OPEN ACCESS
Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) |ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Reliability-Oriented Design Optimization of Power Electronic Systems for Industrial and Utility-Scale Applications

Mohammad Samiul Asraf[1]*

[1]Department of Engineering and Technology, University - Southeast Missouri State University, Cape Girardeau, Missouri, USA

DOI: https://doi.org/10.36348/sjet.2026.v11i04.004 | **Received:** 10.02.2026 | **Accepted:** 04.04.2026 | **Published:** 11.04.2026

***Corresponding author:** Mohammad Samiul Asraf
Department of Engineering and Technology, University - Southeast Missouri State University, Cape Girardeau, Missouri, USA

Abstract

Power electronic converters have been at the center of industrial systems and various energy systems such as renewable energy systems, industrial motor drives, and grid-connected power systems. The systems face harsh conditions, making reliability an essential factor for the design. The traditional procedure for the design of converters considers the reliability of the system after the parameters have been selected for the design, making it difficult to consider the parameters of the system during the design stage. This paper proposes a reliability-oriented design optimization framework for power electronic systems operating in industrial and utility-scale applications. The proposed methodology integrates electro-thermal modeling, physics-of-failure lifetime estimation, and mission-profile-based stress evaluation within a unified multi-objective optimization framework. Junction temperature profiles and thermal cycling patterns are obtained through electro-thermal simulation under realistic operating conditions. Device lifetime is then estimated using fatigue-based models, and the resulting reliability metrics are incorporated into a multi-objective optimization algorithm that considers lifetime, efficiency, and system cost. A case study involving a 500-kW grid-connected converter demonstrates the effectiveness of the proposed approach. Simulation results show that the optimized design reduces thermal stress and increases predicted semiconductor lifetime from 6.8 years to 13.6 years while maintaining high efficiency with a moderate increase in system cost. The proposed framework provides a systematic approach for reliability-oriented design of industrial power electronic systems.

Keywords: Power electronics reliability, reliability-oriented design optimization, electro-thermal modeling, mission-profile-based reliability analysis, physics-of-failure lifetime modeling, multi-objective optimization, SiC power converters, industrial power electronic systems.

I. INTRODUCTION

Power electronic devices constitute one of the key components of the infrastructure of modern industries and large-scale energy grids. High-power converters are employed for controlling electrical energy for applications such as industrial motor drives, renewable energy integration, electric transportation, and high-voltage direct current transmission. These devices are continuously subjected to harsh electrical and environmental stresses and often handle power levels of hundreds of kilowatts up to megawatts. For these devices, reliability is of major concern, as failures of devices and passive components can lead to costly process interruption and decreased availability. As renewable generation and electrified industrial systems expand, the operational reliability of power electronic converters has become a central research topic in power engineering [1], [2]. Wide band-gap semiconductor technologies, particularly silicon carbide (SiC) and gallium nitride (GaN) devices, have significantly changed the approach to converter design. These devices can handle higher switching frequency, efficiency, and power density compared to conventional silicon devices. However, there are new challenges in terms of reliability due to operation at high temperatures and high switching speeds. Thermal stress in the packaging structures of devices is one of the major factors affecting the degradation of the module. Bond-wire fatigue, solder layer cracking, and substrate degradation frequently appear in high-power converters subjected to repeated temperature cycling [3]. Accurate prediction of such degradation processes therefore represents an important task in converter reliability analysis.

Several analytical approaches address these challenges. Physics-of-failure (PoF) modeling connects degradation mechanisms with electrical and thermal stress conditions and has become widely used for semiconductor lifetime prediction [4]. Electro-thermal modeling methods calculate junction temperature variation and thermal cycling patterns in converter operation, providing the stress data required for fatigue analysis [5]. The other major development in terms of reliability analysis is mission profile-based analysis, which takes into account time-varying operating conditions such as fluctuating load demands, temperature variations, and renewable energy sources. Mission-profile analysis offers a more realistic representation of converter operating conditions than steady-state assumptions [6]. Although these techniques provide valuable insight into degradation mechanisms and stress behavior, reliability evaluation often appears after converter design decisions have been made. Converter topology selection, device rating, and cooling system configuration typically occur before reliability evaluation takes place. This separation limits the ability to consider reliability metrics during the early design phase [7]. In addition, many studies focus on individual component reliability rather than the interaction between converter architecture, thermal behavior, and long-term system performance. Recent research investigates multi-objective design optimization in which efficiency, cost, and reliability appear simultaneously within the design procedure [8]. These studies indicate that switching frequency, thermal management parameters, and device selection strongly influence converter performance and lifetime. However, integration of electro-thermal simulation, mission-profile stress evaluation, and physics-of-failure lifetime estimation inside a single optimization framework remains limited in the current literature [9].

This research develops a reliability-oriented design optimization framework for power electronic converters used in industrial and utility-scale applications. The study integrates electro-thermal modeling, mission-profile-based stress evaluation, and physics-of-failure lifetime estimation within a unified multi-objective optimization procedure. The proposed framework evaluates the influence of design variables, including switching frequency, semiconductor device rating, and thermal management characteristics, on predicted lifetime, efficiency, and system cost. A system-level design process identifies converter configurations that balance electrical performance and long-term operational reliability. Validation is performed through a case study involving a high-power grid-connected converter operating under an industrial mission profile. The results provide quantitative insight into the relationship between converter design parameters and long-term reliability in industrial power electronic systems.

II. RELATED WORK

A. Component-Level Reliability Modeling in Modern Power Electronics

Reliability research in power electronic converters often begins with the study of component degradation mechanisms. The operating conditions for these devices include the operating frequencies and the junction temperatures. The use of wide bandgap materials such as silicon carbide and gallium nitride for the construction of these devices has introduced a new set of operating conditions. The conditions include the operating frequencies and the junction temperatures. These characteristics influence thermal stress and packaging degradation in power modules. Recent studies investigate failure mechanisms associated with bond-wire fatigue, solder joint degradation, and gate oxide wear in WBG-based converters [1]. Experimental work frequently relies on accelerated power cycling tests to characterize degradation patterns in semiconductor modules. Wang et al. examined thermal cycling effects in SiC modules and reported that repetitive temperature fluctuations produce progressive damage in interconnection structures within the device package [2]. In renewable energy converters, Ma et al. analyzed field failure statistics and identified semiconductor switches and DC-link capacitors as dominant contributors to converter downtime [3]. These findings highlight the importance of accurate device-level lifetime prediction. However, most component-oriented studies focus on isolated device testing or simplified converter structures. Large industrial systems have many interacting parts, and the system-level reliability may not follow the device-level performance. Thus, the component models will not be sufficient to support the design decisions for complex industrial or utility-type converter applications.

