

RESEARCH ARTICLE

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RISK COST OPTIMIZED AUTONOMOUS SWITCHING FOR WEATHER DRIVEN RENEWABLE INTEGRATED SMART GRIDS

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ABSTRACT

Growing penetration of solar photovoltaic and wind energy in smart grids introduces operational uncertainty and power quality challenges due to weather-driven variability. Conventional switching mechanisms rely on deterministic thresholds and local meteorological sensors, leading to reactive behavior, increased infrastructure cost, and excessive switching operations. A sensorless IoT-enabled weather-informed control framework is developed to enhance renewable coordination without dedicated environmental sensors. Cloud-based meteorological information is integrated with real-time electrical measurements to infer renewable variability. A probabilistic operational risk model is formulated using power deficit probability and severity indices derived from voltage deviation, frequency variation, and total harmonic distortion. A multi-objective optimization structure simultaneously minimizes operational risk and economic cost while enforcing voltage, frequency, and IEEE 519 harmonic compliance constraints. MATLAB/Simulink validation under varying renewable scenarios demonstrates substantial reduction in total harmonic distortion, decreased switching frequency, improved voltage stability, and lower operational cost compared with conventional and rule-based IoT strategies. The proposed framework enables proactive power quality regulation and scalable renewable integration in intelligent smart grid environments.



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I. INTRODUCTION

The increasing global transition toward low-carbon power generation accelerates the deployment of renewable energy sources (RES), particularly solar photovoltaic (PV) and wind systems, within modern smart grids. Recent advances in Internet of Things (IoT)-based automatic transfer switching systems have enabled intelligent coordination of hybrid energy sources [1-4]. Renewable penetration continues to expand due to environmental regulations and global sustainability initiatives [5], while smart grid technologies support distributed energy integration and real-time monitoring [6]. Rapid variations in solar irradiance and wind speed cause fluctuations in power output that may lead to voltage deviations, frequency imbalance, and increased total harmonic distortion (THD). These disturbances adversely affect sensitive loads and reduce system reliability if not properly mitigated [7], [8]. In inverter-dominated smart grids, harmonic propagation and switching-induced transients further complicate power quality management [9]. IoT-enabled monitoring platforms provide real-time supervision and automated decision-making in distributed energy systems [10], [11]. These systems improve operational visibility and response speed; however, most implementations rely on reactive threshold-based switching rather than predictive control. Parallel research focuses on renewable forecasting techniques using meteorological data and hybrid models to predict solar and wind generation [12], [13]. Although forecasting improves scheduling accuracy, many approaches depend on dedicated sensors and are not directly integrated into switching control strategies.

Probabilistic risk modeling methods have been introduced to quantify uncertainty in renewable-integrated systems [14]. Multi-objective optimization techniques further enhance system performance by balancing reliability and economic cost [15], [16]. However, integration of risk modeling, optimization, and IoT-based switching within a unified framework remains limited. Advanced IoT-enabled energy management approaches demonstrate improved coordination but lack power quality enforcement mechanisms [17]. Furthermore, compliance with harmonic standards such as IEEE 519 is essential to maintain acceptable power quality [18]. Harmonic mitigation strategies have been widely studied in inverter-based systems [19], yet they are rarely embedded within switching decision frameworks. Cloud-based IoT architectures and distributed control systems provide scalable solutions for renewable integration [20], while advanced optimization approaches continue to evolve for improved efficiency [21]. To address these limitations, this study proposes a sensorless IoT-enabled weather-informed control framework integrated with a risk–cost optimized autonomous switching strategy for renewable-integrated smart grids.

II. THEORETICAL REFERENCE

The integration of renewable energy sources within smart grids requires coordinated interaction between communication infrastructure, forecasting mechanisms, probabilistic risk assessment, and optimization-based control strategies. The conceptual architecture of the IoT-enabled renewable smart grid framework is illustrated in Figure 1.

