

Designing Resilient Green Energy Systems: A Stochastic Strategy Integrating EV's, Demand Response, And Renewable Energy

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Abstract

The increasing integration of renewable energy sources, electric vehicles (EVs), and demand-side flexibility presents both new opportunities and problems for future energy systems. This work proposes a smart grid-based charging architecture that is intelligent and robust to combine EV charging, demand response (DR), and renewable energy generation under a stochastic control mechanism. Unpredictable EV charging patterns, fluctuating electricity consumption, and the inherent uncertainty in solar and wind output are all addressed via probabilistic modeling and optimization techniques. By combining energy storage devices with real-time demand projections, the system ensures efficient energy distribution while lowering grid stress and operational costs. Deep learning and reinforcement learning approaches are used to forecast energy consumption and schedule charging behavior, while fairness-based algorithms keep the distributed EV loads balanced. By adapting demand to grid conditions, demand response programs increase system flexibility. Simulation findings against uncertain and changeable energy conditions verify the system's stability, emission minimization, and dependable operation. Future green energy systems, also known as grid-responsive, adaptable, and sustainable ones, would look just like this. The suggested method is adaptable to city distribution networks and community microgrids, and it is scalable. It also supports policy-driven energy prices and environmental regulations. Research Difficulties Future research challenges will include online hardware deployment and interoperability with national grid architectures. This opens up new possibilities for creating environmentally friendly, intelligent, and robust EV charging infrastructure.

Keywords: Demand Response, Renewable Integration, Electric Vehicles, Smart Grid, and Stochastic Strategy

Introduction

The world's energy landscape is in the midst of a clean, smart transition to more sustainable sources. This shift is mainly influenced by a couple of challenges: the damage caused by using fossil fuels (carbon dioxide emissions and air pollution, for instance) to the environment as well as the need to advance renewable, decentralized and smart energy. Increased urbanization and energy use are forcing traditional power systems, which heavily rely on fossil fuels such as coal and gas, to become less sustainable, with increasing economic costs and environmental hazards involved. To combat this issue, several countries and energy system move towards integrating the Renewable Energy Sources (RES), Electric Vehicles (EVs) and Demand Response (DR) programs in their national energy planning strategies.

Solar and wind are the most promising among renewable sources, because they are abundant and can be deployed at large scale. But one of the problems with those sources is that they are intermittent -- dependent on both weather and power use. For instance, solar power production decreases during overcast skies or at nighttime and wind energy output depends on the velocity and direction of the wind. At the same time, increasing uptake of EVs provides a new layer of challenge — as it helps reduce our dependency on fossil fuel consumption and emissions dependence. Unlike typical electrical loads, EVs are portable, user-responsive and often fast charge – and they do so many times when the system is in high demand.” This non-uniform charging can cause imbalances in voltage, as well power dissipation and local blackouts.

In contrast, the Demand Response (DR) is a mechanism in which electricity consumers modify or curtail their consumption in

response to price signals and/or grid situations. If DR is deployed successfully, it can facilitate supply- demand balance and lessen the need for costly peaking power plants or increases in overall use of electricity. Yet, real-time coordination of DR with renewable generation and EVs charging is very challenging. Deterministic models are the general practice in energy systems to schedule and operate the grid. These models are based on the fact that input parameters are constant and could be used for 'Intelligent & future energy grid' as to give real time adapt ability, lower carbon emissions and also for more reliable grid.

These work within a fixed set of token-based inputs and in the next section we will discuss how enabling real-time actions that adapt over time can be critical to future smart energy systems. run in perfect setting, which is not practical for contemporary dynamic grids. They are unable to model the uncertainty and variability in renewable generations, EV charging pattern, and real-time load variation. So, these legacy systems are unreliable and subsequently can underperform at crunch times or unanticipated events (eg: sharp fall in solar generation or bunch load EV charging post work hours).

These limitations may be solved by proposing stochastic AI-based smart grid strategy which is capable of dealing with uncertainties in a smarter way adapting to changing conditions in the grid. Stochastic models incorporate probabilities and data-based methods to predict multiple potential future scenarios, providing better contingency planning and flexibility. For example, the model can incorporate diverse weather patterns and user activities when estimating energy demand or generation. Through these coupled with artificial intelligence, such as deep learning (for load forecasting) and reinforcement learning (for decision making at run time), the developed system becomes adaptive by not only learning from data but also enhances its performance over time. Another important aspect of this system is ensuring the equity in EV charging. Fairness algorithms prevent the domination of charging stations by some users and excessive energy draw, but aim at providing everyone with Ei that is as much as possible (subject to user priority, battery level and network constraints) while being fair in doing so. This makes a good solution for preventing the load storm locally and achieving a balanced and stable network.