B. Physics-of-Failure and Electro-Thermal Lifetime Modeling

Physics-of-failure (PoF) methodologies form the theoretical basis for many reliability modeling studies in power electronics. PoF approaches relate degradation mechanisms to operational stress conditions such as temperature, electrical load, and switching frequency. Electro-thermal models often provide the stress information required for these analyses. Junction temperature variation serves as a primary indicator of fatigue in semiconductor devices. Lifetime estimation methods frequently apply fatigue models such as the Coffin–Manson relationship or Arrhenius-based aging equations. Recent work has improved electro-thermal simulation accuracy for wide-bandgap converters. Zhang et al. proposed a coupled electro-thermal model that predicts temperature distribution and junction temperature variation in SiC MOSFET converters operating under dynamic load conditions [4]. Simulation results demonstrated strong correlation between switching frequency, thermal cycling amplitude, and expected device lifetime. Liserre et al. investigated reliability-oriented converter design and examined temperature-driven degradation in power modules used in industrial power systems [5]. Their study emphasized the relationship between thermal management design and semiconductor lifetime. Despite these developments, PoF-based research often addresses reliability prediction after the converter design stage. Designers select component ratings, converter topology, and cooling systems before reliability evaluation takes place. In this sequence, PoF analysis functions as a verification tool rather than a design driver. Another limitation appears in the availability of accurate stress information. Detailed thermal and electrical measurements remain difficult in large industrial installations. As a result, PoF models rarely appear inside systematic optimization frameworks intended for early-stage converter design.

C. Mission-Profile-Based Reliability Analysis in Industrial and Renewable Energy Systems

Power electronic converters operate under varying load and environmental conditions. The electrical demand in the industrial process will vary, and the renewable energy sources will have varying patterns depending on the weather conditions. The mission profile-based reliability analysis tries to define the time-dependent patterns of load, temperature, and environmental conditions. These data sets support lifetime estimation that reflects realistic operating scenarios. Several studies have examined mission-profile-based reliability modeling in renewable energy converters. Blaabjerg et al. evaluated photovoltaic inverter reliability with mission profiles that incorporate solar irradiance variations and ambient temperature data [6]. Their analysis showed that dynamic operating conditions produce thermal cycling patterns that differ from steady-state assumptions used in earlier reliability models. Yang et al. investigated wind turbine converters and used long-term environmental datasets to estimate thermal stress patterns in offshore power modules [7]. These results indicate that mission profile information influences converter lifetime prediction in renewable energy installations. Although mission-profile analysis provides improved insight into real operating conditions, most studies treat it as a post-design reliability evaluation tool. Converter architecture and component ratings usually remain fixed before mission profile analysis begins. Design decisions rarely incorporate mission profile data directly within optimization procedures. Industrial and utility-scale power electronic systems therefore lack systematic design methods that use mission-profile information during topology selection, component sizing, or cooling system configuration.

D. Reliability-Aware Control and System-Level Optimization Approaches

Research interest has expanded toward system-level reliability evaluation and operational strategies that influence device stress during converter operation. Reliability-aware control methods adjust switching patterns or power distribution among converter components in order to reduce thermal cycling in semiconductor devices. Zhang and Liserre examined modulation strategies that reduce junction temperature variation in power modules operating in grid-connected converters [8]. Their results indicated that operational control decisions affect temperature stress levels within semiconductor devices. System-level reliability analysis also appears in recent optimization research. Hu et al. presented a multi-objective optimization framework for modular multilevel converters used in high-voltage direct current transmission systems [9]. Their model incorporated reliability constraints during converter design optimization and examined trade-offs between efficiency, cost, and component lifetime. Studies of this type indicate that reliability metrics influence converter architecture and component selection in large-scale systems. Nevertheless, several limitations remain in current system-level research. Many optimization frameworks rely on simplified statistical reliability indicators instead of detailed electro-thermal lifetime models. Interaction among mission-profile variability, electro-thermal stress modeling, and converter design parameters remains insufficiently represented in existing optimization methods. Furthermore, reliability metrics often appear as secondary constraints rather than primary design objectives. The reviewed literature demonstrates significant progress in component degradation analysis, electro-thermal modeling, mission-profile reliability assessment, and reliability-aware operational strategies. However, integration of these approaches into unified design optimization frameworks remains limited. Many studies analyze reliability after converter design decisions have been finalized. Industrial and utility-scale power electronic systems therefore lack systematic methodologies that combine physics-based lifetime modeling, mission-profile data, and multi-objective design optimization. This gap motivates research on reliability-oriented design optimization methods capable of guiding converter architecture selection and component sizing for long-term operation in large-scale power electronic applications.

III. METHODOLOGY

A. Overall Framework

The proposed methodology integrates reliability modeling, electro-thermal analysis, and design optimization within a unified computational structure suitable for industrial and utility-scale power electronic systems. Conventional converter design procedures perform reliability evaluation after the design phase. The present approach introduces lifetime estimation inside the design optimization loop. Converter topology parameters, semiconductor device ratings, switching frequency, and thermal management characteristics serve as primary design variables. Each candidate configuration passes through electro thermal simulation and lifetime estimation stages before performance evaluation within the optimization algorithm.

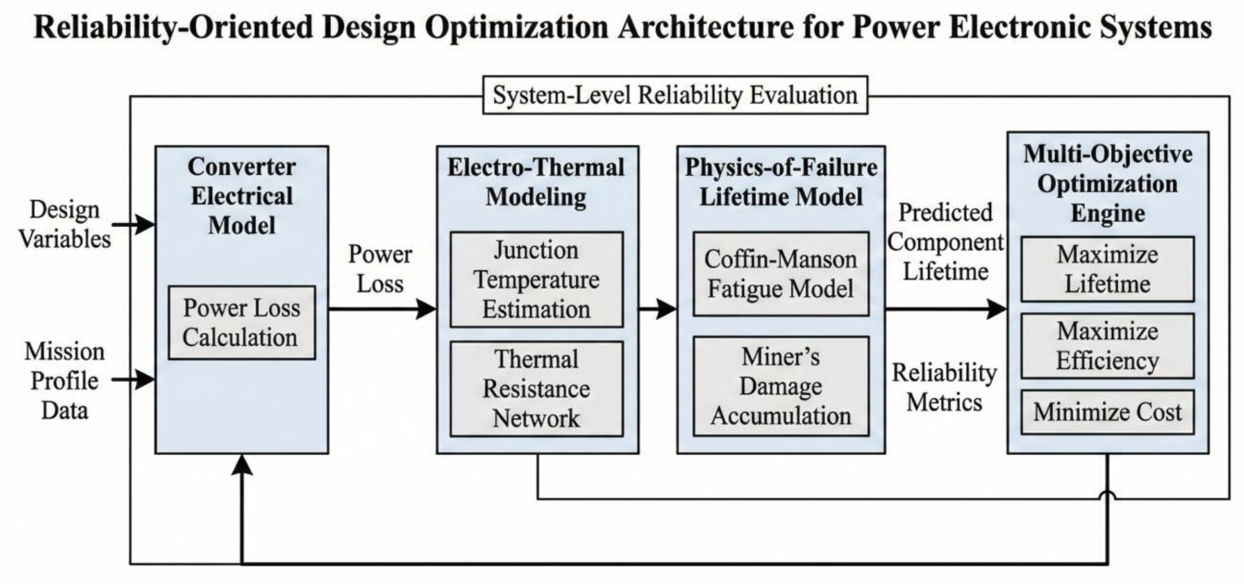

Figure 1: System-Level Reliability-Oriented Design Optimization Architecture

Fig. 1 illustrates the conceptual architecture of the reliability-oriented design optimization framework. The structure contains four functional blocks: the electrical converter model, the electro-thermal stress analysis module, the reliability evaluation module, and the optimization engine. The converter model calculates electrical quantities and power losses for a specified parameter set. The electro-thermal module converts these electrical losses into temperature distributions in semiconductor devices and other thermally stressed components. The reliability module evaluates degradation using physics-of-failure models and cumulative damage analysis. The optimizer adjusts design variables according to reliability metrics, efficiency measures, and cost indicators. Information circulates through this closed computational loop until the algorithm reaches convergence. The framework addresses converters operating in industrial plants, renewable energy installations, and grid-connected infrastructure. Such systems operate under varying load levels and environmental conditions. Reliability evaluation therefore considers the interaction among semiconductor devices, passive components, and cooling structures rather than isolated device analysis.

