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Intelligent Statistical Learning Framework for Optimal Distributed Energy Planning in Industrial Parks

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Abstract: Industrial parks are undergoing rapid transformation toward decentralized and renewable-based energy infrastructures to improve sustainability, operational efficiency, and economic competitiveness. However, distributed energy planning remains a challenging optimization problem because renewable energy resources exhibit significant spatial and temporal uncertainty, making conventional deterministic planning approaches inadequate. Statistical learning techniques provide an effective mechanism for extracting hidden patterns from historical energy data, while probabilistic scenario generation improves planning robustness under uncertain operating conditions. This paper proposes an intelligent statistical learning framework that integrates probabilistic scenario generation, statistical forecasting, Bayesian learning, and optimization strategies for distributed energy planning in industrial parks. The framework combines renewable scenario generation with statistical learning to model uncertain wind energy behavior, generate representative operating scenarios, and support optimal planning decisions. Bayesian generative learning, deep scenario generation, dependent stochastic optimization, and frequency-based forecasting collectively improve prediction accuracy while reducing planning risk. The proposed methodology establishes a systematic workflow consisting of data acquisition, statistical preprocessing, probabilistic scenario generation, uncertainty modeling, optimization, and decision support. Analytical findings indicate that integrating statistical learning with stochastic optimization significantly enhances planning flexibility, energy utilization efficiency, renewable penetration, and operational reliability. The framework also supports adaptive planning under changing environmental conditions and provides practical guidance for intelligent industrial energy management. The proposed research contributes an integrated planning architecture that combines modern statistical learning with distributed energy optimization for future smart industrial parks.

Keywords: Distributed Energy Planning; Statistical Learning; Renewable Energy; Bayesian Learning; Scenario Generation; Industrial Parks; Stochastic Optimization; Machine Learning; Energy Forecasting.

INTRODUCTION

1.1 Background

Industrial parks represent one of the largest consumers of electrical energy worldwide. Increasing production capacity, electrification of industrial processes, environmental regulations, and renewable energy integration have fundamentally changed how industrial energy systems are planned and operated. Rather than relying exclusively on centralized electricity generation, modern industrial parks increasingly deploy distributed energy resources including wind turbines, photovoltaic systems, battery storage, combined heat and power systems, and intelligent energy management platforms.

Although distributed energy systems provide considerable environmental and economic advantages, they introduce substantial uncertainty into planning processes. Renewable generation depends heavily on weather conditions, seasonal variation, and stochastic environmental behavior. Consequently, planners must simultaneously consider multiple uncertain operating scenarios while minimizing operational costs and maintaining system reliability.

Traditional mathematical optimization methods often assume deterministic inputs and therefore cannot adequately represent renewable uncertainty. Statistical learning techniques overcome this limitation by learning probabilistic characteristics directly from historical observations. Instead of producing a single deterministic prediction, intelligent statistical learning models generate multiple realistic operating scenarios that support robust planning decisions under uncertainty (Chen, Li, & Zhang, 2018).

Recent developments in probabilistic machine learning have significantly improved renewable scenario generation. Bayesian learning, deep generative models, and stochastic optimization provide planners with richer representations of renewable variability than classical forecasting methods. Consequently, distributed energy planning is evolving from deterministic optimization toward intelligent probabilistic decision-making.

1.2 Problem Statement

Despite considerable advances in renewable energy forecasting, many distributed energy planning models continue to employ simplified statistical assumptions that inadequately capture nonlinear uncertainty. Independent forecasting models frequently ignore temporal dependence among renewable resources, while deterministic optimization approaches fail to consider multiple possible future operating conditions.

Industrial parks require planning strategies capable of integrating uncertain renewable generation with fluctuating industrial demand. Existing planning frameworks often suffer from limited adaptability because they generate insufficient scenario diversity or rely on overly restrictive probability distributions. Consequently, planning decisions may become economically inefficient or operationally unreliable when actual renewable generation deviates from expected values.

Furthermore, modern industrial energy systems require coordinated integration of statistical forecasting, probabilistic learning, uncertainty quantification, and optimization within a unified decision-making framework. Such integration remains relatively limited in current planning methodologies.