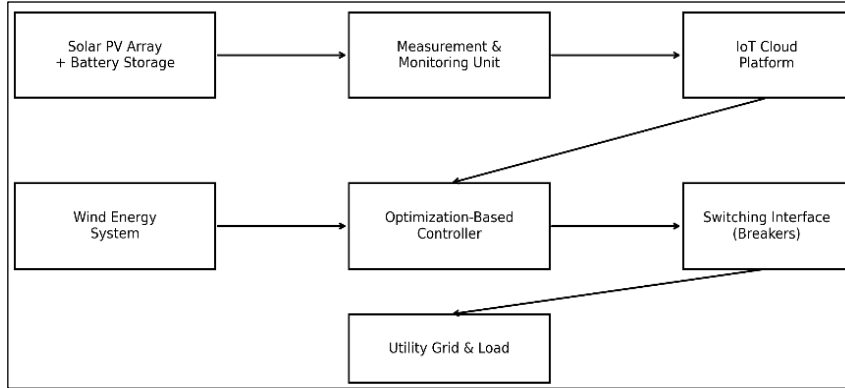


Figure 1: IoT-enabled renewable smart grid architecture integrating renewable sources, IoT cloud layer, and optimization controller.
Source: Authors, (2026).

The system integrates renewable power modeling, risk estimation, and economic evaluation into a unified decision structure. The theoretical interaction between these elements is depicted in Figure 2.

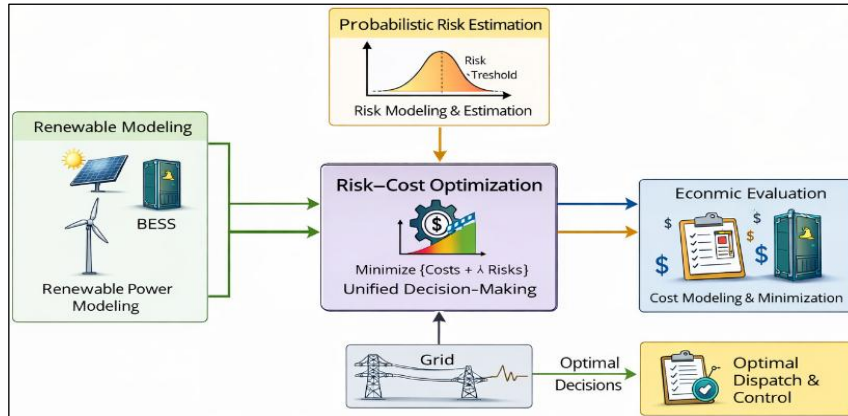


Figure 2: Risk–cost optimization framework combining renewable modeling, probabilistic risk estimation, and economic cost minimization.
Source: Authors, (2026).

Power quality monitoring remains essential to ensure compliance with IEEE 519 standards [12]. The monitored parameters and their acceptable limits are summarized in Table 1.

Table 1: Power quality parameters monitored in the proposed system.

Parameter	Description	Acceptable Limit
Voltage Deviation	Deviation from nominal voltage	±5%
Frequency Deviation	Deviation from nominal frequency	±0.5 Hz
Total Harmonic Distortion	Harmonic content in voltage waveform	≤ 5%

Source: Authors, (2026).

II.1 IOT-BASED SWITCHING IN HYBRID RENEWABLE SYSTEMS

Internet of Things (IoT) technologies enable real-time monitoring, remote supervision, and automated switching in distributed power systems. Several studies demonstrate the feasibility of IoT-based automatic transfer switch (ATS) systems for hybrid energy applications [1-4], [10], [17]. These systems utilize embedded controllers, cloud platforms, and communication modules to coordinate power source selection between grid supply, solar PV, and backup generators. Smart grid communication architectures further enhance system observability and allow distributed energy resource management through data aggregation and remote control [11], [16], [20]. IoT-driven monitoring platforms improve operational transparency and response speed. However, most implementations rely on fixed thresholds for voltage or source availability. Switching decisions are typically triggered when predefined limits are violated rather than through predictive evaluation of renewable variability or power quality degradation. Furthermore, existing IoT-based switching mechanisms emphasize supply continuity rather than integrated power quality compliance. Harmonic distortion, voltage stability, and switching-induced transients are rarely embedded within the switching decision logic. As renewable penetration increases, such reactive approaches may lead to excessive switching frequency and increased operational stress.

