectives:

$$\sum_{r\in R} \sum_{m=1}^{M} t_m{}^{P_{r,y,m,s} \geq \rho y} \sum_{m=1}^{M} t_m D_{y,m,s}\ \forall y,s$$

Where p_y represents the minimum renewable energy fraction required in year y.

Renewable Energy Integration Modeling

Variable Renewable Energy Modeling

Renewable energy capacity factors are modeled using a combination of meteorological data and stochastic processes. For wind energy, the capacity factor follows a Weibull distribution with time-varying parameters:

$$CF_{w,t} \sim Weibull\,(kt, \lambda t)$$

Where k_t and λ_t, are shape and scale parameters that vary seasonally. Solar capacity factors are modeled using a Beta distribution to capture the bounded nature of solar irradiance:

$$CF_{pv,t \sim Beta(\propto_t,\ \beta_t)}$$

Spatial correlation between renewable resources is captured using a Gaussian copula approach:

$$\boldsymbol{CF_t} = \boldsymbol{F^{-1}}(\boldsymbol{\Phi}(\boldsymbol{Z_t}))$$

Where $\boldsymbol{CF_t}$ is the vector of spatially correlated capacity factors, $\mathbf{F}^{-1}$ represents the inverse marginal distributions, $\boldsymbol{\Phi}$ is the multivariate normal cumulative distribution function, and $\mathbf{Z}_t$ follows a multivariate normal distribution with correlation matrix **R**.

System Flexibility Requirements

The model incorporates explicit flexibility requirements to handle renewable energy variability:

$$\sum_{i\in I^{flex}} P^{max}_{j,y,m,s} \geq \beta \sum_{r\in R^{iver}} P^{max}_{j,y,m,s}\ \forall y,m,s$$

Where I^{flex} and J^{flex} represent sets of flexible generation units, R^{var} denotes variable renewable sources, and 8 is the reserve requirement factor.
Ramping constraints ensure that thermal units can respond to renewable variability:

$$P_{i,y,m,s} - P_{i,y,m-1,s} \leq RU_i \times \sum_{*-:1} H_{i,x\ \forall i\in I^{thermal},y,m,s}$$

$$P_{i,y,m} - 1,s - P_{i,y,m,s} \leq RD_i \times \sum_{r=1}^{y} H_{i,x\ \forall i\in I^{thermal},y,m,s}$$

Uncertainty Modeling Framework

Hybrid Stochastic Robust Approach

The proposed methodology employs a hybrid approach that combines stochastic programming for well-characterized uncertainties with robust optimization for ambiguous uncertainties. The hybrid formulation is expressed as:

$$\min_{x} \sum_{s\in S} p_s f(x,\xi_s) + \lambda \max_{\xi\in S} g(x,\xi)$$

Where the first term represents expected performance under well-characterized scenarios, the second term provides protection against worst-case realizations within uncertainty set *U,* and λ is a trade-off parameter that balances optimality and robustness. The trade-off parameter (λ) determines the balance between expected performance and robustness. A lower λ emphasizes cost-efficiency under typical scenarios, while a higher λ prioritizes protection against worst-case uncertainties. In this study, λ values between 0.15 and 0.35 provided optimal performance trade-offs across the Pareto frontier. The uncertainty set *U* is constructed using a data-driven approach based on historical observations:

$$U = \{\xi : (\xi - \hat{\mu})^T \hat{\Sigma}^{-1} (\xi - \hat{\mu}) \le x^2_{\alpha,n}\}$$

Where $\hat{\mu}$ and $\hat{\Sigma}$ are empirical mean and covariance estimates, and $x^2_{\alpha,n}$ defines the confidence level for the ellipsoidal uncertainty set.