1.3 Research Relevance

Statistical learning has emerged as one of the most influential paradigms for modeling uncertainty in complex engineering systems. Unlike purely deterministic algorithms, statistical learning continuously improves prediction capability by identifying probabilistic relationships within historical datasets.

For industrial parks, statistical learning enables planners to evaluate numerous possible renewable generation scenarios before infrastructure investments are made. Bayesian renewable scenario generation further improves uncertainty representation by estimating probability distributions instead of single-point forecasts (Chen, Li, & Zhang, 2018). This probabilistic perspective allows planners to evaluate operational risks more effectively.

Additionally, recent advances in deep generative learning have significantly enhanced renewable scenario diversity, producing realistic operating conditions that better represent future uncertainties (Chen, Wang, & Zhang, 2018). These developments substantially improve strategic planning for distributed energy systems.

1.4 Research Objectives

The objectives of this study are:

- To develop an intelligent statistical learning framework for distributed energy planning.
- To integrate statistical forecasting with probabilistic renewable scenario generation.
- To improve uncertainty representation through Bayesian statistical learning.
- To establish an optimization strategy capable of supporting intelligent industrial energy planning.
- To analyze the effectiveness of integrated statistical learning techniques for renewable energy management.

1.5 Scope and Significance

This research focuses on distributed energy planning within industrial parks where renewable energy resources introduce substantial operational uncertainty. The study synthesizes statistical learning, Bayesian scenario generation, stochastic optimization, and machine learning into a unified planning framework.

The significance of this research lies in demonstrating how intelligent statistical learning can improve infrastructure planning, renewable integration, operational reliability, and investment decision-making simultaneously. Rather than replacing optimization methods, statistical learning complements mathematical programming by providing more realistic uncertainty information for planning algorithms.

LITERATURE REVIEW

The increasing penetration of renewable energy has transformed scenario generation into one of the central research topics in distributed energy planning. Unlike conventional deterministic planning approaches, recent research increasingly emphasizes probabilistic modeling capable of representing uncertainty through statistically generated operating scenarios.

Morales, Mínguez, and Conejo (2010) introduced an influential methodology for generating statistically dependent wind speed scenarios. Their work demonstrated that renewable resources exhibit strong temporal dependence, making independent scenario generation inadequate for practical planning applications. By preserving statistical dependence among renewable variables, their methodology significantly improved planning realism and operational reliability.

Yunus, Thiringer, and Chen (2016) proposed an ARIMA-based frequency decomposition approach for wind speed forecasting. Their statistical methodology separated high-frequency and low-frequency components before prediction, thereby improving forecasting performance under complex weather conditions. Frequency decomposition demonstrated that renewable forecasting accuracy can be substantially improved when different temporal behaviors are modeled independently rather than collectively.

While classical statistical forecasting provides accurate prediction under moderate uncertainty, deep learning approaches have introduced substantially greater flexibility for nonlinear scenario generation. Chen, Wang, and Zhang (2018) proposed an unsupervised deep learning approach for scenario forecasting that automatically extracts hidden statistical representations from historical datasets. Their model reduced dependence upon manually engineered features while improving renewable scenario diversity.

A major advancement in renewable scenario generation was presented by **Chen, Li, and Zhang (2018)**, who developed Bayesian renewable scenario generation through deep generative networks. Their Bayesian framework integrates probabilistic inference with deep learning, allowing uncertainty to be represented directly within generated renewable scenarios instead of relying solely on deterministic forecasts. Unlike traditional prediction methods that produce single expected values, Bayesian deep generative learning generates probability-aware scenarios capable of supporting robust planning under uncertain renewable conditions. Because distributed energy planning fundamentally depends upon uncertainty representation, Bayesian renewable generation provides a powerful theoretical foundation for intelligent statistical learning throughout this study **(Chen, Li, & Zhang, 2018)**.

Generative Adversarial Networks have further expanded renewable scenario generation capabilities. Jiang et al. (2018) proposed improved GAN architectures specifically designed for wind power scenario generation. Their methodology enhanced statistical similarity between generated and observed renewable outputs, allowing optimization algorithms to evaluate more realistic operating conditions. Improved adversarial learning also reduced distribution mismatch commonly observed in earlier generative models.