II.2 RENEWABLE ENERGY VARIABILITY AND FORECASTING MODELS

Solar photovoltaic and wind generation systems exhibit inherent intermittency due to environmental dependence. Solar output power is primarily governed by irradiance and panel efficiency, while wind turbine output depends on air density, rotor characteristics, and wind velocity [12], [13]. The nonlinear relationship between wind speed and power output results in significant short-term variability. Advanced forecasting techniques incorporate meteorological data and hybrid statistical or machine learning methods to predict short-term renewable generation [12], [13]. These methods improve scheduling accuracy and reduce uncertainty in grid operation. However, most forecasting frameworks require dedicated local weather sensors, increasing installation cost and limiting scalability in distributed deployments. Moreover, forecasting outputs are often processed independently from real-time switching algorithms. The lack of integration between renewable prediction and switching control reduces the effectiveness of predictive decision-making. A sensorless inference mechanism that combines cloud-based meteorological information with electrical behavior analysis can improve adaptability while reducing infrastructure complexity.

II.3 POWER QUALITY AND HARMONIC CONSIDERATIONS

The integration of inverter-based distributed generation introduces harmonic distortion and transient instability within smart grids [19]. Rapid switching transitions and fluctuating renewable output may increase total harmonic distortion (THD) at the point of common coupling (PCC). Excessive harmonic levels degrade equipment lifespan and violate regulatory standards. The IEEE 519 standard specifies harmonic limits to ensure acceptable power quality in electric power systems [12]. Maintaining THD within prescribed thresholds requires coordinated control of inverter operation and switching behavior. Conventional switching frameworks do not explicitly incorporate harmonic constraints into decision-making, potentially leading to non-compliance under stressed conditions. Therefore, any intelligent renewable switching strategy must integrate harmonic monitoring and compliance enforcement within its operational logic.

II.4 PROBABILISTIC RISK MODELING IN RENEWABLE-INTEGRATED SYSTEMS

Renewable-integrated smart grids operate under uncertainty due to fluctuating generation and load demand. Probabilistic risk assessment methods quantify the likelihood and severity of operational disturbances [14]. Risk modeling typically considers power deficit probability, voltage deviation, and frequency variation as indicators of system vulnerability. Recent studies explore multi-objective optimization techniques for renewable-integrated power systems to balance reliability and economic objectives [20], [21]. These approaches incorporate cost functions, switching penalties, and energy balancing constraints. However, many existing models treat reliability and cost independently without embedding harmonic compliance or IoT-based switching logic within the same framework. A unified risk-cost formulation enables simultaneous consideration of uncertainty, operational expenditure, and power quality constraints. Such integration supports proactive rather than reactive switching behavior.

II.5 ECONOMIC CONSIDERATIONS IN SMART GRID OPERATION

Operational cost in renewable-integrated systems includes grid energy expenses, maintenance cost, and switching-related penalties. Frequent breaker operations increase mechanical wear and maintenance requirements. Economic analysis of hybrid renewable systems highlights the importance of minimizing unnecessary switching actions while maximizing renewable utilization [15], [16]. Multi-objective optimization frameworks address cost minimization under technical constraints [14], [19]. These methods provide structured decision-making tools but are rarely combined with probabilistic risk indices and IoT-enabled supervisory control in renewable switching applications. Integrating economic evaluation within autonomous switching logic ensures balanced trade-offs between reliability and cost efficiency.