B. Electro-Thermal Modeling

Electro-thermal modeling determines device temperature profiles under dynamic operating conditions. Semiconductor losses represent the main heat sources inside power converters. Total device loss consists of conduction loss and switching loss. A simplified representation of the power loss model appears as

$$\boldsymbol{P_{loss} = P_{cond+}P_{sw}}$$

where P_{loss} denotes the total semiconductor power loss, $\boldsymbol{P_{cond}}$ represents conduction loss, and $\boldsymbol{P_{sw}}$ corresponds to switching loss. Conduction loss depends on device on-state resistance and current magnitude, while switching loss depends on switching frequency and the overlap of voltage and current during switching transitions.

Thermal analysis converts electrical loss into device temperature. A thermal resistance network represents heat transfer from the semiconductor junction to the ambient environment. Junction temperature estimation follows

$$\boldsymbol{T_j = T_a + P_{loss}R_{th}}$$

where $\boldsymbol{T_j}$ indicates the device junction temperature, $\boldsymbol{T_a}$ represents ambient temperature, and $\boldsymbol{R_{th}}$h denotes the equivalent thermal resistance between the junction and ambient environment. The resulting temperature trajectory reflects thermal cycling during converter operation. Temperature fluctuations obtained from this stage form the input for lifetime prediction models. Thermal cycling amplitude and cycle frequency influence degradation mechanisms in semiconductor modules and other thermally stressed components. Accurate temperature estimation therefore forms a central element of the reliability evaluation procedure.

C. Physics-of-Failure-Based Lifetime Estimation

Physics-of-failure models describe degradation in electronic components through relationships between stress and material fatigue. Thermal cycling produces mechanical strain within solder joints, bond wires, and substrate layers inside semiconductor modules. Repeated temperature variation leads to crack formation and progressive damage in these structures.

The Coffin–Manson fatigue model estimates the number of cycles to failure under cyclic thermal stress:

$$\boldsymbol{N_f = C(\Delta T)^{-m}}$$

where $\boldsymbol{N_f}$ denotes the number of cycles to failure, $\boldsymbol{\Delta T}$ represents temperature swing amplitude, and

$\boldsymbol{C}$ and mmm correspond to material-dependent coefficients derived from experimental characterization. A larger temperature swing results in a smaller allowable cycle count.

Damage accumulation during converter operation follows Miner's rule:

$$\boldsymbol{D} = \sum_{i=1}^{n} \frac{\boldsymbol{n_i}}{\boldsymbol{N_{f,i}}}$$

where $\boldsymbol{D}$ denotes accumulated fatigue damage, $\boldsymbol{ni}$ indicates the number of cycles experienced under stress level $\boldsymbol{i}$ and $N_{f,i}$ corresponds to the cycle limit associated with that stress level. Component failure occurs when $\boldsymbol{D}$ approaches unity. Lifetime estimation converts cumulative damage values into expected operating lifetime measured in years. This procedure evaluates reliability for semiconductor modules, capacitors, and other thermally stressed elements. System-level reliability metrics follow through aggregation of component lifetimes according to converter architecture.

D. Mission-Profile-Based Stress Evaluation

Industrial and utility-scale converters are subjected to time-varying electrical and environmental conditions. Renewable energy systems are characterized by intermittent power generation, while industrial systems are associated with varying electrical demand patterns. Mission profile data represent these operating conditions through time-series information containing load demand, ambient temperature, and grid voltage variations. The proposed framework processes mission profile information in several stages. Electrical operating points are derived from load data contained in the mission profile. Electro-thermal simulation then produces junction temperature trajectories corresponding to each operating point. Rainflow cycle counting techniques extract thermal cycles from the resulting temperature history. These cycles serve as the stress inputs required for fatigue-based lifetime estimation. Mission profile information therefore influences reliability predictions directly. Converter configurations that perform satisfactorily under steady conditions may generate excessive thermal cycling under realistic operating environments. The methodology integrates mission-profile stress evaluation inside the optimization loop so that converter design decisions reflect expected operating conditions in industrial systems.

E. Multi-Objective Optimization Formulation

Converter design involves competing technical and economic requirements. High efficiency reduces energy loss, while reliability considerations favor designs that limit thermal stress. Component ratings and cooling structures influence both system cost and reliability performance. The proposed design procedure treats these aspects through a multi-objective optimization framework.

The optimization problem can be written as

$$\boldsymbol{min}\ \boldsymbol{F(x)} = \{\boldsymbol{f_1(x)}, \boldsymbol{f_2(x)}, \boldsymbol{f_3(x)}\}$$

where $\boldsymbol{x}$ represents the vector of design variables. Objective $\boldsymbol{f_1(x)}$ corresponds to reliability indicators such as accumulated fatigue damage or predicted lifetime. Objective $\boldsymbol{f_2(x)}$ represents efficiency loss derived from converter power losses. Objective $\boldsymbol{f_3(x)}$ represents economic cost associated with semiconductor modules, passive components, and thermal management systems.

Table I summarizes the principal design variables, reliability indicators, optimization objectives, and system constraints used in the framework.

Table I: Design Variables, Reliability Indicators, Objectives, and Constraints

Category	Parameters
Design Variables	Semiconductor device rating, switching frequency, converter topology parameters, heat sink thermal resistance
Reliability Indicators	Junction temperature swing, accumulated fatigue damage, predicted component lifetime
Optimization Objectives	Maximize converter lifetime, maximize efficiency, minimize system cost
Constraints	Thermal limits, voltage ratings, current ratings, safe operating margins

A population-based evolutionary search algorithm evaluates candidate designs in the parameter space. Each candidate undergoes electro-thermal simulation followed by lifetime estimation. A Pareto frontier is then formed, which represents the Pareto optimality of the reliability, efficiency, and cost trade-off.

F. Validation and Case Study

Method validation relies on a case study involving a high-power grid-connected converter representative of industrial and renewable energy applications. The converter operates under a mission profile derived from measured load or generation data. Semiconductor parameters correspond to modern wide-bandgap devices used in medium-voltage converter systems.