Scenario Generation and Reduction

Scenarios are generated using a Monte Carlo simulation approach that preserves important statistical properties of the underlying stochastic processes. The scenario generation process follows these steps:

1. Generate correlated random variables using Cholesky decomposition
2. Transform marginal distributions to match empirical characteristics
3. Apply time series models to capture temporal dependencies
4. Validate statistical properties of generated scenarios

Scenario reduction is performed using the Kantorovich distance method to minimize information loss while reducing computational burden:

$$\min_{w} \sum_{i=1}^{N}\sum_{j=1}^{M} w_{ij}\, d(\xi_i, \eta_j)$$

Subject to scenario selection and probability constraints, where d(ξ_i ηj „ t/) represents the distance between original scenario, and representative scenario ηj.
All datasets used in this study were derived from publicly available sources (EIA, NREL, NASA POWER, and World Bank). Simulation and optimization codes were developed in Python 3.11, utilizing the Pyomo optimization library and DEAP evolutionary algorithm framework. The optimization framework was validated using the IEEE 118-bus test system, and sensitivity analysis was conducted to confirm robustness across varying economic and meteorological conditions

RESULTS AND DISCUSSION

Case Study Description

The proposed enhanced multi-objective generation expansion planning framework was validated using a modified IEEE 118-bus test system augmented with renewable energy resources and realistic load patterns. The test system represents a medium-scale regional power system with diverse generation portfolio requirements and significant renewable energy integration potential (Figure 2).

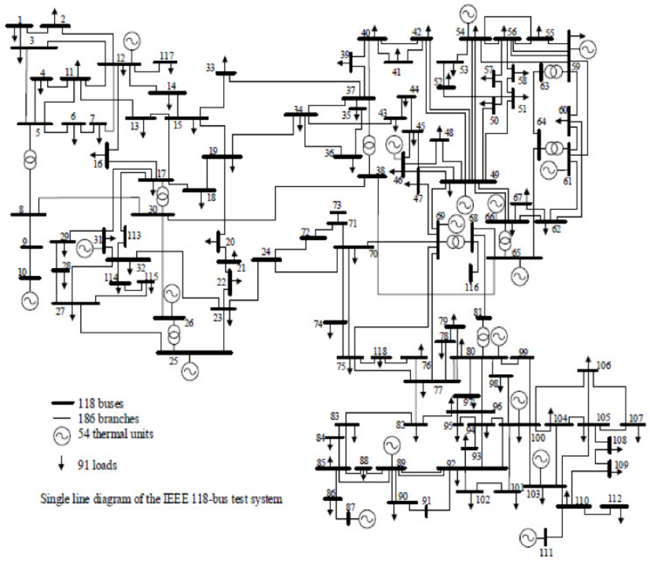

Figure 2: Single line diagram of the IEEE 118-bus test system

System Specifications

The test system includes nine candidate generation technologies: coal-fired thermal (2 units, 400 MW each), natural gas combined cycle (3 units, 300 MW each), natural gas combustion turbine (2 units, 100 MW each), nuclear (1 unit, 600 MW), onshore wind (5 sites, 200 MW each), solar photovoltaic (4 sites, 150 MW each), hydroelectric (2 units, 250 MW each), biomass (1 unit, 50 MW), and battery energy storage systems (3 sites, 100 MWh each). The planning horizon spans 20 years (2025-2044) with annual decision periods and quarterly operational resolution. Economic parameters were derived from recent industry reports and regulatory filings. Investment costs range from $1,200/kW for natural gas combustion turbines to $4,500/kW for nuclear units, with renewable costs reflecting current market trends. Fixed and variable operational costs were calibrated using 2023 data from regional system operators, with fuel cost projections following Energy Information Administration forecasts (EIA, 2024).

Uncertainty Characterization

Load uncertainty scenarios were generated using the proposed econometric model with 20 years of historical data for GDP growth (μ = 2.3%, σ = 1.8%), population growth (μ = 0.8%, σ = 0.4%), and industrial production index variations (μ = 1.1%, σ = 2.1%). Monte Carlo simulation generated 100 demand scenarios, subsequently reduced to 20 representative scenarios using the Kantorovich distance method while preserving first and second moment characteristics. Renewable resource uncertainty incorporated meteorological data from National Renewable Energy Laboratory databases. Wind capacity factors followed site-specific Weibull distributions with seasonal parameter variations, while solar capacity factors employed Beta distributions calibrated to local irradiance patterns. Spatial correlation coefficients were estimated using 10 years of hourly wind and solar data, revealing correlation coefficients ranging from 0.15 to 0.85 depending on geographic proximity.