II.6 IDENTIFIED RESEARCH DIRECTION

The reviewed theoretical foundations demonstrate significant advancements in IoT-based monitoring [1] [4], renewable forecasting [12], [13], probabilistic risk modeling [14], and economic optimization [15], [16]. Nevertheless, limited research integrates these elements within a sensorless, optimization-driven switching architecture that simultaneously enforces IEEE 519 harmonic compliance [12]. This study builds upon the established theoretical background by combining:

- IoT-enabled monitoring and supervisory control,
- Sensorless weather-informed renewable inference,
- Probabilistic operational risk assessment,
- Economic cost modeling with switching penalties, and
- Multi-objective optimization under power quality constraints.

The subsequent section presents the detailed materials and methods used to implement and validate the proposed framework.

III. MATERIALS AND METHODS

This section describes the research design, system modeling approach, optimization framework, and simulation configuration adopted to evaluate the proposed risk–cost optimized autonomous switching strategy for renewable-integrated smart grids. The proposed system was implemented using MATLAB/Simulink with integrated renewable subsystems, inverter interface, breaker logic, and optimization controller. The key simulation parameters used for evaluation are summarized in Table 2.

Table 2: Variables used in the risk–cost optimization model.

Symbol	Description
P_{ren}	Total renewable power
P_L	Load demand
$R(t)$	Operational risk index
$C_{\text{tot}}(t)$	Total economic cost
$u(t)$	Operating mode decision variable
THD(t)	Total harmonic distortion

Source: Authors, (2026).

III.1 SYSTEM CONFIGURATION

The proposed system consists of a grid-connected hybrid renewable configuration integrating solar photovoltaic (PV) generation, wind energy conversion, battery energy storage, intelligent switching interfaces, and an IoT-enabled supervisory control layer. The architecture enables dynamic coordination between renewable sources and the utility grid to maintain voltage stability, frequency regulation, harmonic compliance, and economic efficiency.

The system comprises the following major components:

- Solar PV array with DC–DC boost converter and maximum power point tracking (MPPT)
- Wind turbine generator with rectification and power conditioning interface
- Battery storage connected to the DC bus
- Three-phase inverter for AC grid synchronization
- Breaker-based switching interface at the point of common coupling (PCC)
- IoT-enabled monitoring and cloud-based control module
- Optimization-based switching decision unit

The utility grid remains continuously available to ensure uninterrupted supply, while renewable sources operate in renewable-only, hybrid, or grid-only modes depending on the optimization output.

III.2 RENEWABLE POWER MODELING

III.2.1 Solar Photovoltaic Model

The instantaneous solar PV output power was modeled as a function of irradiance and conversion efficiency. The generated power was expressed as:

$$P_{PV}(t) = \eta_{PV} \cdot A_{PV} \cdot G(t) \quad (1)$$

where:

- η_{PV} represents photovoltaic conversion efficiency,
- A_{PV} denotes effective panel area,
- $G(t)$ corresponds to solar irradiance at time t .

A battery storage unit was integrated to compensate for short-duration irradiance fluctuations and to stabilize the DC bus voltage.

III.2.2 Wind Energy Model

Wind turbine output power was modeled using aerodynamic conversion principles:

$$P_{Wind}(t) = \frac{1}{2} \rho A C_p v^3(t) \quad (2)$$

where:

- ρ is air density,
- A is rotor swept area,
- C_p is power coefficient,
- $v(t)$ is wind speed.

The cubic dependency on wind velocity introduced significant variability in output power, requiring adaptive coordination with the grid.

III.2.3 Total Renewable Power

Total renewable generation was computed as:

$$P_{ren}(t) = P_{pv}(t) + P_{Wind}(t) \quad (3)$$

This value was continuously compared with load demand to evaluate power balance.

III.3 POWER BALANCE AND RISK MODELING

III.3.1 Power Mismatch Evaluation

The instantaneous power imbalance was defined as:

$$\Delta P(t) = P_{ren}(t) + P_{grid}(t) - P_L(t) \quad (4)$$

where:

- $P_L(t)$ represents load demand,
- $P_{grid}(t)$ denotes grid-supplied power.