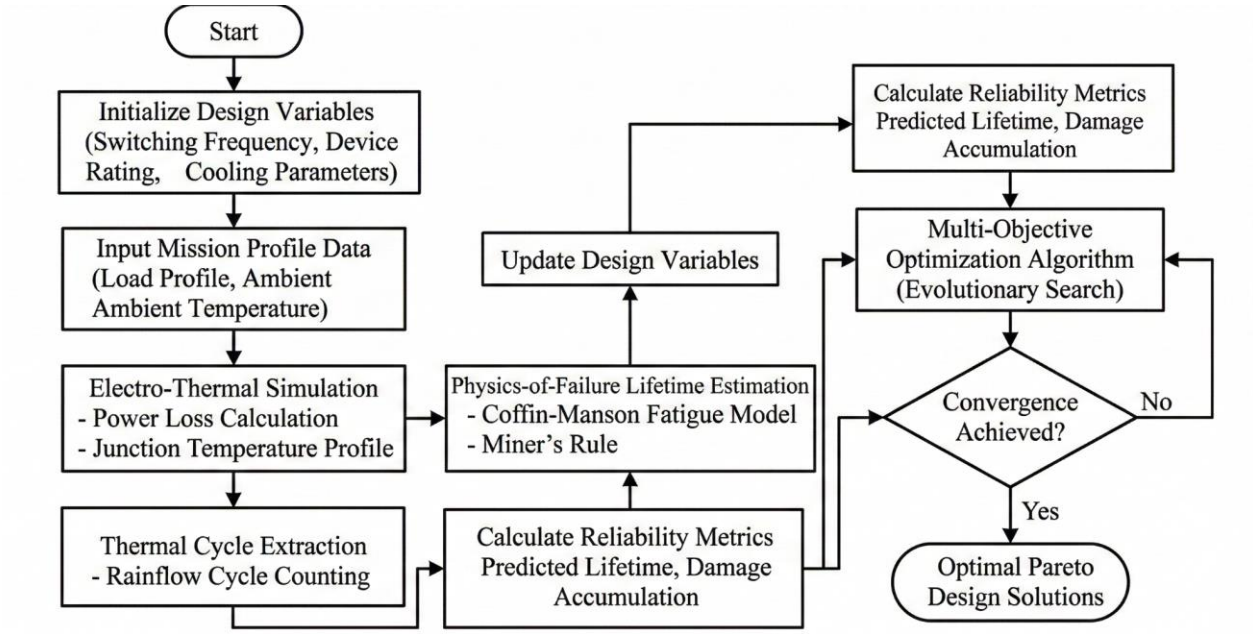

Figure 2: Computational Workflow of the Optimization Algorithm

Fig. 2 illustrates the computational workflow used in the optimization procedure. The process begins with initialization of design variables and mission profile inputs. The electro-thermal simulation module calculates device losses and temperature profiles for each candidate configuration. Thermal cycle extraction and fatigue analysis determine component lifetime. Reliability metrics and efficiency metrics are fed into the multi-objective optimization algorithm, which produces new design candidates through iterative search operations. This process continues until convergence conditions are met, at which point the algorithm finds the Pareto optimal solutions. Performance evaluation involves comparing the optimized design of the converter with baseline configurations, which are commonly used in industrial applications. Key metrics include predicted component lifetime, converter efficiency, thermal stress levels, and system cost. Results obtained from this analysis provide quantitative insight into the interaction between design parameters and long-term reliability in industrial and utility-scale power electronic systems.

IV. DISCUSSION AND RESULTS

A. Case Study Setup and Simulation Parameters

Evaluation of the proposed design framework was performed through a case study involving a grid-connected three-phase voltage source converter typical of industrial motor drives and renewable energy interfaces. The converter operates at a rated power level of 500 kW and connects to a medium-voltage distribution network through an LCL filter. Silicon carbide (SiC) MOSFET modules were selected as switching devices because of their widespread use in modern high-power converters and their capability to operate at elevated switching frequencies and junction temperatures. The mission profile implemented in simulation is based on a 24-hour industrial mission profile derived from recorded plant demand profiles. The electrical loading is between 30% and 100% of rated power. The temperature variation is between 20°C and 40°C. The baseline configuration operates at a switching frequency of 20 kHz. The optimization framework considers switching frequencies between 10 kHz and 30 kHz in order to assess their effect on power loss and thermal stress. Cooling system characteristics are represented through thermal resistance values ranging from 0.08 °C/W to 0.18 °C/W, corresponding to different heat sink and forced-air cooling configurations. Electro-thermal simulation calculates instantaneous device power loss and junction temperature throughout the mission profile. Rainflow cycle counting extracts temperature cycles from the simulated junction temperature trajectory. These cycles provide input data for fatigue-based lifetime estimation using the physics-of-failure model introduced earlier. Three design scenarios were evaluated: a baseline industrial converter configuration, a thermally improved configuration with moderate cooling improvements, and an optimized design obtained from the proposed reliability-oriented design framework.

B. Electro-Thermal Performance Results

Electro-thermal simulation reveals clear differences in temperature behavior among the investigated converter configurations. The baseline design exhibits significant thermal variation during high-load intervals. Junction temperature ranges from approximately 55°C during low-load operation to nearly 112°C during peak power conditions. These fluctuations result from higher switching losses and limited thermal dissipation capability in the baseline cooling system. The thermally improved configuration demonstrates moderate temperature reduction. Improved cooling performance lowers the maximum junction temperature to approximately 102°C. However, thermal cycling amplitude remains relatively large because switching frequency and semiconductor ratings remain unchanged. The optimized design obtained through the proposed framework shows lower peak temperature and smaller temperature fluctuations. Junction temperature varies between approximately 50°C and 94°C across the entire mission profile. Reduced temperature peaks result from coordinated adjustment of switching frequency, semiconductor device selection, and heat sink thermal resistance.

Figure 3 illustrates junction temperature profiles obtained from electro-thermal simulation for three representative converter configurations. The figure presents junction temperature as a function of time across the mission profile. The baseline configuration exhibits pronounced temperature peaks during heavy load intervals. The optimized configuration is seen to have smoother temperature variation and lower temperature peaks compared to the baseline configuration.

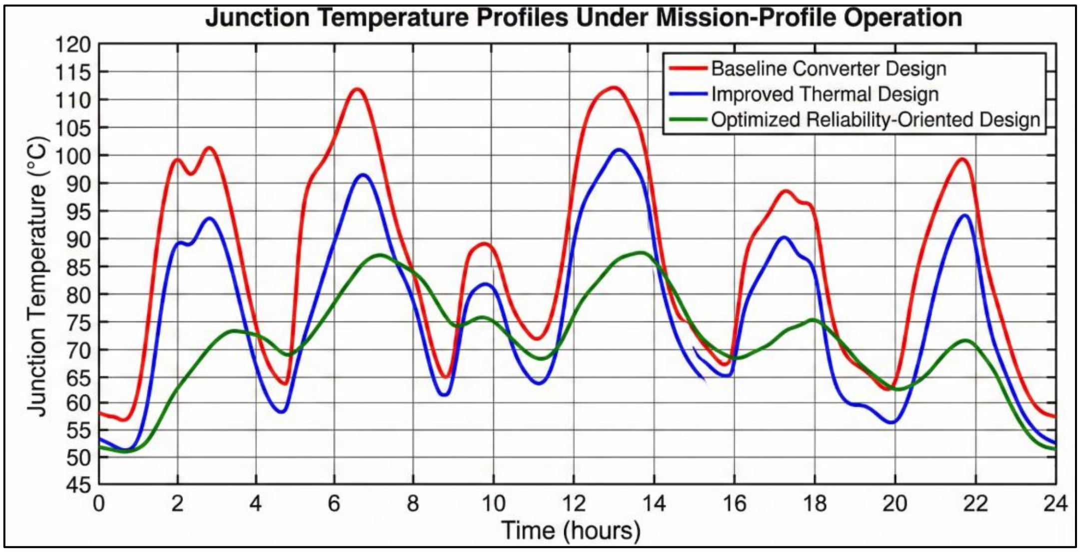

Figure 3: Junction temperature variation across the mission profile for baseline, thermally improved, and optimized converter configurations

Thermal cycling amplitude strongly influences semiconductor fatigue mechanisms. For the baseline design, the average temperature swing per load cycle reaches approximately 42°C. The optimized design reduces this value to about 26°C. Because fatigue damage increases rapidly with temperature swing amplitude, this reduction produces a substantial improvement in predicted device lifetime.