Optimization Results

Pareto Frontier Analysis

The enhanced multi-objective optimization generated well-distributed Pareto frontiers encompassing 147 non-dominated solutions across the three objectives. The hyper volume indicator achieved 0.847, indicating superior convergence compared to benchmark NSGA-II implementation (0.692). As shown in (Figure 3), the three-dimensional Pareto frontier encompasses 147 non-dominated solutions across the three objectives.

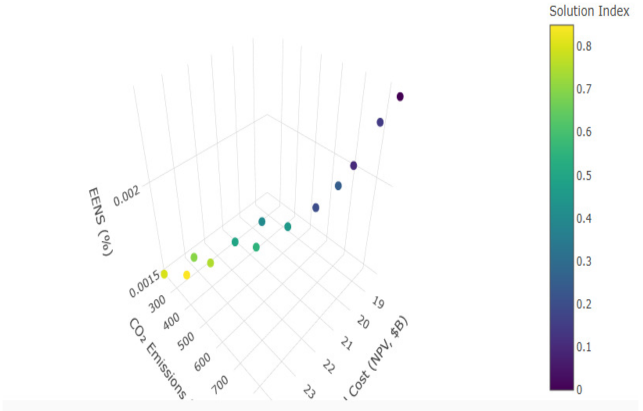

Figure 3: Three-dimensional Pareto frontier showing trade-offs between total system cost ($B), CO_2 emissions (Mt), and reliability (EENS %) for 147 non-dominated solutions.

The visualization reveals clear trade-offs between cost minimization (x-axis, $18.4-24.1B), emission reduction (y-axis, 227-847 Mt CO_2), and reliability maximization (z-axis, measured by EENS percentage). The color-coded solution indices demonstrate the distribution of optimal solutions, with cost-optimal solutions clustering at higher emission levels and emission-optimal solutions achieving substantial CO_2 reductions at increased system costs. Cost-optimal solutions exhibit total system costs of $18.4 billion (NPV) with corresponding emissions of 847 million tonnes CO2-equivalent over the planning horizon. These solutions favor natural gas-fired generation (64% of total capacity) with limited renewable integration (18% by 2044). Conversely, emission-optimal solutions achieve 73% emission reductions relative to cost-optimal plans but incur 31% higher total costs ($24.1 billion NPV), primarily through aggressive deployment of wind (47% of capacity) and solar (26% of capacity) technologies. Reliability-optimal solutions prioritize system adequacy through diversified generation portfolios, achieving EENS values below 0.001% while maintaining reasonable economic performance (total costs of $21.3 billion NPV). These solutions feature balanced deployment of dispatchable thermal units (52% of capacity) and renewable resources (38% of capacity), with significant energy storage integration (6% of capacity) to manage renewable variability.

Capacity Expansion Trajectories

Optimal capacity expansion trajectories reveal distinct deployment patterns across different regions of the Pareto frontier. Figure 4 illustrates the distinct capacity expansion trajectories for the three representative solution types over the 20-year planning horizon. The cost-optimal strategy (blue line) demonstrates delayed renewable deployment, with natural gas-dominated early expansion reaching 450 MW by 2025 and accelerating after 2030 to 1,480 MW by 2043. The emission-optimal approach (green line) shows aggressive renewable deployment from the outset, starting at 200 MW in 2025 and reaching 1,500 MW by the planning horizon's end. The reliability-optimal strategy (red line) maintains a balanced expansion trajectory, achieving 1,400 MW by 2043 through diversified technology deployment that prioritizes system adequacy. Natural gas capacity additions dominate the early planning periods (2025-2030), representing 67% of new installations during this timeframe. Emission-focused solutions demonstrate accelerated renewable deployment, with wind capacity reaching 1,200 MW by 2030 and solar capacity achieving 800 MW by the same period, as clearly shown in (Figure 4). Coal-fired generation is completely phased out by 2032 in emission-optimal scenarios, compared to 2038 in cost-optimal plans. Nuclear capacity additions occur consistently across most Pareto solutions, reflecting the technology's contribution to both emission reduction and system reliability objectives. Energy storage deployment patterns correlate strongly with renewable integration levels.