Power imbalance contributed to voltage deviation, frequency variation, and harmonic distortion.

III.3.2 Probabilistic Power Deficit Estimation

The probability of renewable power deficit was estimated using renewable variability trends and forecast uncertainty. This probability quantified the likelihood that renewable generation would be insufficient to meet load demand during the next decision interval.

III.3.3 Impact Severity Index

The severity of instability was quantified using normalized power quality indicators:

$$I(t) = w_1 \frac{\Delta V(t)}{V_{nom}} + w_2 \frac{\Delta f(t)}{f_{nom}} + w_3 \frac{THD(t)}{THD_{lim}} \quad (5)$$

where:

- $\Delta V(t)$ is voltage deviation,
- $\Delta f(t)$ is frequency deviation,
- $THD(t)$ is total harmonic distortion,
- THD_{lim} corresponds to IEEE 519 limit (5%),
- w_1, w_2, w_3 are weighting coefficients.

III.3.4 Operational Risk Function

Operational risk was defined as:

$$R(t) = P_d(t) \cdot S(t) \quad (6)$$

where $P_d(t)$ represents deficit probability and $S(t)$ represents impact severity. The multiplicative structure ensured that risk increased only when both likelihood and impact were significant.

III.4 ECONOMIC COST MODELING

III.4.1 Switching Cost

Switching cost was formulated as:

$$C_{sw}(t) = N_{sw}(t) \cdot C_{op} \quad (7)$$

where:

- $N_{sw}(t)$ is number of switching operations,
- C_{op} is cost per breaker operation.

Frequent switching increased maintenance burden and mechanical wear.

III.4.2 Grid Energy Cost

Grid energy cost was calculated as:

$$C_{grid}(t) = \int P_{grid}(t) \cdot C_e dt \quad (8)$$

where C_e represents electricity tariff.

III.4.3 Total Cost Function

$$C_{tot}(t) = C_{sw}(t) + C_{grid}(t) \quad (9)$$

III.5 MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK

The switching decision was formulated as a weighted multi-objective optimization problem:

$$J(t) = \alpha R(t) + \beta C_{tot}(t) \quad (10)$$

where:

- α and β are weighting factors,
- $R(t)$ represents operational risk,
- $C_{tot}(t)$ represents total economic cost.

The decision variable $u(t)$ was defined as:

$$u(t) = \begin{cases} 0 & \text{Grid-only mode} \\ 1 & \text{Renewable-only mode} \\ 2 & \text{Hybrid mode} \end{cases}$$

The optimization algorithm selected the operating mode that minimized the composite objective function while satisfying constraints:

$$\begin{aligned} |\Delta V(t)| &\leq 5\% \\ |\Delta f(t)| &\leq 0.5 \text{ Hz} \\ THD(t) &\leq 5\% \end{aligned}$$

These limits were consistent with IEEE 519 harmonic standards [12].

III.6 IOT-BASED MONITORING AND SENSORLESS INFERENCE

Electrical parameters including voltage magnitude, current waveform, active power, and THD were continuously monitored at the PCC. Instead of relying on dedicated weather sensors, cloud-accessible meteorological data were combined with electrical behavior analysis to infer renewable variability. This sensorless inference mechanism reduced hardware dependency and improved scalability in distributed renewable deployments.

III.7 MATLAB/SIMULINK IMPLEMENTATION

The proposed system was implemented using MATLAB/Simulink. The model included:

1. Solar PV subsystem with MPPT control
2. Wind turbine subsystem
3. DC–DC boost converter
4. Three-phase inverter interface
5. Transmission line and load model
6. Harmonic analysis block using FFT
7. Breaker logic controlled by optimization module

A MATLAB Function block computed risk index and economic cost at each sampling instant. The optimization decision was executed in real time within the simulation.