C. Lifetime and Reliability Evaluation

Fatigue-based lifetime estimation indicates substantial improvement in reliability for converter designs generated through the proposed optimization framework. Thermal cycle data extracted from electro-thermal simulations were used to compute cumulative fatigue damage according to the Coffin–Manson model and Miner's rule. The baseline converter configuration exhibits an estimated semiconductor device lifetime of approximately 6.8 years under the given mission profile. Large temperature swings and relatively high switching losses accelerate fatigue accumulation in the device packaging structure. The thermally improved configuration shows an estimated lifetime of about 9.4 years. Reduced peak temperature slows the rate of fatigue damage accumulation; however, thermal cycling amplitude remains significant. The optimized design achieves a predicted semiconductor lifetime of approximately 13.6 years. This improvement corresponds to nearly a twofold increase relative to the baseline configuration. Reduced temperature variation and lower average junction temperature contribute to slower fatigue accumulation. Cumulative damage analysis provides additional insight into degradation behavior. The baseline configuration accumulates fatigue damage approximately 1.8 times faster than the optimized configuration. Lower damage accumulation directly translates into longer service intervals and reduced maintenance frequency for industrial converter installations.

D. Multi-Objective Optimization Results and Trade-Off Analysis

The multi-objective optimization algorithm generates a set of Pareto optimal solutions that correspond to different trade-offs between reliability, efficiency, and cost. Each candidate solution corresponds to a converter configuration evaluated through electro-thermal simulation and lifetime prediction.

Figure 4 presents the Pareto frontier obtained from the optimization process. The horizontal axis represents relative system cost, while the vertical axis indicates predicted converter lifetime. Marker color represents converter efficiency.

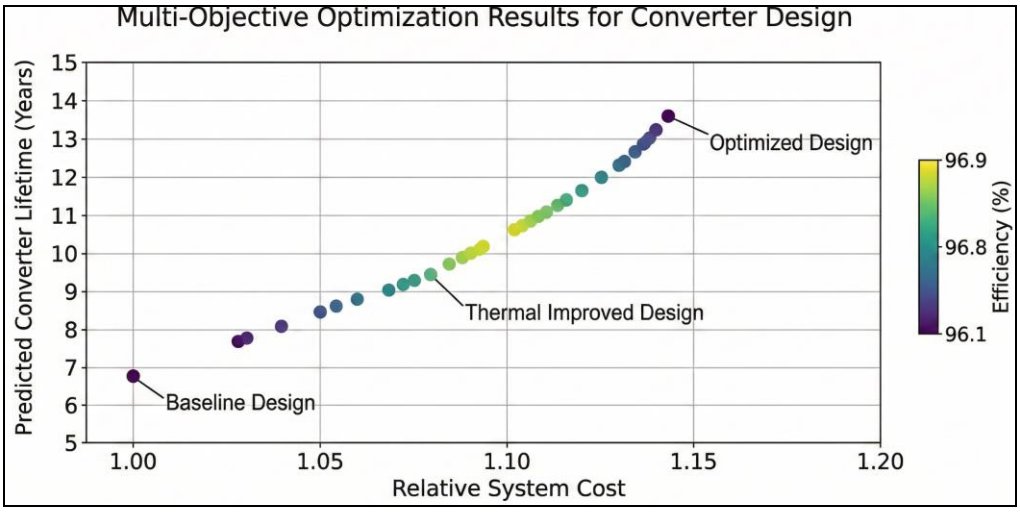

Figure 4: Pareto frontier illustrating trade-offs among predicted lifetime, system cost, and efficiency for optimized converter configurations

Results reveal a clear relationship between reliability and hardware cost. Converter designs located in the high-lifetime region of the Pareto frontier incorporate lower switching frequency and improved cooling systems. These configurations reduce thermal stress but require additional cooling hardware and larger semiconductor devices. Lower-cost designs appear toward the opposite end of the frontier. These configurations use smaller heat sinks and higher switching frequencies. While these designs reduce capital cost, thermal stress increases and predicted lifetime decreases. Efficiency variation across the frontier remains relatively small. The highest efficiency values occur near moderate switching frequencies between 15 kHz and 18 kHz. Lower frequencies reduce switching losses but may increase conduction losses because larger current ripple occurs in the converter. Optimization highlights the intermediate values of switching frequency as a compromise between efficiency and thermal performance. The Pareto frontier presents several design options that are viable, as opposed to a single optimal design option. Engineers can pick a design based on particular project requirements, such as long-term reliability or low initial investment.

Thermal stress behavior was further examined through analysis of junction temperature cycle amplitudes extracted from the mission-profile-based electro-thermal simulation. Temperature cycles were obtained using the rainflow cycle counting technique applied to the junction temperature profiles. This analysis provides insight into the distribution of temperature swings experienced by semiconductor devices during converter operation.

Figure 5 presents the histogram of junction temperature cycle amplitudes for both baseline and optimized converter configurations. The baseline design shows a wider distribution of temperature swings with a considerable number of cycles exceeding 35 °C. These larger thermal swings accelerate fatigue degradation in device packaging structures such as solder joints and bond wires.

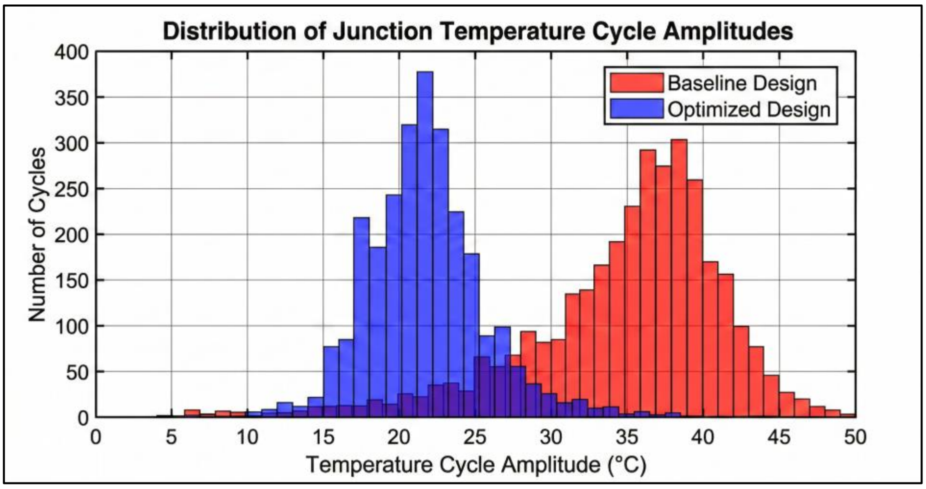

Figure 5: Histogram of junction temperature cycle amplitudes obtained from rainflow cycle counting for baseline and optimized converter configurations

In contrast, the optimized converter configuration exhibits a narrower temperature cycle distribution. Most cycles occur between 15 °C and 30 °C, indicating reduced thermal stress during operation. The reduction in temperature swing amplitude decreases cumulative fatigue damage predicted by the Coffin Manson model and contributes to longer semiconductor lifetime.