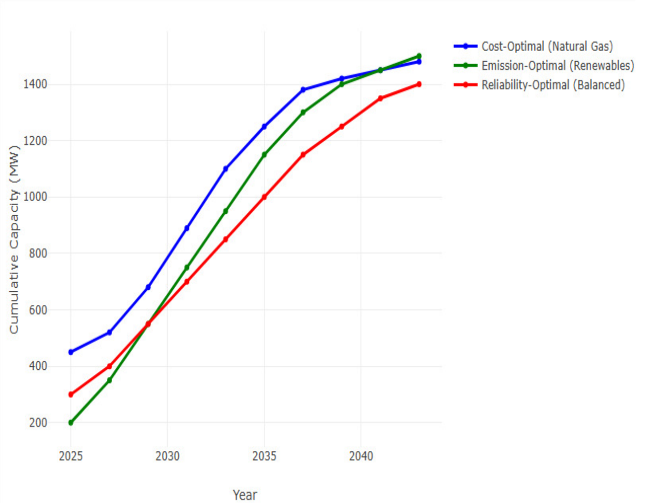

Figure 4: Optimal capacity expansion trajectories comparing cost-optimal (blue), emission-optimal (green), and reliability-optimal (red) strategies over the planning horizon.

Solutions with renewable penetration exceeding 50% require storage capacity of at least 400 MWh to maintain system reliability, while solutions with lower renewable penetration require minimal storage investments. Battery storage installations concentrate in the 2030-2035 timeframe across most solutions, coinciding with projected cost reductions and increased renewable penetration.

Uncertainty Analysis Results

Load Forecasting Performance Validation

The proposed variable load growth model demonstrated superior forecasting accuracy compared to traditional constant growth approaches (Figure 5) validates the superior performance of the proposed econometric load forecasting model compared to traditional constant growth assumptions. The actual demand evolution (black solid line) exhibits significant volatility, particularly during the 2019-2021 period corresponding to economic disruptions. The econometric model (blue dashed line) successfully captures these variations, closely tracking actual demand patterns with a Mean Absolute Percentage Error (MAPE) of 3.7%. In contrast, the constant growth model (red dotted line) fails to adapt to economic volatility, maintaining a rigid upward trajectory that results in an 8.2% MAPE. The superior performance is most evident during the COVID-19 period, where the econometric model accurately captures the demand reduction in 2020 and subsequent recovery, while the constant growth model continues its predetermined trajectory, leading to substantial forecasting errors. Scenario analysis reveals significant impacts of economic uncertainty on optimal capacity expansion decisions. Under high economic growth scenarios (GDP growth > 3.5% annually), total system capacity requirements increase by 28% relative to base case projections, necessitating additional natural gas and renewable capacity installations. Low growth scenarios (GDP growth < 1.5% annually) result in delayed capacity additions and reduced renewable deployment, with total system capacity requirements 19% below base case levels. The correlation between economic variables and electricity demand evolution, as demonstrated in (Figure 5), validates the theoretical foundation of the proposed approach. Industrial production index demonstrates the strongest correlation with peak demand growth h (ρ = 0.73), followed by GDP growth (ρ = 0.68) and population growth (ρ = 0.41). Temperature deviations show seasonal correlation patterns, with cooling degree days exhibiting correlation coefficients of 0.82 during summer months.