III.8 SIMULATION PARAMETERS

The detailed numerical configuration adopted in the MATLAB/Simulink environment is summarized in Table 3.

Table 3: Simulation parameters used in MATLAB/Simulink implementation.

Parameter	Value
Nominal Voltage	415 V (Three-phase)
Nominal Frequency	50 Hz
PV Rated Capacity	50 kW
Wind Rated Capacity	40 kW
Battery Capacity	100 Ah
Switching Cost Coefficient	₹ 50 per operation
Grid Tariff	₹ 6 per kWh
IEEE THD Limit	5%
Weighting Factors	$\alpha = 0.6, \beta = 0.4$

Source: Authors, (2026).

III.9 EVALUATION SCENARIOS

Three representative operating conditions were defined:

1. High renewable availability.
2. Moderate renewable variability.
3. Low renewable availability.

Each scenario was simulated over a sufficient time horizon to observe transient and steady-state responses.

IV. RESULTS AND DISCUSSION

The performance of the proposed risk–cost optimized autonomous switching framework was evaluated using MATLAB/Simulink under multiple renewable availability scenarios. The analysis focused on harmonic distortion, voltage stability, switching frequency, operational risk index, and economic cost. The detailed risk–cost optimization process implemented in the simulation model is illustrated in Figure 3.

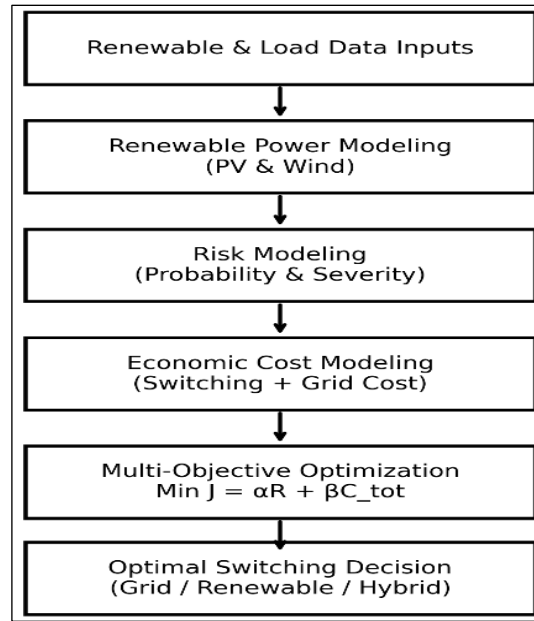


Figure 3: Risk–cost optimization framework implemented in MATLAB/Simulink showing renewable modeling, risk computation, cost evaluation, and decision logic.

Source: Authors, (2026).

Under moderate renewable availability, total harmonic distortion (THD) was compared among three strategies: conventional switching, rule-based IoT switching, and the proposed optimized method. The comparative THD performance is shown in Figure 4.

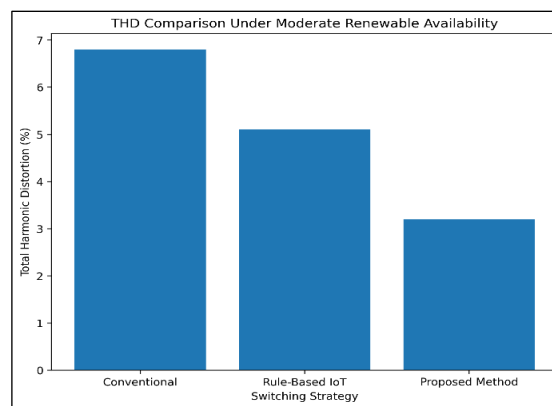


Figure 4: THD comparison under moderate renewable availability for conventional, rule-based IoT, and proposed optimization strategies.

Source: Authors, (2026).