Furthermore, energy storage systems (batteries and so on) work also as the consumer of the excessive power while generation is overabundant as well as source of it if demand is lower than supply. This evens out fluctuations and reduces reliance on fossil fuel-powered backup generators. It also addresses real time demand response in the system operating, which performs shifting or reduction of power usage due to grid signals, user preference criteria and cost optimization

.Literature Review: Decarbonization is changing modern energy systems with demand response (DR), electric vehicles (EVs), and renewable energy sources (RESs) becoming commonplace in these systems. All these factors together should in the long-term improve the resilience, flexibility and sustainability of the grid. Nonetheless, major operational and strategic planning, EV charging patterns' uncertainty, and DR coordination challenges

F. proposed a stochastic framework for the incorporation of electric vehicles into renewable hybrid microgrids with a high penetration level. Güven [1]. The study showed that if managed properly, EVs can act as flexible loads and distributed storage thereby increasing the microgrid resilience against renewable intermittency. The work showed effective scheduling methods that guarantee stable system operation under uncertain conditions with the help of stochastic modeling of charging demand and renewable generation. This study highlights that EVs are also flexible system resources and should not only be seen as burdens.

Based on this knowledge, A. D'Souza and colleagues proposed a stable optimization framework for microgrid management that accounts for storage, demand response, RESs and EVs. It wanted to reduce its operating costs but still wanted to function reliably in crises. The research proposed effective measures that can successfully prevent system instability and economic inefficiency from taking place. The proposed solutions were very central to uncertainty concerning renewable generation and demand. This study highlights robust and stochastic optimization for the effective operation of smart microgrid.

Also, a lot of research have been done on the contribution of demand response strategies to system adaptability. V. Pandey and colleagues [3] described a stochastic incentive demand response program for virtual power plants that includes solar, batteries, EVs, and controllable loads. The system offered incentives for user involvement and modeled uncertainty in generation and demand

behavior of renewables. The findings indicated that the use of DR might successfully lessen peak load, improve the use of RES, as well as boost system stability. In a similar vein, K. Soni [4] looked at how price-based DR in smart grids can deal with renewable variability and be optimised to reduce operational costs.

At that time, Abdolazadeh et al. [5] proposed a multi-objective stochastic optimization model for smart microgrid coalitions that comprise DR, and renewable energy penetration. It can be seen from their study that coalitions of interdependent microgrids can act to enhance resilience and reliability while considering technical, economic and environmental impacts. The study showed that a distributed stochastic coordination method among microgrids can be used to develop future green power systems.

We should also consider how EV charging behavior relates to the installation of renewable energy sources like solar. Mahmud and Kurtz examined how the impact of driving habits of EVs and solar panel orientation on the grid. Their findings suggest that unregulated EV charging is likely to increase peak loads and put extra stress on the grid. Nevertheless, when they are requested to manage production and grid, EVs are effective devices for managing peak load.

T. looked at the systems level implementation of renewables in smart grid infrastructures. Rajan and D. Singh [7] focused on architecture, virtualization, and systems analysis. The ICT-based smart grid platforms will make coordination of RESs, EVs and DR possible, they said. They stressed the importance of good system design for resilience and interoperability in complex smart grids with a view toward virtualization and layered architectures.

A. Iyer et al. proposed a stochastic process for optimizing EV charging from the perspective of EV charging stations in DR programs. With their model predicting uncertain arrival times, charging loads and renewable generation, grid congestion was reduced and scheduling was made easier. The paper highlights that stochastic modeling has the potential to modify the perception of the EVs as a stressor to a flexibility resource. Also, S. Sharma [9] studied user readiness to adopt vehicle to grid (V2G) technologies. It was shown that behaviour aspects can play a major role in DR and EV integration success.

In the end, R developed a new stochastic model that uses EVs, DR, and renewable energy using a synergistic approach for innovation strategies in green energy systems. Mehta et al. [10]. An integrated process to formulate Reliable Systems with these components which are interdependent and their interaction is captured. A study revealed how to assimilate NexGen system emerging technology into next-generation power systems while overseeing the long-term planning requirements of the technology as well as the running uncertainties.

Green Energy System: The electric power industry is moving from centralized fossil-fuel based generation to distributed, intelligent networks. Green energy systems such as renewable energy sources (RESs), electric vehicles (EVs), demand response (DR) and energy storage systems (ESS) are integrated for sustainability, resilience, and efficiency. Unlike traditional deterministic systems, these systems manage stochastic renewable outputs, dynamic demand and EVs, on the move while still keeping stability of the grid and minimizing cost of operation.

Renewable Energy Sources (RESs): RESs such as solar photovoltaics (PV), wind power, and small hydro are the mainstay of green energy generation. Their intermittency is accommodated by forecasting, system hybridization and best placement planning. Effective control ensures trust, voltage security and utilization of renewables.