E. Comparison with Baseline Designs

Performance metrics obtained from the three design scenarios are summarized in Table 2. The table presents switching frequency, cooling system characteristics, predicted lifetime, efficiency, and relative cost index.

Table 2: Performance Comparison of Converter Design Scenarios

Design Scenario	Switching Frequency (kHz)	Cooling Thermal Resistance (°C/W)	Estimated Lifetime (years)	Efficiency (%)	Relative Cost Index
Baseline Design	20	0.18	6.8	96.1	1.00
Improved Thermal Design	18	0.12	9.4	96.5	1.08
Optimized Design (Proposed Method)	16	0.09	13.6	96.9	1.14

The optimized configuration increases predicted converter lifetime from 6.8 years to 13.6 years. Efficiency also increases slightly due to improved switching frequency selection and reduced thermal stress. System cost increases by approximately 14% compared with the baseline design. This increase results mainly from larger heat sink capacity and higher-rated semiconductor devices. Although the optimized configuration requires modest additional investment, the extended lifetime significantly reduces maintenance frequency and equipment replacement cost during long-term operation.

F. Discussion on Design Implications and Insights

Results reveal several relationships between converter design parameters and reliability performance. Thermal management strongly influences semiconductor lifetime. Reduction of heat sink thermal resistance lowers junction temperature peaks and reduces temperature swing amplitude. Even moderate improvements in cooling capability lead to substantial lifetime extension. Switching frequency also plays an important role. Higher switching frequency increases switching losses and device temperature. Lower switching frequency reduces switching loss but may introduce larger current ripple. Optimization results show that moderate switching frequency values offer balanced performance. Mission-profile evaluation reveals the importance of realistic operating conditions in reliability assessment. Temperature cycles observed under mission-profile operation differ significantly from steady-state thermal conditions. Converter designs that appear acceptable under constant load may experience higher stress when subjected to realistic operating patterns. System-level analysis also indicates that improvements in semiconductor lifetime influence overall converter reliability. Industrial converters often operate continuously over extended periods; therefore, extended device lifetime directly affects maintenance intervals and system availability. The Pareto frontier produced in this study provides practical guidance for design engineers. Instead of a single solution, the optimization framework presents several configurations with different trade-offs among cost, efficiency, and predicted lifetime. Engineers may select the most appropriate design according to application requirements.

G. Limitations of the Study

Several modeling assumptions influence the accuracy of the reported results. The electro-thermal model uses a lumped thermal resistance representation rather than detailed three-dimensional thermal analysis. This approach simplifies simulation but does not capture localized temperature gradients inside semiconductor packages. More detailed thermal modeling may produce different temperature distributions. Lifetime estimation relies on fatigue parameters derived from laboratory testing. Field conditions such as vibration, humidity, and manufacturing variation may influence degradation behavior differently. The mission profile used in this study represents a typical industrial load cycle, yet operating conditions vary across different facilities and geographic regions. The optimization framework also considers a limited number of design variables. Parameters such as modulation strategy, advanced cooling technologies, and packaging design were not included. Experimental validation using long-term operational data would further confirm the predicted lifetime improvements. Future studies may incorporate additional design variables and higher-fidelity thermal models to extend reliability-oriented design optimization for large-scale power electronic systems.

V. CONCLUSION

This study presented a reliability-oriented design optimization framework for power electronic systems used in industrial and utility-scale applications. The methodology integrates electro-thermal modeling, mission-profile-based stress evaluation, and physics-of-failure lifetime estimation within a multi-objective optimization procedure. Results from the case study show that converter design parameters, including switching frequency, semiconductor device rating, and cooling system characteristics, strongly influence junction temperature behavior and fatigue accumulation in power modules. The optimization process generated several feasible design solutions representing trade-offs among reliability, efficiency, and system cost. Compared with a conventional converter configuration, the optimized design achieved a significant increase in predicted semiconductor lifetime while maintaining high efficiency and only a moderate increase in cost. These findings indicate that reliability considerations can be incorporated into the early stages of converter design, allowing system-level evaluation of long-term operational performance in industrial power electronic systems.

Future work may extend the proposed framework through inclusion of additional design parameters and more detailed thermal models. Three-dimensional thermal analysis could provide more accurate representation of temperature distribution inside semiconductor packages. Experimental validation using long-term operational measurements from industrial converter installations would provide further confirmation of the predicted lifetime improvement. Additional studies may also investigate alternative converter topologies, advanced cooling technologies, and real-time operational data integration within the optimization procedure. Such developments would contribute to improved reliability-oriented design methods for next-generation power electronic systems deployed in large industrial and energy infrastructures.