Similarly, Saatci and Wilson (2017) introduced Bayesian GAN, combining adversarial learning with Bayesian probability estimation. Their approach improved uncertainty estimation while reducing overfitting during scenario generation. Bayesian GAN represents an important bridge between probabilistic machine learning and statistical optimization, particularly for renewable energy planning where uncertainty plays a central role.

Hoeltgebaum, Fernandes, and Street (2018) further extended renewable scenario generation by developing non-Gaussian models with time-varying parameters. Their work demonstrated that renewable energy distributions frequently violate Gaussian assumptions commonly adopted in classical statistical models. Time-varying probabilistic parameters significantly improved scenario realism and enhanced optimization performance under changing environmental conditions.

Beyond renewable energy applications, Liu et al. (2019) demonstrated the effectiveness of Wasserstein Generative Adversarial Networks for small-sample augmentation. Although their case study focused on biological datasets, the underlying statistical principle has important implications for distributed energy planning where historical renewable datasets may be limited. Data augmentation techniques improve model generalization and reduce overfitting, making statistical learning more robust under sparse observations.

The optimization component of distributed energy planning is strongly supported by the stochastic optimization theory proposed by Liu (1997). Dependent-chance programming introduced a flexible mathematical framework for handling uncertain decision variables while satisfying probabilistic constraints. Unlike deterministic optimization, dependent-chance programming explicitly incorporates uncertainty into optimization models, making it highly relevant for renewable energy planning.

Collectively, the reviewed literature indicates significant progress in renewable scenario generation, statistical forecasting, probabilistic learning, and stochastic optimization. However, most studies emphasize individual components rather than their integrated application within industrial energy planning systems. Forecasting models primarily improve prediction accuracy, while optimization studies frequently assume simplified uncertainty models. Similarly, Bayesian deep learning and adversarial generation remain insufficiently integrated into comprehensive distributed energy planning frameworks.

Therefore, this research positions itself by proposing an integrated intelligent statistical learning framework that combines Bayesian renewable scenario generation, statistical forecasting, probabilistic uncertainty modeling, and stochastic optimization within a unified planning architecture. The framework builds directly upon Bayesian renewable generation proposed by **Chen, Li, and Zhang (2018)** while incorporating complementary advances in statistical dependence modeling, deep scenario generation, and optimization theory. This integrated perspective addresses existing research gaps and provides a comprehensive methodology for intelligent distributed energy planning in modern industrial parks.

METHODOLOGY

3.1 Research Framework

The proposed methodology develops an intelligent statistical learning architecture that transforms historical energy and environmental observations into probabilistic planning decisions. The central premise is that distributed energy planning should not depend on a single forecasted renewable generation value. Instead, the planning model should evaluate a collection of statistically credible future operating conditions.

The proposed framework consists of six interconnected stages: data acquisition, statistical preprocessing, renewable-energy forecasting, probabilistic scenario generation, stochastic optimization, and planning decision analysis. Historical wind generation, renewable availability, industrial electricity demand, weather-related observations, and existing distributed-energy-system characteristics constitute the primary information sources.

The methodological workflow can be represented as:

Historical Data → Statistical Processing → Learning Model → Scenario Generation → Stochastic Optimization → Optimal Energy Plan

The first stage establishes a reliable data foundation. The second stage identifies temporal dependence and frequency characteristics. The third stage estimates renewable-energy behavior. The fourth stage generates multiple possible renewable-energy scenarios. The fifth stage evaluates investment and operational decisions against those scenarios. Finally, the sixth stage identifies the planning configuration that provides an appropriate balance among cost, reliability, renewable utilization, and operational flexibility.

This architecture differs from conventional deterministic planning because uncertainty is incorporated before the optimization stage rather than being treated as an external disturbance after the planning decision has been made.

3.2 Data Acquisition and Preprocessing

The statistical learning model requires historical observations describing both energy supply and demand. For an industrial park, the dataset can hypothetically include hourly electricity consumption, wind generation, photovoltaic output, battery charging and discharging records, electricity purchase prices, and relevant environmental measurements.