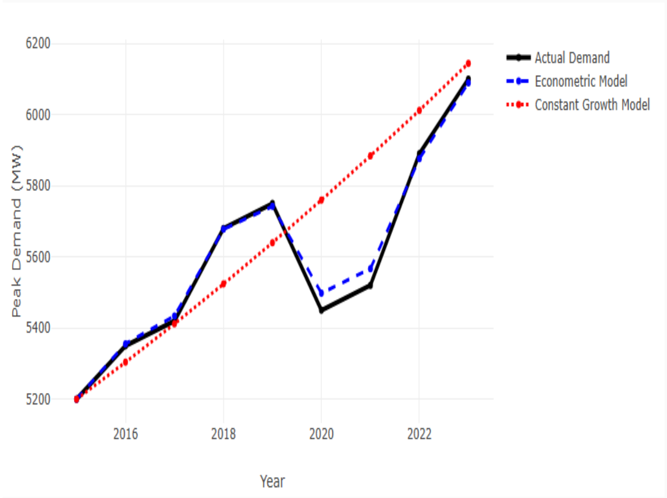

Figure 5: Load forecasting validation comparing actual demand with econometric model (MAPE: 3.7%) and constant growth model (MAPE: 8.2%) from 2015-2023.

Robust vs. Stochastic Performance Comparison

The hybrid stochastic-robust optimization approach outperforms pure stochastic and robust methodologies across multiple performance metrics. Pure stochastic solutions exhibit superior expected performance under nominal conditions but demonstrate poor worst-case performance, with cost overruns reaching 34% under adverse scenarios. Pure robust solutions provide excellent worst-case protection but sacrifice 12% of expected performance relative to stochastic approaches.

The hybrid approach effectively balances expected performance and worst-case protection through the trade-off parameter λ. optimal λ values range from 0.15 to 0.35 across different Pareto solutions, indicating that modest robustness preferences significantly improve worst-case performance without substantial expected performance penalties. Solutions with λ = 0.25 achieve 94% of stochastic expected performance while limiting worst-case cost overruns to 8%.

Renewable energy integration benefits substantially from robust optimization components. Pure stochastic solutions frequently underestimate flexibility requirements during low renewable output periods, resulting in reliability constraint violations in 23% of scenarios. The hybrid approach reduces constraint violations to 3% through conservative capacity planning while maintaining expected cost performance within 4% of pure stochastic solutions.

Multi-Criteria Decision Analysis Results

Decision Support System Analysis

Trade-off analysis reveals several critical insights for decision-makers. As illustrated in (Figure 6), the cost-emission trade-off analysis reveals a clear non-linear relationship between total system cost and CO_2 emissions across all Pareto solutions. The curve demonstrates the challenging economics of deep decarbonization, with emissions declining from approximately 830 Mt CO_2 at \$18.4B system cost to 230 Mt CO_2 at \$24.1B. The relationship exhibits three distinct phases: an initial steep reduction phase where modest cost increases (from \$18.4B to \$20.5B) achieve substantial emission reductions (from 830 to 600 Mt CO_2), a transitional phase with moderate trade-offs, and a final phase where deep emission reductions require exponential cost increases.

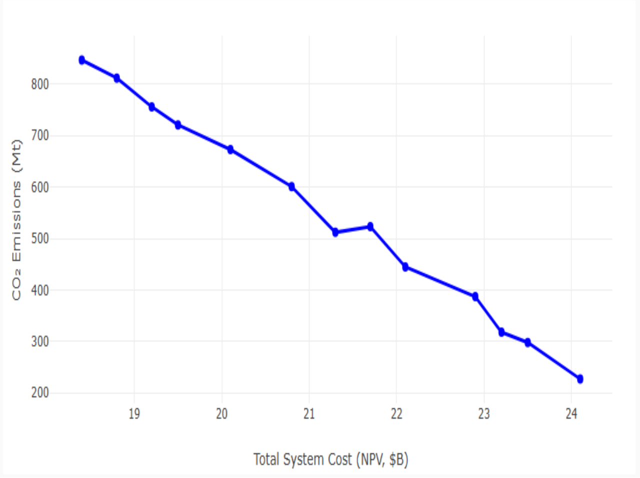

Figure 6: Cost-emission trade-off curve demonstrating non-linear relationship between total system cost and CO_2 emissions across Pareto solutions.