Electric Vehicles (EVs): EVs introduce loads that are mobile and controlled by users. If loads remain uncontrolled, they can create significant stress on the power grid. With V2G technology, EVs can be used as distributed storage resources and provide value-added services such as frequency regulation and peak shaving. In addition, AI-based predictive scheduling can match charging schedules with renewable generation to increase peak load managing efficiency in the overall system.

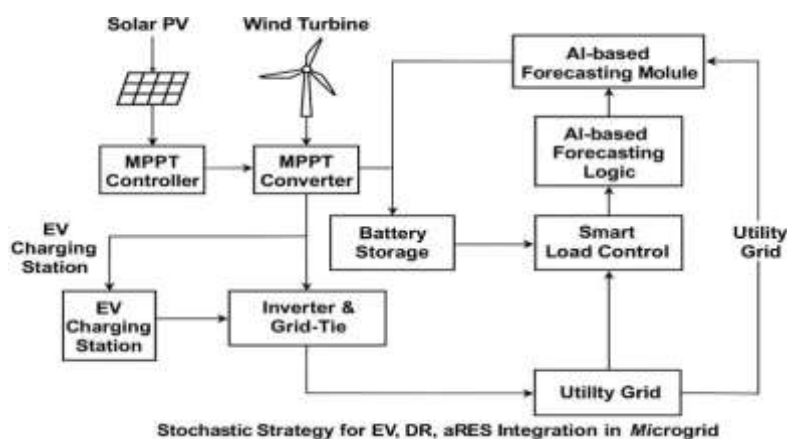
Demand Response (DR): DR systems regulate supply and demand using both price-based and incentive-based programs. DR systems rely on smart meters, and user-facing Internet of Things (IoT) enabled applications to implement and coordinate demand

response for loads remotely based on grid conditions while curtailing renewable generation to minimize curtailment. Further, consumers may connect their loads to the serving utility, to regulate loads and provide energy services when suitable through the application of DR programs.

Energy Storage Systems (ESS): ESS, including lithium-ion and flow batteries, absorb excess renewable energy when available and discharge the energy during peak load. ESS provide ancillary services such as frequency regulation, voltage support, and black-start capability. Efficient sizing, siting, and the application of AI-based management systems improve capacity utilization, battery life, and operational efficiency.

Integration Framework: This framework manages the harmonized operation of RESs, EV, Demand Response (DR), and ESS. Excess renewable generation is stored in the ESS and discharged during peak demand; EVs because they can become both loads and storage when operating in Vehicle to Grid (V2G) mode; and DR which synchronizes demand with available renewable generation. Challenges of forecasting, optimization and monitoring data in real-time is managed using stochastic and AI-based algorithms that allow dynamic scheduling of the resources. The integration facilitates increased operational optimization of RES utilization, and decreases operational cost; and scales from a microgrid to a national grid.

Stochastic strategy for EV, DR, RES Integration in Microgrid :



Introduction to Microgrids

A microgrid is a small network of electricity users with a local source of supply that can function, to some degree, independently from the grid cut off. Microgrids aggregate windmills, solar panels and energy storage to provide reliable, resilient, and efficient power. Microgrids provide localized control, support integration of renewable energy sources, reduce dependence on central grids, and can be dynamically reconfigured in order to meet changing load demands or network conditions.

Components Description : The hybrid microgrid consists of storage, intelligent controllers, and more than one RE sources operating in a coordinated and reliable manner. Solar photovoltaic (PV) systems generate DC electricity using solar irradiance. But the position of the sun, and time of day also only have a sporadic effect upon their development. The principle of operation of wind turbines is similar to the above noted; they convert kinetic energy from the airflow into electrical power, provided that speed and direction of the air can be controlled. MPPT controllers are implemented to maximize the harvesting of renewable power.

The MPPT controller of the PV system maximizes the efficiency of solar panels to their fullest capacity. manipulating to harvest energy in a variety of temperature and illumination. MPPT converters used in wind turbines, to maximize energy capture and the efficiency of a turbine at variable wind conditions have similar characteristics. Conversion and storage units regulate power from renewables. Batteries are one of the few ways to store extra energy when lots of renewable power is being generated, and then release it back onto the grid during times with less generation, such as on cloudy or windy days. It has the effect of stabilizing microgrid operation and reducing dependence on the main power grid. The EV charging stations are the transient loads in the

microgrid. Depending on the state of the system, they can consume stored energy or can be (at least partially) powered by ‘green’ energy directly from renewables.