Let the historical observation at time t be represented by

$X_t=[D_t,W_t,S_t,P_t,E_t]$

where D_t represents industrial electricity demand, W_t represents wind generation, S_t represents solar generation, P_t represents electricity-market conditions, and E_t represents environmental variables.

Preprocessing involves missing-value treatment, temporal alignment, normalization, outlier identification, and statistical dependency analysis. This stage is particularly important because erroneous observations can propagate through scenario-generation models and ultimately distort planning decisions.

Temporal dependence is retained rather than eliminated. This principle follows the importance of statistically dependent renewable scenarios demonstrated by Morales, Mínguez, and Conejo (2010). For example, wind generation during adjacent hours is generally correlated; randomly shuffling observations would therefore destroy useful information required for realistic scenario generation.

3.3 Statistical Forecasting Layer

The forecasting layer estimates the expected temporal behavior of renewable resources. ARIMA-based frequency decomposition provides a useful statistical foundation because renewable signals may contain both slowly changing trends and short-term fluctuations.

Following the conceptual approach of Yunus, Thiringer, and Chen (2016), the renewable time series can be separated into frequency components:

$$W_t = W_t^L + W_t^H$$

where W_t^L represents the low-frequency component and W_t^H represents the high-frequency component.

The low-frequency component captures persistent weather patterns, whereas the high-frequency component captures short-term variability. Separate statistical models can then be developed for the two components before their predictions are recombined.

This decomposition provides an important advantage for industrial planning. A planning model may respond differently to long-duration renewable shortages and short-duration fluctuations. The former can influence capacity requirements, whereas the latter may primarily influence battery-storage requirements.

3.4 Bayesian Renewable Scenario Generation

The central learning component of the proposed framework is Bayesian scenario generation. Rather than producing a single deterministic renewable forecast, the model estimates a conditional probability distribution:

$$p(W_{t+1:T} \mid X_{1:t})$$

where $W_{t+1:T}$ represents future renewable generation and $X_{1:t}$ represents historical information.

The Bayesian learning mechanism is particularly appropriate because planning decisions must account for both expected generation and uncertainty surrounding that generation. Chen, Li, and Zhang (2018) demonstrated the value of Bayesian deep generative learning for renewable scenario generation by combining probabilistic inference with deep representation learning.

Within the proposed framework, the Bayesian generator produces a scenario set:

$$\Omega = \{\omega_1, \omega_2, \ldots, \omega_N\}$$

where each ω_i represents one possible future renewable-energy trajectory and is associated with probability p_i.

The scenarios should satisfy three fundamental requirements: statistical similarity to historical observations, temporal dependence, and sufficient diversity. Excessively similar scenarios provide little additional information to the optimization model, whereas unrealistic scenarios can cause unnecessary conservatism.

The Bayesian approach is therefore used to balance scenario diversity with probabilistic consistency. This is a critical methodological component because renewable planning decisions depend not only on the expected renewable output but also on the probability of extreme low-generation and high-generation conditions.

3.5 Deep Generative Scenario Enhancement

Bayesian scenario generation is complemented by deep generative learning to capture nonlinear relationships that conventional statistical models may not adequately represent. Chen, Wang, and Zhang (2018) demonstrated that unsupervised deep learning can learn scenario representations without requiring explicit target labels.

The proposed framework can therefore employ a generative model with latent representation z:

$$z \sim p(z)$$

and

$$\hat{W} = G(z, X)$$

where G denotes the learned generator and $\hat{W}$ represents a generated renewable-energy trajectory.

Generative adversarial learning provides another mechanism for improving scenario realism. Jiang et al. (2018) demonstrated the applicability of improved GAN-based approaches for wind-power scenario generation. In the proposed framework, the discriminator evaluates whether generated scenarios exhibit statistical characteristics similar to historical renewable observations.

A conceptual adversarial objective can be expressed as:

$$\min_G \max_D V(D,G) = E_{x \sim p_{data}}[\log D(x)] + E_{z \sim p(z)}[\log(1 - D(G(z)))]$$

where G represents the scenario generator and D represents the discriminator.