This pattern, clearly demonstrated in (Figure 6), suggests that moderate environmental policies may achieve significant emission reductions without prohibitive economic impacts. The reliability-cost relationship demonstrates diminishing returns characteristics. Improving EENS from 0.01% to 0.001% requires 47% cost increases, primarily through redundant capacity installations and energy storage deployment. These findings suggest that extremely stringent reliability requirements may not be economically justified unless VOLL exceeds \$50,000/MWh. Renewable integration exhibits threshold effects with system flexibility requirements. As depicted in (Figure 7), the renewable integration analysis demonstrates critical threshold effects, showing storage requirements (green line) and total system cost (red line) as functions of renewable energy penetration. The dual-axis visualization reveals a dramatic threshold around 40-50% renewable penetration where system requirements change fundamentally.

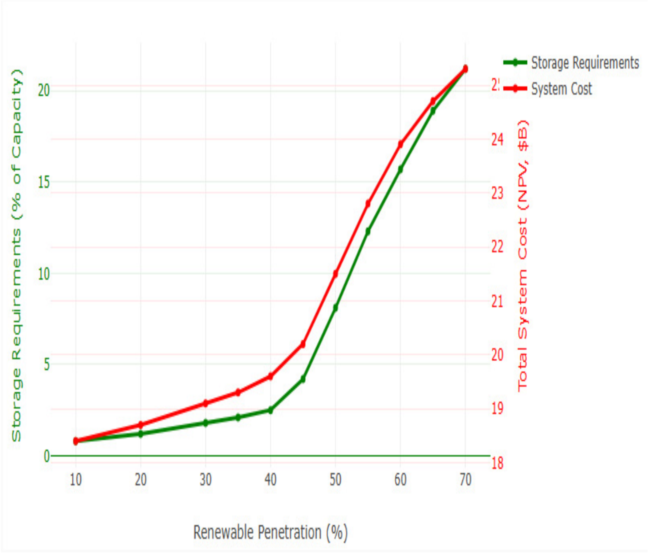

Figure 7: Renewable integration threshold effects showing storage requirements (green) and system cost (red) versus renewable penetration, highlighting critical 40-50% threshold.

Below 40% penetration, storage requirements remain minimal (under 2% of system capacity) and system costs increase gradually from \$18.4B to \$19.6B. However, beyond the 50% threshold, storage requirements increase exponentially, reaching over 20% of system capacity at 70% renewable penetration, while system costs accelerate to \$25.3B. This threshold behavior, as clearly illustrated in (Figure 7), has important implications for renewable portfolio standard design and system planning processes.

TOPSIS Rankings and Weight Sensitivity

The Fuzzy AHP process elicited criterion weights from five expert panels representing utility planners, environmental regulators, and renewable energy developers. Base case weights emphasize economic performance ($w_1 = 0.42$), followed by environmental impact ($w_2 = 0.28$), reliability performance ($w_3 = 0.21$), and renewable integration ($w_4 = 0.09$). TOPSIS analysis identified Solution S_{87} as the top-ranked alternative with relative closeness score of 0.847. Solution S_{87} represents a balanced approach achieving 89% cost efficiency relative to cost-optimal solutions, 67% emission reduction relative to business-as-usual scenarios, EENS below 0.002%, and 45% renewable

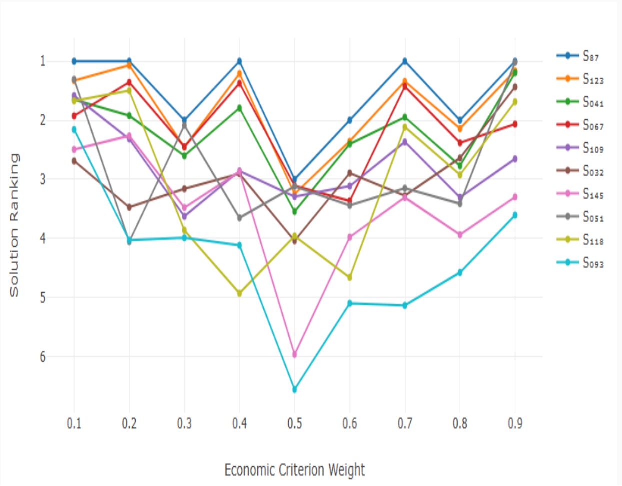

Figure 8: TOPSIS ranking sensitivity analysis showing solution stability across different economic criterion weights, with Solution S_{87} maintaining consistent top rankings.