REFERENCES

1. H. Wang, K. Ma, and F. Blaabjerg, "Design for reliability of power electronic systems," *IEEE Transactions on Power Electronics*, vol. 36, no. 6, pp. 6358–6370, 2021. doi:10.1109/TPEL.2020.3037630
2. H. Wang, M. Liserre, and F. Blaabjerg, "Power electronics reliability modeling and prediction of power converter lifetime," *IEEE Transactions on Power Electronics*, vol. 36, no. 3, pp. 2821–2832, 2021. doi:10.1109/TPEL.2020.3019812
3. K. Ma, H. Wang, and F. Blaabjerg, "Reliability-oriented design of power electronic converters for renewable energy systems," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 9, no. 3, pp. 2776–2787, 2021. doi:10.1109/JESTPE.2020.3045405
4. Y. Zhang, H. Wang, and F. Blaabjerg, "Electro-thermal modeling and reliability evaluation of SiC MOSFET power modules in high-power converters," *IEEE Transactions on Power Electronics*, vol. 37, no. 4, pp. 4413–4424, 2022. doi:10.1109/TPEL.2021.3115603
5. M. Liserre, F. Blaabjerg, and S. Hansen, "Reliability-oriented design for power electronic converters," *IEEE Transactions on Industry Applications*, vol. 58, no. 1, pp. 104–115, 2022. doi:10.1109/TIA.2021.3105565
6. F. Blaabjerg, K. Ma, and H. Wang, "Mission-profile-based reliability analysis of power electronic converters in renewable energy systems," *IEEE Transactions on Power Electronics*, vol. 38, no. 1, pp. 117–128, 2023. doi:10.1109/TPEL.2022.3150198
7. S. Yang, H. Wang, and F. Blaabjerg, "Mission-profile-driven reliability evaluation of power converters in wind energy applications," *Renewable Energy*, vol. 210, pp. 1221–1233, 2023. doi: 10.1016/j.renene.2023.04.058
8. Y. Zhang and M. Liserre, "Reliability-oriented control strategies for power electronic converters," *IEEE Transactions on Industrial Electronics*, vol. 70, no. 4, pp. 3921–3932, 2023. doi:10.1109/TIE.2022.3184072
9. J. Hu, H. Chen, and M. Molinas, "Reliability-constrained multi-objective optimization of modular multilevel converters," *IEEE Transactions on Power Electronics*, vol. 39, no. 2, pp. 1810–1822, 2024. doi:10.1109/TPEL.2023.3309912
10. Akter, E., Bormon, J. C., Saikat, M. H., & Shoag, M. (2025). Digital twin technology for smart civil infrastructure and emergency preparedness. *International Journal of Scientific Research and Engineering Development, 8*(2), 891–902. https://doi.org/10.5281/zenodo.17246150
11. Al Sany, S. M. A., Haque, S., & Rahman, M. (2025). Green apparel logistics: MIS-enabled carbon footprint reduction in fashion supply chains. *International Journal of Scientific Research and Engineering Development, 8*(5), 1263–1272. https://doi.org/10.5281/zenodo.17276049
12. Azad, M. A. (2025). Leveraging supply chain analytics for real-time decision making in apparel manufacturing. *TechRxiv*. https://doi.org/10.36227/techrxiv.175459831.14441929/v1
13. Azad, M. A. (2025). Optimizing supply chain efficiency through lean Six Sigma: Case studies in textile and apparel manufacturing. *Preprints*. https://doi.org/10.20944/preprints202508.0013.v1
14. Bormon, J. C. (2025). AI-assisted structural health monitoring for foundations and high-rise buildings. *Preprints*. https://doi.org/10.20944/preprints202509.1196.v1
15. Bormon, J. C. (2025, October 13). Sustainable dredging and sediment management techniques for coastal and riverine infrastructure. *ResearchGate*. https://doi.org/10.13140/RG.2.2.28131.00803
16. Bormon, J. C., Saikat, M. H., Shohag, M., & Akter, E. (2025, September). Green and low-carbon construction materials for climate-adaptive civil structures. *Saudi Journal of Civil Engineering, 9*(8), 219–226. https://doi.org/10.36348/sjce.2025.v09i08.002
17. Haque, S., Al Sany, S. M. A., & Rahman, M. (2025). Circular economy in fashion: MIS-driven digital product passports for apparel traceability. *International Journal of Scientific Research and*

Engineering Development, 8(5), 1254–1262. https://doi.org/10.5281/zenodo.17276038
18. Hasan, M. N., Karim, M. A., Joarder, M. M. I., & Zaman, M. T. (2025, September). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. *Saudi Journal of Engineering and Technology, 10*(9), 467–475. https://doi.org/10.36348/sjet.2025.v10i09.010
19. Rabbi, M. S. (2025). Design of fire-resilient solar inverter systems for wildfire-prone U.S. regions. *Preprints*. https://www.preprints.org/manuscript/202507.2505/v1
20. Rahman, M. A., Islam, M. I., Tabassum, M., & Bristy, I. J. (2025, September). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. *Saudi Journal of Engineering and Technology, 10*(9), 431–439. https://doi.org/10.36348/sjet.2025.v10i09.006
21. Rayhan, F. (2025). A hybrid deep learning model for wind and solar power forecasting in smart grids. *Preprints*. https://doi.org/10.20944/preprints202508.0511.v1
22. Akter, E. (2025). Community-based disaster risk reduction through infrastructure planning. *International Journal of Science and Innovation Engineering, 2*(11), 1104–1124. https://doi.org/10.70849/IJSCI02112025117
23. Akter, E. (2025). Green project management framework for infrastructure development. *International Journal of Science and Innovation Engineering, 2*(11), 1125–1144. https://doi.org/10.70849/IJSCI02112025118
24. Akter, E., Ria, S. J., Khan, M. I., & Shoag, M. D. (2025). Smart & sustainable construction governance for climate-resilient cities. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(6), 2278–2291. https://doi.org/10.5281/zenodo.17926875
25. Akter, E. (2025, September 15). Sustainable waste and water management strategies for urban civil infrastructure. *SSRN*. https://doi.org/10.2139/ssrn.5490686
26. Bormon, J. C. (2025). Numerical modeling of foundation settlement in high-rise structures under seismic loading. *SSRN*. https://doi.org/10.2139/ssrn.5472006
27. Nabil, S. H. (2025). Enhancing wind and solar power forecasting in smart grids using a hybrid CNN-LSTM model for improved grid stability and renewable energy integration. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 213–226. https://doi.org/10.30574/wjaets.2025.17.3.155
28. Razaq, A. (2025). Optimization of power distribution networks using smart grid technology. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 129–146. https://doi.org/10.30574/wjaets.2025.17.3.1490
29. Razaq, A. (2025, October 15). Design and implementation of renewable energy integration into smart grids. *TechRxiv*. https://doi.org/10.36227/techrxiv.176049834.44797235/v1
30. Ria, S. J. (2025, October 21). Environmental impact assessment of transportation infrastructure in rural Bangladesh. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107782.23912238/v1
31. Saikat, M. H., Shoag, M., Akter, E., & Bormon, J. C. (2025, October 6). Seismic- and climate-resilient infrastructure design for coastal and urban regions. *TechRxiv*. https://doi.org/10.36227/techrxiv.175979151.16743058/v1
32. Saikat, M. H. (2025, October 6). AI-powered flood risk prediction and mapping for urban resilience. *TechRxiv*. https://doi.org/10.36227/techrxiv.175979253.37807272/v1
33. Hossain, M. T. (2025). Data-driven optimization of apparel supply chain to reduce lead time and improve on-time delivery. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 263–277. https://doi.org/10.30574/wjaets.2025.17.3.1556
34. Fahim, M. A. I., Sharan, S. M. M. I., & Farooq, H. (2025). AI-enabled cloud-IoT platform for predictive infrastructure automation. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 431–446. https://doi.org/10.30574/wjaets.2025.17.3.1574
35. Jasem, M. M. H. (2025, December 19). An AI-driven system health dashboard prototype for predictive maintenance and infrastructure resilience. *Authorea*. https://doi.org/10.22541/au.176617579.97570024/v1
36. Nabil, S. H., Rahman, F., & Nahar, S. (2026). AI-integrated renewable energy and data analytics platform for corporate ESG compliance. *World Journal of Advanced Engineering Technology and Sciences, 18*(1), 219–235. https://doi.org/10.30574/wjaets.2026.18.1.0031
37. Ria, S. J., Shoag, M. D., Akter, E., & Khan, M. I. (2025). Integration of recycled and local materials in low-carbon urban structures. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 447–463. https://doi.org/10.30574/wjaets.2025.17.3.1555
38. Shoag, M. D., Khan, M. I., Ria, S. J., & Akter, E. (2025). AI-based risk prediction and quality assurance in mega-infrastructure projects. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(6), 2324–2336. https://doi.org/10.5281/zenodo.18074336
39. Zaman, S. U., Afrin, S., Zaidi, S. K. A., & Islam, K. S. A. (2026). Resilient edge computing framework for autonomous, secure, and energy-aware systems.