The objective is not simply to generate visually or statistically plausible trajectories. Generated scenarios must remain useful for downstream optimization. Therefore, scenario quality is assessed through statistical distribution similarity, temporal correlation, variability, and planning relevance.

3.6 Non-Gaussian and Time-Varying Uncertainty Modeling

A major limitation of conventional statistical planning is the assumption that renewable generation follows a fixed Gaussian distribution. Renewable resources can exhibit skewness, heavy tails, and changing statistical characteristics.

Hoeltgebaum, Fernandes, and Street (2018) demonstrated the importance of non-Gaussian models with time-varying parameters for renewable generation scenarios. Accordingly, the proposed framework does not impose a fixed probability distribution across all operating periods.

The conditional distribution can be represented as:

$W_t \sim F(\theta_t)$

where F represents the selected probability structure and θ_t represents time-dependent parameters.

This allows the uncertainty model to adapt to seasonal or operational changes. For example, the distribution of wind generation during a high-wind season may differ substantially from that observed during low-wind periods.

Such adaptability improves the robustness of planning because infrastructure decisions are evaluated against changing probability characteristics rather than a single static uncertainty model.

3.7 Small-Sample Data Enhancement

Industrial parks may not always possess sufficiently long historical datasets, particularly when newly installed renewable systems have only recently become operational. Limited data can result in overfitting and unreliable probability estimation.

The proposed methodology therefore incorporates data augmentation as an optional preprocessing layer. Wasserstein GAN-based augmentation provides a theoretical basis for generating additional statistically plausible observations from limited datasets (Liu et al., 2019).

For a small historical dataset D, the generator produces an augmented dataset:

$D' = D \cup \hat{D}$

where $\hat{D}$ contains synthetic observations generated from the learned distribution.

The objective is not to replace real observations but to supplement them. Excessive synthetic augmentation may introduce model bias if generated samples do not accurately reflect physical renewable behavior. Therefore, synthetic data should be subjected to statistical validation before being incorporated into the scenario-generation stage.

3.8 Scenario Dependence and Correlation Preservation

The proposed framework explicitly preserves temporal and cross-variable dependencies. This is necessary because independent renewable scenarios may produce physically unrealistic operating conditions.

For example, a scenario containing maximum wind generation at one hour followed by an unrelated minimum value in the next hour may not correspond to realistic meteorological behavior. Morales et al. (2010) established the importance of statistical dependence in wind-speed scenario generation.

For multiple renewable resources, the dependency structure can be represented through a correlation matrix:

R=1ρSWρDWρWS1ρDSρWDρSD1

where the coefficients represent relationships among wind, solar, and demand variables.

Maintaining these relationships improves the realism of generated operating scenarios and prevents the optimization algorithm from making decisions based on statistically incompatible resource conditions.

3.9 Stochastic Energy Planning Model

The generated scenarios are incorporated into a stochastic optimization model. Let the primary planning decision vector be

$$x=[C_W,C_S,C_B,P_G]$$

where C_W represents wind capacity, C_S represents solar capacity, C_B represents battery capacity, and P_G represents grid-support capacity.

The objective is to minimize the expected total planning and operational cost:

$$\min_x C_{inv}(x)+\sum_{i=1}^{N} p_i C_{op}(x,\omega_i)+\lambda R(x)$$

where C_{inv} is investment cost, C_{op} is scenario-dependent operational cost, p_i is the probability of scenario i, and $R(x)$ represents an energy-security or uncertainty-related risk measure. The parameter λ determines the importance assigned to risk.

This formulation directly connects statistical learning with planning decisions. The learning model determines the uncertainty structure, while the optimization model identifies the infrastructure configuration that performs effectively across the generated scenarios.

Dependent-chance programming provides an important theoretical foundation for this stochastic planning perspective because it explicitly considers uncertainty when evaluating optimization decisions (Liu, 1997).

3.10 Operational Constraints

The optimization model must satisfy energy-balance constraints for each scenario and planning period:

$$P_{W,t}^{i}+P_{S,t}^{i}+P_{G,t}^{i}+P_{B,t}^{dis,i}=D_t+P_{B,t}^{ch,i}$$

where P_W, P_S, P_G, and P_B represent wind, solar, grid, and battery power respectively.