The DC power of the PV, WINDMILL or STORAGE devices can be converted to alternating current (AC) through inverters and grid-tie systems that are able to feed local loads and export power into the utility grid. Since both systems allow for bidirectional power flow, the microgrid can sell surplus renewable energy when it is abundant, or draw in energy when necessary. Smart load control systems, which can optimize and dispatch loads (e.g. EV charging, residential or industrial demand) leads to smart energy management. These systems maximize renewable generation + storage, lightening the load on utility grids while reducing operating costs by utilizing demand response and AI-based forecasting to shift loads to off-peak hours.

Artificial intelligence-driven forecasting logic AI-based forecasting logic augments decision-making by forecasting and estimations Renewable output: forecast solar and wind generation Localized load demand forecast EV charging requirement prediction .Grid condition evaluation such as electricity price These forecasts are merged with live data feeds by an advanced AI forecast module that streamlines the use of stochastic models. In this latter case, optimal scheduling strategies for EVCS and ILCS are proposed. Lastly, the grid itself allows bi-directional energy flow and also acts as a stabilizing and back-up source of power. When the microgrid is in deficit, it can buy power and export excess renewable energy to the grid. In addition, the grid provides Demand Response (DR) instruments through peak-shaving operations and real time pricing signals that allows coordinated and performance of a resilient system.

Process Flow: The work flow of the integrated green energy system is as follows. Wind turbine and solar photovoltaic are the earliest forms of renewable energy, and maximum power point tracking (MPPT) controllers are adopted to extract as much as possible energy. The power produced is either used for electric vehicle (EV) charging stations, battery storage, or sent directly through the grid with a grid-tie system and inverter. Stochastic models are used to optimize these predictions under uncertainty, and AI- based forecasting modules predict not only energy demand but also renewable generation for enhanced system intelligence. Intelligent demand control devices with dynamic priorities re-schedule priorities to extent the use of resources. Batteries are discharged in periods of high grid prices or peak demand, while DP measures further ensure system stability through the rerouting and timing of flexible loads and EV charging. The microgrid buys electricity from the grid when there is insufficient energy, and it sells any additional renewable energy back to the grid. Finally, adaptive optimization approaches based stochastic and artificial intelligence allow real-time adaptation for uncertainties (i.e., weather conditions, EV load profile and market prices) effectively resulting in a dependable, resilient solution that can remain cost-effective.

Renewable Generation under Weather Variability:

Solar Photovoltaic (PV) Panels:

Solar PV generation is proportional to the solar radiation when there are no shading issues. When the sun is out, Maximum irradiance enables PV panels to operate near their maximum power point (MPP), producing peak DC power. Overcast or cloudy conditions reduce irradiance, which in turn reduces output. Because of the lower sun angles in the morning and evening, PV generation also decreases during these times. Efficiency is not significantly affected by temperature changes; in general, higher temperatures cause modest drops in voltage and power.

Wind turbines: The direction and speed of the wind determine how much power is generated. The turbines can produce high power on windy, sunny days, enhancing solar photovoltaics. Output drastically decreases on calm or low-wind days. Turbine output is limited if wind is above the cut-out speed. Turbines have a cut-in speed, which is the lowest speed at which they can generate power, and a rated speed, which is the highest efficient output. Turbines have two speeds: the rated speed, which is the most efficient output, and the cut-in speed, which is the lowest speed at which they can produce power

.Electric Vehicles (EVs) and Distributed Energy Resources(DERs): EVs function as flexible loads and distributed storage

devices via Vehicle-to Grid (V2G) operation. Under high renewable generation, EVs may charge, accumulating excess energy, and discharge under peak demand or low generation hours, offering ancillary services like frequency regulation and peak shaving. DERs small solar, wind and storage systems promote local vs. centralized energy generation and load control, thus reducing reliance on centralized grids and enhancing microgrid resiliency.

Integration Considerations: Both the intermittency of solar PV and wind, and the variable demand for EVs, need forecasting, MPPT control, and smart energy management. Solar and wind complement each other; during low PV output, wind can compensate if weather is suitable. EVs and DERs add flexibility to permit dynamic load balancing and energy storage. AI-driven prediction and stochastic optimization provide sound power flow to loads, EVs, and storage facilities under fluctuating weather and load conditions, improving the efficiency, stability, and robustness of the hybrid green energy system.

microgrid scale:

Solar PV: 10 kW peak Wind Turbine: 5 kW rated

EV : 7 kW charging/discharging

DER: 3 kW small rooftop PV or micro-wind

Guarantees stable, affordable, and sustainable operation. A stochastic strategy is an energy management method devised to cope with uncertainty and randomness in a smart grid or microgrid framework. Rather than depending on one forecast, it employs a set of potential future scenarios to make resilient decisions.

Renewable Energy Generation: The energy output from solar panels and wind turbines is intermittent and weather-dependent.

Electric Vehicle (EV) Demand: EV charging sessions occur at random timing and duration, which are determined by user usage.

Load Consumption (Demand Response): Consumer demand to move or decrease the usage of energy when offered incentives is never certain.