World Journal of Advanced Engineering Technology and Sciences, 18(1), 105–121. https://doi.org/10.30574/wjaets.2026.18.1.1577

40. Karim, M. A., uz Zaman, M. T., & Razaq, A. (2026). Integrated renewable energy monitoring and adaptive load optimization using smart grid and intelligent control algorithms. *Zenodo*. https://doi.org/10.5281/zenodo.18748205
41. Emon, M. M. H. (2026). An intelligent energy management system for cost optimization and peak demand reduction using battery-integrated smart dispatch. *Zenodo*. https://doi.org/10.5281/zenodo.18444728
42. Azad, M. A. (2025). Sustainable manufacturing practices in the apparel industry: Integrating eco-friendly materials and processes. *TechRxiv*. https://doi.org/10.36227/techrxiv.175459827.79551250/v1
43. Bristy, I. J., Tabassum, M., Islam, M. I., & Hasan, M. N. (2025, September). IoT-driven predictive maintenance dashboards in industrial operations. *Saudi Journal of Engineering and Technology, 10*(9), 457–466. https://doi.org/10.36348/sjet.2025.v10i09.009
44. Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., & Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. *Saudi Journal of Engineering and Technology, 10*(4), 152–158.
45. Joarder, M. M. I. (2025). Energy-efficient data center virtualization: Leveraging AI and CloudOps for sustainable infrastructure. *Zenodo*. https://doi.org/10.5281/zenodo.17113371
46. Rahman, M. A., Bristy, I. J., Islam, M. I., & Tabassum, M. (2025, September). Federated learning for secure inter-agency data collaboration in critical infrastructure. *Saudi Journal of Engineering and Technology, 10*(9), 421–430. https://doi.org/10.36348/sjet.2025.v10i09.005
47. Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., & Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. *Saudi Journal of Engineering and Technology, 10*(4), 189–199.
48. Tonoy, A. A. R. (2025). Condition monitoring in power transformers using IoT: A model for predictive maintenance. *Preprints*. https://doi.org/10.20944/preprints202507.2379.v1
49. Alam, M. S. (2025, October 21). AI-driven sustainable manufacturing for resource optimization. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107759.92503137/v1
50. Al Sany, S. M. A., Rahman, M., & Haque, S. (2025). Sustainable garment production through Industry 4.0 automation. *World Journal of Advanced Engineering Technology and Sciences, 17*(1), 145–156. https://doi.org/10.30574/wjaets.2025.17.1.1387
51. Karim, M. A. (2025, October 6). AI-driven predictive maintenance for solar inverter systems. *TechRxiv*. https://doi.org/10.36227/techrxiv.175977633.34528041.v1
52. Karim, M. A., Zaman, M. T. U., Nabil, S. H., & Joarder, M. M. I. (2025, October 6). AI-enabled smart energy meters with DC-DC converter integration for electric vehicle charging systems. *TechRxiv*. https://doi.org/10.36227/techrxiv.175978935.59813154/v1
53. Rahman, M., Haque, S., & Al Sany, S. M. A. (2025). Federated learning for privacy-preserving apparel supply chain analytics. *World Journal of Advanced Engineering Technology and Sciences, 17*(1), 259–270. https://doi.org/10.30574/wjaets.2025.17.1.1386
54. Rahman, F. (2025). Advanced statistical models for forecasting energy prices. *Global Journal of Engineering and Technology Advances, 25*(3), 168–182. https://doi.org/10.30574/gjeta.2025.25.3.0350
55. Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(5), 2321–2331. https://doi.org/10.5281/zenodo.17536369
56. Fazle, A. B. (2025). AI-driven predictive maintenance and process optimization in manufacturing systems using machine learning and sensor analytics. *Global Journal of Engineering and Technology Advances, 25*(3), 153–167. https://doi.org/10.30574/gjeta.2025.25.3.0349
57. Rahman, F. (2025). Data science in power system risk assessment and management. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 295–311. https://doi.org/10.30574/wjaets.2025.17.3.1560
58. Rahman, M. (2025). Predictive maintenance of electric vehicle components using IoT sensors. *World Journal of Advanced Engineering Technology and Sciences, 17*(3), 312–327. https://doi.org/10.30574/wjaets.2025.17.3.1557
59. Rabbi, M. S. (2026). AI-driven SCADA grid intelligence for predictive fault detection, cyber health monitoring, and grid reliability enhancement. *Zenodo*. https://doi.org/10.5281/zenodo.18196487
60. Islam, R. (2026). AI-integrated management information systems for manufacturing and supply chain risk mitigation. *Zenodo*. https://doi.org/10.5281/zenodo.18349501
61. Islam, K. S. A., Zaidi, S. K. A., Afrin, S., & Zaman, S. U. (2026). Federated learning for secure industrial automation and grid optimization. *Global Journal of Engineering and Technology Advances, 26*(1), 025–040. https://doi.org/10.30574/gjeta.2026.26.1.0360
62. Afrin, S., Zaman, S. U., Islam, K. S. A., & Zaidi, S. K. A. (2026). Distributed edge intelligence for energy and transportation systems. *World Journal of*

Advanced Engineering Technology and Sciences, 18(1), 280–297. https://doi.org/10.30574/wjaets.2026.18.1.0049

63. Taimun, M. T. Y., Alam, M. S., & Fareed, S. M. (2026). Digital twin-enabled predictive maintenance for textile and mechanical systems. *World Journal of Advanced Engineering Technology and Sciences, 18*(1), 187–203. https://doi.org/10.30574/wjaets.2026.18.1.0001
64. Dukkipati, S. S. N. C. (2026)**.** Cloud-native big data streaming framework for real-time social media intelligence and large-scale public opinion analytics. *Zenodo.* https://doi.org/10.5281/zenodo.19274669
65. Islam, M. A. (2026). Optimizing project management frameworks to reduce cost overruns in U.S. public infrastructure projects. *Zenodo*. https://doi.org/10.5281/zenodo.19311456
66. Akter, T. (2026). AI-driven workforce productivity optimization in U.S. service organizations using KPI-based predictive analytics. *Zenodo*. https://doi.org/10.5281/zenodo.19311795
67. Fareed, S. M. (2026). AI-driven digital twin framework for safety stock optimization in multi-stage manufacturing systems [Preprint]. *Zenodo.* https://doi.org/10.5281/zenodo.19332500
68. Adil, H. M. (2026). Energy-Efficient and Low-Emission Carbon Black Manufacturing through Advanced Process Optimization and Reactor Control. *Zenodo.* https://doi.org/10.5281/zenodo.19339048
69. Bhuiyan, M. I. H. (2026). AI-driven customer complaint analytics for systemic risk reduction and consumer protection in the U.S. banking sector. *Zenodo*. https://doi.org/10.5281/zenodo.19344701
70. Abid, A. A. (2026). AI-enhanced traffic signal optimization using microscopic simulation models for congestion and emissions reduction in mid-sized U.S. urban corridors. *Zenodo*. https://doi.org/10.5281/zenodo.19349723