Battery operation is constrained by:

$$SOC_{min}\le SOC_t\le SOC_{max}$$

and renewable generation is bounded by installed capacity:

$$0\le P_{W,t}\le C_W \quad 0\le P_{S,t}\le C_S$$

These constraints prevent the optimization algorithm from producing mathematically optimal but physically infeasible solutions.

3.11 Bayesian Learning and Decision Optimization Integration

The key innovation of the proposed methodology is the integration of probabilistic learning with planning optimization. Bayesian renewable scenario generation provides the probabilistic information required by the optimization model, while optimization evaluates whether the generated scenarios materially affect infrastructure decisions.

Chen, Li, and Zhang (2018) provide the methodological foundation for this integration because Bayesian deep generative learning enables renewable uncertainty to be represented through probabilistic scenarios rather than deterministic forecasts.

The resulting feedback mechanism can be expressed as:

Historical Data → Bayesian Learning → Scenario Generation → Optimization → Planning Evaluation → Model Updating

If generated scenarios repeatedly lead to poor planning performance under subsequently observed conditions, the learning model can be recalibrated. This creates an adaptive planning architecture rather than a one-time optimization procedure.

3.12 Evaluation Criteria

The framework should be evaluated using both forecasting and planning indicators. Scenario-generation quality can be assessed through statistical similarity, temporal dependence, distributional consistency, and scenario diversity.

Planning performance can be assessed through total energy cost, renewable-energy utilization, grid dependency, renewable curtailment, storage utilization, and reliability.

A generic renewable utilization indicator can be expressed as:

REU=Erenewable,availableErenewable,used×100

A planning solution with lower cost but substantially higher renewable curtailment may not be preferable to a slightly more expensive solution that achieves significantly greater renewable utilization. Therefore, evaluation should consider multiple objectives rather than cost alone.

RESULTS

The integrated framework produces several analytically important findings. First, probabilistic scenario generation provides a more informative representation of renewable uncertainty than deterministic forecasting. By generating multiple possible trajectories, the planning model can evaluate both normal operating conditions and adverse renewable-generation events. This improves the robustness of infrastructure decisions.

Second, combining statistical forecasting with Bayesian scenario generation provides complementary benefits. Frequency-based forecasting captures temporal characteristics of renewable signals, while Bayesian learning represents uncertainty around those predictions. The combination is therefore more appropriate for industrial parks where both short-term fluctuations and long-term renewable variability influence energy planning.

Third, preserving temporal and cross-resource dependence improves scenario realism. Independent sampling may generate combinations of wind, solar, and demand that are statistically inconsistent with observed operating behavior. Dependence-aware scenario generation reduces this problem and provides a stronger foundation for stochastic optimization.

Fourth, deep generative approaches increase scenario diversity. The findings are consistent with the direction established by Chen, Wang, and Zhang (2018) and Jiang et al. (2018), where deep learning and adversarial generation provide greater flexibility than conventional parametric models for representing complex renewable patterns.

Fifth, Bayesian scenario generation provides a particularly important contribution because planning decisions can incorporate the probability of alternative renewable outcomes. Chen, Li, and Zhang (2018) demonstrate the relevance of Bayesian deep generative modeling for renewable scenario generation, and the proposed framework extends this principle from scenario generation toward integrated industrial energy planning.

The framework also indicates that optimization performance depends strongly on scenario quality. A large number of unrealistic scenarios does not necessarily improve planning. Instead, representative scenarios with accurate probability assignments provide more useful information while reducing computational burden.

From an industrial perspective, the framework can support decisions regarding renewable capacity, battery deployment, grid dependence, and energy-management strategies. For example, an industrial park experiencing highly variable wind production may obtain greater value from additional storage capacity than from simply installing additional renewable generation. Conversely, a park with relatively stable renewable output but rapidly increasing industrial demand may prioritize generation capacity.

The findings therefore indicate that intelligent planning should be data-driven and uncertainty-aware rather than based exclusively on average energy demand or expected renewable output.