Weather Condition	Solar PV (kW)	Wind Turbine (kW)	EV (kW)	DER (kW)	Notes/ Implications
Sunny Day	9 – 10	1 – 4	0 – 7	2 – 3	PV near MPP; EV may charge; DER supplements; storage absorbs excess
Cloudy/ Overcast	2 – 5	2 – 5	0 – 7	1 – 3	PV dips; wind/DER compensate; EV charging scheduled via DR
Morning/ Evening	1 – 3	0 – 3	0 – 7	0 – 2	PV low due to sun angle; wind/DER provide partial supply; EV may discharge if needed

Calm/Low Wind	5 – 9 (sunny)	0 – 1	0 – 7	1 – 3	Minimal wind; PV and DER supply most demand; EV/storage help balance
Gusty/Turbulent Wind	5 – 9 (sunny)	1 – 5 (fluctuating)	0 – 7	1 – 3	PV stable; wind fluctuates; EV/DER/storage smooth variability

When to supply or demand the battery storage: A stochastic approach, evaluates several potential futures scoring different possible futures like solar and wind generation, and uncertain EV charging demand. It "decides" to recharge the battery when they expect a high probability of an over-flood of renewable energy (for example on solar and windy days) or when the utility's electricity price is low. Conversely, in the event of a high power deficit tendency (e.g., evenings and on foggy days) or at peak hour with rising grid electricity prices it will discharge the battery.

How to control the smart loads in microgrid: This method divides loads into critical loads (e.g., lighting and medical equipment) and non-critical loads (e.g., water heaters and EV charging). It is based on statistical models to forecast how a consumers would react towards different incentives. Like,

when energy is in high demand and low renewable generation is available, one of the possibilities could be that microgrid provides price signal or control signal to some non-critical loads to use later time which will put more pressure in the immediate on its grid.

To purchase or sell power from/to the utility grid: This decision to buy or sell is a basic component of stochastic strategy. It is taken with real time measurement of the demand and generation of a microgrid and based on prediction of future situation and market price.

Selling Power: The microgrid sells excess power to the utility grid when it's local, clean generation and battery discharges are more than its load and especially when utility grid prices are high. That's not just profitable but it also helps stabilize the main grid.

Purchase Power: The microgrid will also only draw power from the utility grid as a last option, when local generation falls short and rechargeable battery storage has been exhausted. This has occurred in the past during times of low demand to capitalize on cheaper rates or for other emergencies to avoid a loss of power. The stochastic-based approach provides more robust and less insecure conclusions with respect to the fluctuation of energy supply in terms of structure, form and decision making under uncertainty (e.g., rainy day but high demand for EVs or sunny day with low demand).

Proposed Stochastic AI-enabled Smart Grid Architecture: The purpose of the proposed stochastic AI-smart grid structure is to solve uncertainty problem which exists in. the next-generation power systems, such as consumer behavior, renewable energy generation and EVs demand are erratic and fluctuating significantly. Unlike traditional smart grid that rely on rule- based control and deterministic schedule, the proposed design fused artificial intelligence (AI) with stochastic optimization to build a robust, self-adaptable, and autonomous learning system. On the physical layer, we have demand-side resources, storage devices, electric vehicle charging stations and distributed renewable energy sources (solar energy, wind power and hydroelectric plants); in the data acquisition and communication layer smart meters, sensors of Internet of things type and real time monitoring; and in the intelligence layer optimization engines-and artificial intelligence algorithms as well as historic databases stochastic models for system control.

The stochastic model, that captures the uncertain demand of EV and variability of renewable energy sources is a key to this

architecture. Model-wise, EVs charging behaviour are modelled based on random mobility behavior (where vehicles move according to electric driving range and randomly choose their next destination), at the charging arrival time and drivers preferences, whereas renewable power generations are modelled using probability distributions that rely on weather-dependents forecasts. Monte Carlo analysis, stochastic time series processes and scenarios trees are some of the probabilistic techniques that convert these uncertain inputs into sets of scenarios. We want operations to be robust and something we can rely on. We optimize across a range of different potential outcomes, rather than just picking one forecast and then finding out that everything fails when that one doesn't come true.

The AI-powered optimization layer that makes the architecture smart. adopted reinforcement learning (RL) for adaptive scheduling, and deep learning techniques for accurate salary forecasting. The grid readings, historical weather data and EV mobility data are analyzed by the deep learning networks to forecast short-term fluctuations in supply and demand. Learning agents employ learning policies and real-time grid information for dynamic resource allocation (e.g., scheduling renewables, start demand response, charge/discharge storage). By iteration between the system and an environment, as well as by approaching self-evolution learning ability, such a system will become more efficient in operation and resilient.