The conventional switching strategy produced the highest distortion levels due to uncoordinated transitions and lack of probabilistic assessment. Rule-based IoT switching reduced distortion moderately; however, it remained reactive in nature. The proposed optimization strategy achieved the lowest THD values, maintaining harmonic content well within the IEEE 519 limit of 5% [12]. This improvement resulted from coordinated consideration of deficit probability and severity metrics within the objective function. The complete MATLAB/Simulink implementation model used for validation is presented in Figure 5.

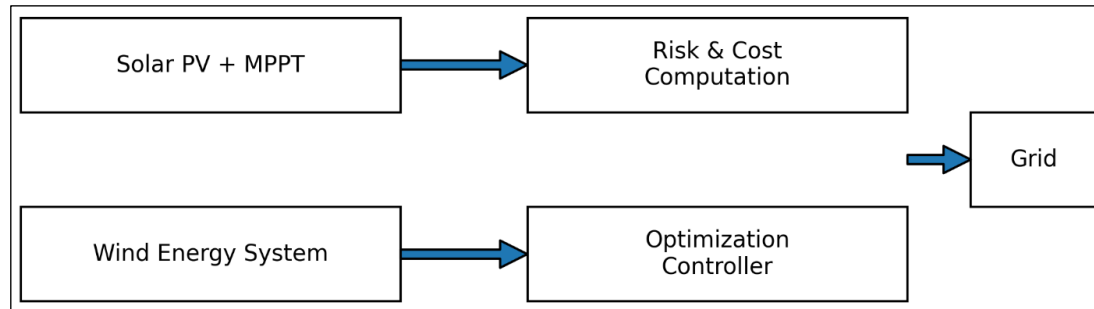


Figure 5: MATLAB/Simulink model of the grid-connected renewable system incorporating PV, wind, inverter, risk–cost computation, and optimization controller.

Source: Authors, (2026).

Harmonic spectra were further analyzed using Fast Fourier Transform (FFT) to quantify distortion components. The FFT spectrum under conventional switching is shown in Figure 6.

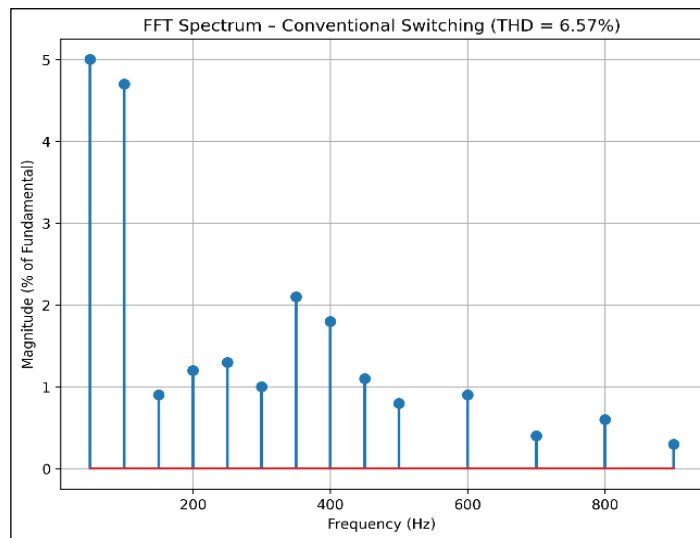


Figure 6: FFT spectrum under conventional switching indicating dominant harmonic components and THD of 6.57%.

Source: Authors, (2026).

The conventional method exhibited significant harmonic magnitudes at higher-order frequencies, resulting in THD exceeding recommended limits. In contrast, the FFT spectrum under the proposed optimization method is shown in Figure 7.