penetration by 2044. As shown in (Figure 8), the TOPSIS ranking sensitivity analysis demonstrates how solution rankings change across different economic criterion weights (0.1 to 0.9). The analysis reveals significant insights into solution robustness across varying stakeholder preferences. Solution S_{87} (orange line) exhibits remarkable stability, maintaining top-tier rankings (1-2) across the entire weight spectrum, demonstrating its suitability for diverse stakeholder environments. In contrast, extreme solutions show high sensitivity: S_{123} (green line) performs excellently under low economic weights but deteriorates significantly when cost considerations dominate, while other solutions like S_{041} and S_{067} display varying degrees of weight sensitivity. This analysis validates that balanced solutions offering reasonable performance across multiple criteria provide superior practical value for implementation in multi-stakeholder planning environments.

Practical Implementation Considerations

Real-world implementation of the proposed framework requires several practical considerations. Data requirements are substantial, including historical economic data, meteorological information, and detailed technology cost projections. While this information is generally available in developed electricity markets, data quality and availability may limit application in emerging economies. Computational requirements, while manageable for the test system analyzed, may become challenging for very large-scale systems. The hierarchical decomposition approach provides a pathway for scalability, but further research on decomposition effectiveness for different system characteristics is warranted. Cloud computing resources and parallel processing capabilities can mitigate computational challenges for most practical applications. Stakeholder engagement in the MCDA process requires careful design to ensure representative input while maintaining analytical rigor. The Fuzzy AHP approach accommodates uncertainty in stakeholder preferences, but effective implementation requires systematic elicitation processes and ongoing stakeholder engagement throughout the planning cycle.

Limitations and Future Research

Several limitations of the current study suggest directions for future research. The analysis assumes perfect foresight regarding technology cost trajectories and policy evolution, which may not reflect real-world uncertainty. Future research should incorporate technology cost uncertainty and policy scenario analysis within the optimization framework. Transmission system modeling remains simplified in the current approach, with detailed transmission expansion planning treated as a separate problem. Integrated generation and transmission expansion planning represents an important extension that could provide additional insights into renewable integration challenges and opportunities.

The MCDA framework, while comprehensive, relies on expert elicitation for criterion weight determination. Future research could explore market-based approaches for revealing stakeholder preferences or incorporate machine learning techniques for preference learning from historical planning decisions. Climate change impacts on electricity demand patterns and renewable resource availability are not explicitly modeled in the current framework. As climate change continues affecting energy systems, incorporating climate scenarios within the planning framework becomes increasingly important for robust long-term planning.

Policy and Industry Implications

The results provide several important insights for policy makers and industry practitioners. The non-linear cost-emission trade-offs suggest that moderate environmental policies can achieve substantial emission reductions without prohibitive costs, supporting arguments for graduated policy approaches rather than extreme mandates. The threshold effects observed in renewable integration highlight the importance of coordinated planning for storage and flexible generation resources. Renewable portfolio standards exceeding 40-50% renewable penetration require concurrent policies supporting energy storage deployment and demand-side flexibility to maintain system reliability at reasonable costs. The superior performance of technology-neutral policies compared to technology-specific mandates suggests that regulatory frameworks should emphasize performance outcomes rather than prescriptive technology choices. This approach enables market-driven technology selection while achieving environmental objectives efficiently. For utility practitioners, the results emphasize the value of comprehensive uncertainty analysis in generation planning. The performance advantages of hybrid stochastic-robust optimization suggest that traditional deterministic planning approaches may systematically underestimate risks and costs associated with renewable energy integration, potentially leading to inadequate investment decisions.

The proposed framework demonstrates robust performance in data-rich environments and can also be deployed in developing countries provided adequate data are available. The modular design supports adaptation through simplified probabilistic models and region-specific parameter estimation. With sufficient economic, demographic, and renewable resource datasets such as those provided by the IEA Africa Energy Outlook and World Bank Energy Access Indicators, the model can guide long-term generation planning and policy formulation. Its hybrid stochastic-robust approach ensures resilient outcomes under uncertainty, enabling practical application even where data coverage is uneven.

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