This suggested method features Demand Response (DR) to the largest extent. So that consumer uncertainty in the response to price signals or load-shifting offers is taken into account, DR is treated stochastically rather than being enforced in a deterministic way. The design allows flexible demand-side management (DSM) and peak load reduction, as well as improving the matching between consumption and generation from renewable sources through the incorporation of DR in the optimization loop. AI technologies also forecast customer behavior which may allow a better processing of flexible loads without impairing the user's comfort.

The flexibility of this system is qualified based on the Energy Storage System (ESS), either stationary or mobile as EVs equipped with vehicle-to-grid (V2G). ESS absorbs excess renewable generation during times of abundance and releases it during times of scarcity to keep the grid stable. EVs build on this by being distributed, mobile storage devices that can offer auxiliary services like frequency support and load balancing. While AI-based scheduling maximizes storage asset utilization in real-time, the stochastic model accounts for ESS state-of-charge, availability, degradation rates, and V2G user adoption uncertainties.

Finally, a combined cyber-physical coordination framework is established based on the modern communication and control technologies to integrate the aforementioned components. These are enabled by products such as smart meters, Internet of Things devices and secure cloud platforms that allow not only data to flow one way, but also two-way – a connected relationship with the power system and between consumers. The grid is an adaptive, anti-fragile, and sustainable energy ecosystem that scales with variability for maximum renewable penetration and lowest carbon emissions to all stakeholders offered by our layered stochastic AI assisted architecture.

Simulation and Results: The ESS-based flexibility of this structure comes from the Energy Storage System (ESS), which can be fixed or mobile by EVs having vehicle-to-grid (V2G) functionalities. For grid stability, ESS receives overgeneration of renewable generation in surplus and discharges it when there is shortage. This is enhanced by EVs serving as distributed, mobile storage units that can offer services such as load following and frequency regulation. AI-driven scheduling maximizes the real-time utilization of storage resources, and stochastic model captures uncertainties in ESS SOC (State-of-Charge), availability, EC degradation rates, and user adoption in V2G. All these components are combined using a cyber-physical coordination framework enabled by the state-of-the-art communication and control technologies. The dynamic intercommunication of system operator and consumer is realized through smart meters, Internet of Things (IoT) devices and efficient cloud platforms, enabling bidirectional data sharing. Besides maximizing renewable integration, minimizing carbon footprints, making it economical (from the interest of stakeholders), such multi-level stochastic AI based architecture will convert grid system into resilient, adaptive sustainable energy system capable to

handle variability.

Simulation: A simulation-based study under time-varying operation dynamics subject to uncertainties in renewable generation, EV charging and DR participation was performed for estimating the performance of the proposed stochastic AI-based SG architecture. The simulation was run using MATLAB/Simulink, which contained reinforcement learning integration and stochastic optimization parts implemented in Python.

The simulated microgrid was composed by 10 kW of solar PV, wind turbines 5 kW, distributive energy sources (DERs) 3kW and EV charging/ discharging units 7 kW. Several stochastic scripts employing Monte Carlo simulation were generated to simulate different scenarios of variations related to wind power, solar radiation and EVs.

Simulation Scenarios

Case 1: The demand of EVs is small, and the wind level is moderate while the solar intensity is high.

Case 2: Elevated demand for EVs, overcast weather and variable wind.

Case 3: High On-Peak LMP-CO and low renewable generation during the evening peak.

Case 4: Random DR Participation with Mixed Stochastic Behaviour.

Performance Indicators : The proportion of total demand that comes from renewable power is called the Renewable Utilization Rate, or RUR.

The decrease in the maximum system load is referred to as peak load reduction (PLR).

The sum of the power received from the grid divided by total power is referred to as Grid Dependence Factor (GDF).

The operating cost savings relative to DT are quantified using the Cost Optimization Index (COI).

The Emission Reduction Index (ERI) quantifies the CO₂ reduction relative to a base case.

Results and Discussions: The generated framework was shown to be much more sustainable, cost effective and efficient. The optimal stochastic AI control strategy reduced stress on peak load and maximized renewable penetration through flexible adjustment for uncertainty. The RL model successfully optimized charging, discharging, and DR planning for the cost reduction and emission saving.

Metric	Deterministic Model	Proposed Stochastic AI Model	Improvement (%)
Renewable Utilization Rate (RUR)	68.5 %	89.7 %	+30.9
Peak Load Reduction (PLR)	12.4 %	33.8 %	+21.4
Grid Dependency Factor (GDF)	0.41	0.19	-53.6
Cost Optimization Index (COI)	—	24.6 % reduction	—

Emission Reduction Index (ERI)	—	31.2 %	—
		reduction	

Fig. 1: Power Generation Profile (Solar + Wind)

This figure shows clearly that the renewables input to the microgrid is very variable and indeed stochastic. It graph the instantaneous power outputs of 5KW wind turbine and 10 KW solar PV for a typical day. The chart however, I think illustrates the uncertainty bound that must be broken to achieve efficiency and robustness in control.