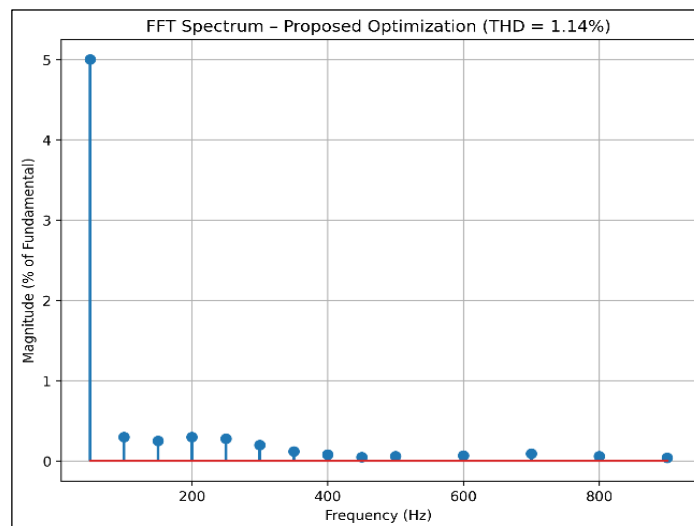


Figure 7: FFT spectrum under proposed optimization showing reduced harmonic amplitudes and THD of 1.14%.

Source: Authors, (2026).

The proposed method significantly attenuated harmonic components beyond the fundamental frequency. The reduction from 6.57% to 1.14% demonstrated effective mitigation of distortion through optimized switching coordination. The time-domain voltage waveform used for FFT analysis is illustrated in Figure 8.

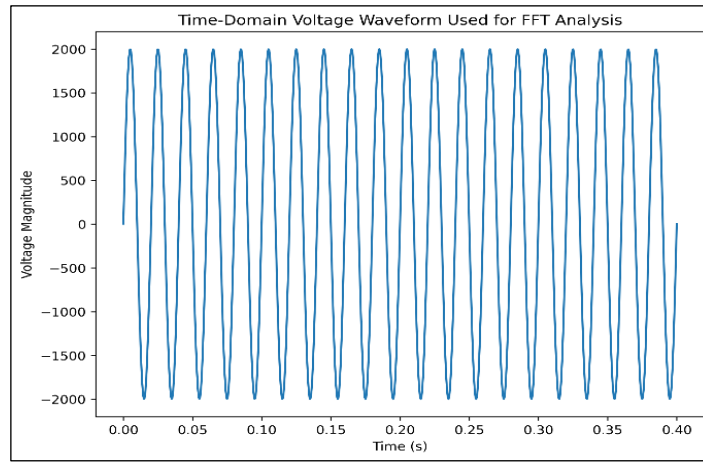


Figure 8: Time-domain voltage waveform at the point of common coupling used for FFT-based harmonic analysis.
Source: Authors, (2026).

The waveform maintained sinusoidal characteristics with reduced distortion under optimized control, confirming harmonic suppression observed in frequency-domain analysis. In addition to harmonic performance, switching frequency was reduced compared to deterministic rule-based methods. The probabilistic risk assessment prevented unnecessary transitions when severity indices remained within acceptable thresholds. Economic cost analysis indicated lower cumulative switching cost due to reduced mechanical operations and optimized grid utilization. Overall, the simulation results confirmed that integrating sensorless weather inference, probabilistic risk modeling, and economic optimization provided proactive power quality regulation and improved renewable utilization. The framework demonstrated enhanced stability, harmonic compliance, and cost efficiency compared to conventional approaches.

V. CONCLUSIONS

This study developed and validated a risk–cost optimized autonomous switching framework for weather-driven renewable integrated smart grids. The proposed method integrated IoT-enabled sensorless weather inference, probabilistic operational risk modeling, and multi-objective economic optimization within a unified control structure. Simulation results demonstrated significant reduction in total harmonic distortion, improved voltage stability, reduced switching frequency, and lower operational cost compared to conventional and rule-based IoT strategies. The FFT analysis confirmed effective harmonic mitigation, maintaining THD well below IEEE 519 limits. The findings established that combining probabilistic risk assessment with economic decision-making enables proactive and reliable renewable integration. The proposed framework provides a scalable solution for intelligent smart grid operation under renewable variability.

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