DISCUSSION

The findings demonstrate that statistical learning can substantially strengthen distributed energy planning when it is integrated with stochastic optimization. The principal theoretical implication is that renewable-energy planning should treat uncertainty as an endogenous component of decision-making rather than as an external forecasting error. This perspective is consistent with the development from statistical scenario generation toward Bayesian and deep generative approaches.

A major advantage of the proposed framework is its ability to combine complementary modeling paradigms. ARIMA-based frequency decomposition provides interpretable statistical forecasting, while deep learning captures nonlinear relationships. Bayesian learning provides probabilistic uncertainty representation, and stochastic optimization converts that information into infrastructure decisions. Consequently, no individual model is required to solve the complete planning problem.

The approach also addresses a key limitation of deterministic planning: sensitivity to forecast error. If planning is based on one expected renewable trajectory, an unexpected reduction in renewable generation can increase grid dependency or create supply shortages. Under the proposed scenario-based methodology, alternative renewable trajectories are incorporated during planning, making the resulting infrastructure configuration more resilient.

The literature also reveals important trade-offs. Deep generative models can produce diverse scenarios but may be computationally expensive and difficult to interpret. Bayesian approaches provide uncertainty estimates but may require substantial computational resources. Classical statistical models are easier to interpret but can be less effective when renewable behavior is highly nonlinear. The proposed hybrid framework therefore treats these techniques as complementary rather than competing alternatives.

Another important issue concerns scenario quantity. Increasing the number of scenarios may improve uncertainty coverage but also increase optimization complexity. Industrial-scale planning therefore requires scenario reduction or representative-scenario selection. A practical implementation should preserve statistically significant operating conditions while eliminating redundant scenarios.

Data availability represents another limitation. Small or biased historical datasets can affect learned probability distributions. The use of synthetic augmentation, as suggested by Liu et al. (2019), can alleviate data scarcity, but generated observations must be validated to avoid introducing artificial statistical characteristics.

The framework also has practical implications for industrial park investment. Energy planners can use scenario-based optimization to compare alternative combinations of renewable generation, storage, and grid capacity. This enables investment decisions to be evaluated not only according to expected cost but also according to uncertainty, renewable utilization, and reliability.

Finally, the framework remains dependent on the quality of the underlying statistical model. Bayesian scenario generation can improve uncertainty representation, but it cannot compensate for fundamentally inadequate or biased input data. Continuous model updating is therefore essential. The adaptive learning mechanism proposed in this research provides a pathway toward progressively improving planning decisions as new operational observations become available.

Overall, the integrated framework provides a theoretically consistent connection between statistical learning and energy-system optimization. Its principal contribution is not a single forecasting algorithm but an integrated decision architecture in which statistical learning directly informs infrastructure planning under renewable uncertainty.

CONCLUSION

This study proposed an intelligent statistical learning framework for optimal distributed energy planning in industrial parks. The framework integrates statistical forecasting, Bayesian renewable scenario generation, deep generative learning, uncertainty modeling, and stochastic optimization into a unified planning architecture.

The analysis demonstrates that probabilistic scenario generation can provide more robust planning information than deterministic renewable forecasts. Incorporating temporal dependence, non-Gaussian characteristics, Bayesian uncertainty, and deep generative representations improves the ability of planners to evaluate realistic future operating conditions.

The framework further establishes a direct connection between renewable-energy learning and infrastructure optimization. Wind, solar, storage, and grid decisions can be evaluated across multiple probabilistic scenarios, allowing industrial parks to balance investment cost, renewable utilization, reliability, and operational flexibility.

The research also identifies several limitations, including computational complexity, dependence on historical data quality, and the challenge of selecting representative scenarios. Future research should therefore investigate adaptive online learning, automated scenario reduction, multi-energy industrial systems, and real-time integration of operational feedback.

The principal contribution of the study is an integrated methodological architecture in which statistical learning is not limited to forecasting but becomes a central component of distributed energy planning. Such an approach provides a foundation for more resilient, data-driven, and uncertainty-aware energy infrastructure in future industrial parks.

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