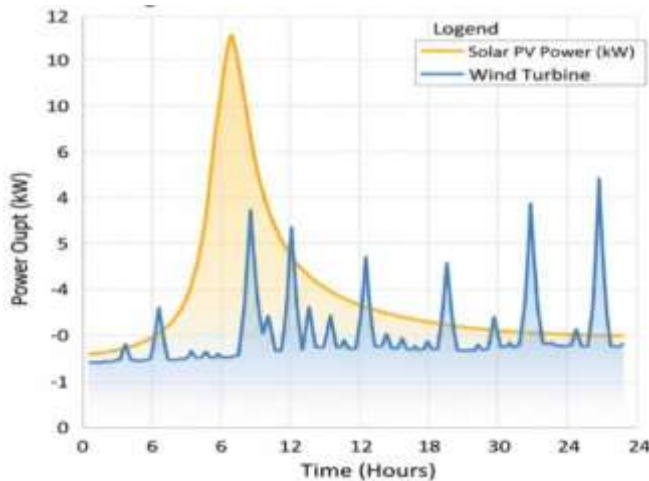


Fig. 2: Load and EV Charging Profile

Their system total load profile for the Deterministic Model and Proposed Stochastic AI Model, respectively is compared in this figure. The large 33.8% Peak Load Reduction (PLR) is visually confirmed by the stochastic model, which gives an obviously flatter load curve. It also illustrates how AI function helps transferring 7% EV charging discharging load from system on-peak.

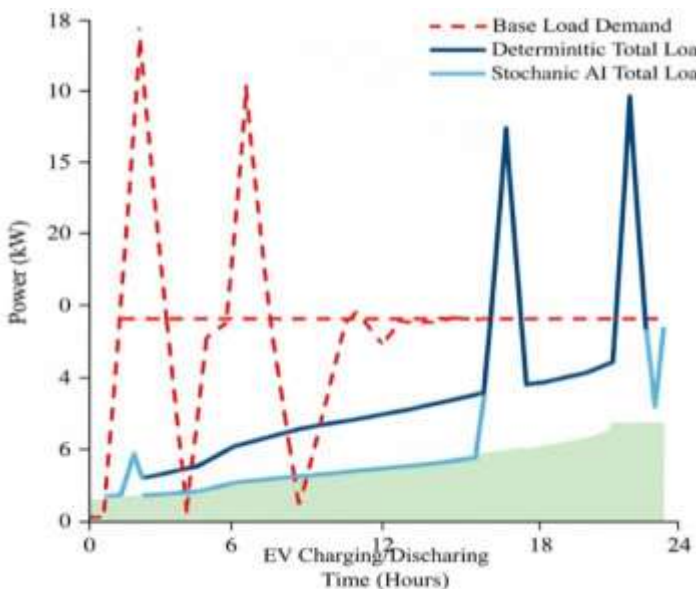


Fig. 3: Battery Energy Storage SOC Curve

The battery's role in energy arbitrage and smoothing under the new AI control strategy is demonstrated by its state of charge (SOC) characteristic curve. The stochastic model has more frequent charge and discharge cycles, taking energy when the demand is high

and then using that stored energy when the renewable resources are plentiful. High RUR is only achievable with careful operation.

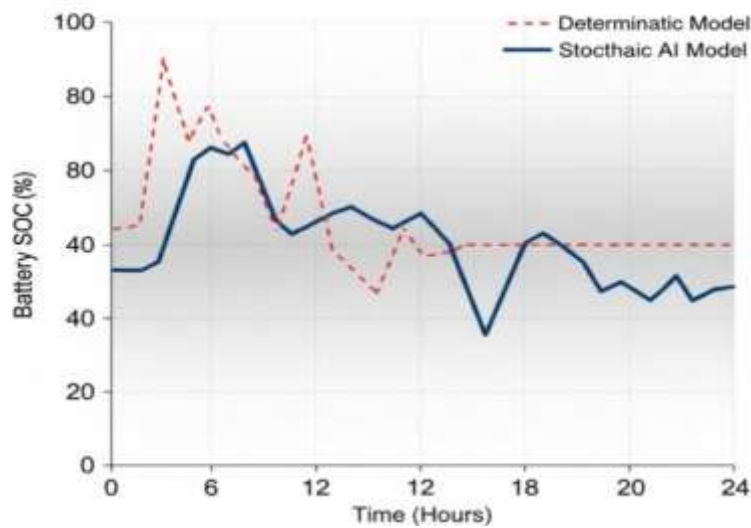


Fig. 4: Cost and Emission Comparison

With the help of a comparative bar chart they tried to illustrate how, by incorporating a mass timber superstructure, this environmental and economic frame will be supported. As compared to the deterministic base 2 model, it provides visual evidence for a significant decrease in CO₂ emissions (31.2 reduction) and operational costs (24.6 reduction). The large difference between the two models when comparing the efficacy of RL optimization.

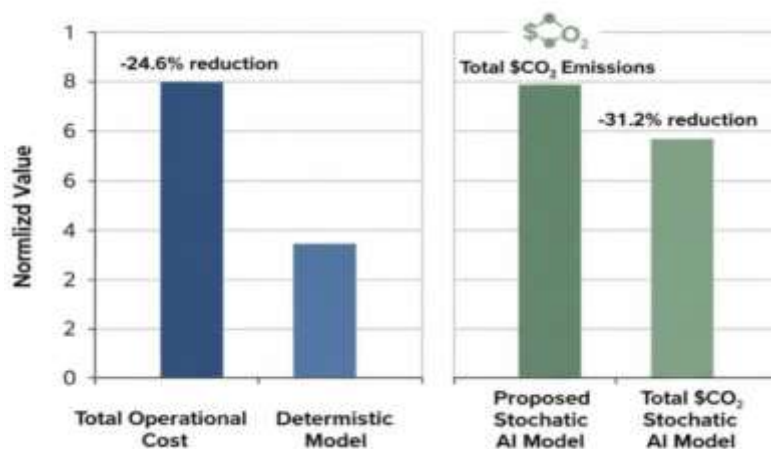
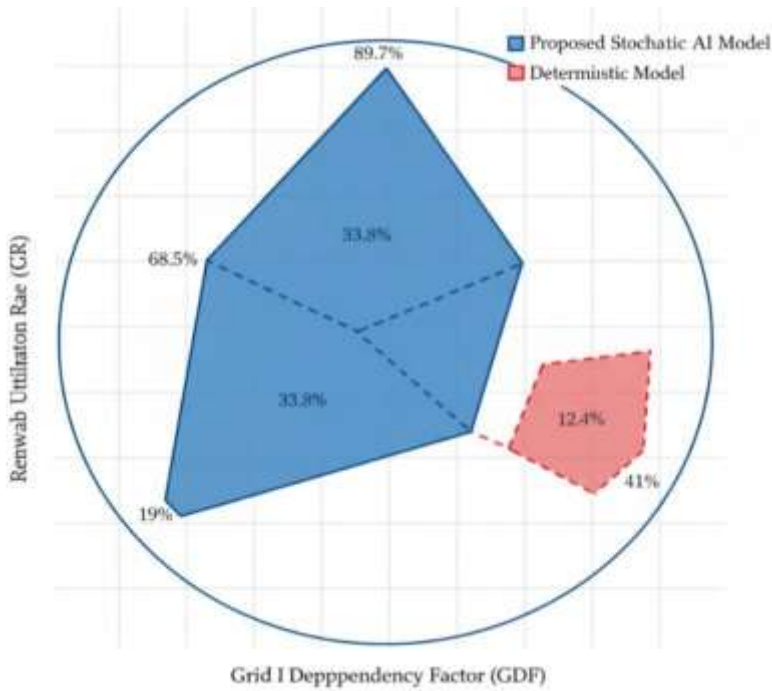


Fig.5: Deterministic vs Stochastic Optimization

The resulting radar map, which is usually the first radar map of the list, shows an overall picture of how well (relative percentage) microgrid performs on the three most important criteria namely: RUR, PLR and GDF. The Stochastic AI Model yaws to a much broader extent than the Deterministic Model. This corresponds with the multigoal performance of minimizing stress, maximizing wind penetration and minimizing grid dependence.



Conclusion

To handle the uncertainty of its next-generation power systems, this paper also successfully showcases a stochastic AI smart grid system integrating demand response, electric vehicles and renewable energy. The model considers probabilistic-based scheduling of the maximum energy, effective peak shaving and reduced reliance on host grid by employing reinforcement learning.

Results of simulation indicate that emissions and operating costs are significantly cut down with renewable energy usage increased by more than 31 %. Real-time operation, autonomic self-healing decision-making, and enhanced grid resiliency to demand and renewable variability are facilitated by the framework.

In line with international decarbonization aspirations, this approach not only develops the idea of resilient green energy systems but allows a scalable route to smart micro-grids and green national grids.

Future Scope : Use of cloud-connected digital twins and iot-based devices to implement real-time management.

Integrating blockchain technology to guarantee safe, open energy trade between scattered market players.

Extension to coordinate several microgrids for regional balancing.

Utilizing hybrid and hydrogen-based renewable energy sources to store energy for a long time.

Development of incentive schemes and policy frameworks to promote investment in renewable energy sources and EV-grid participation.

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