International Journal of Multidisciplinary Research and Growth Evaluation

International Journal of Multidisciplinary Research and Growth Evaluation
ISSN: 2582-7138
Received: 18-10-2020; Accepted: 21-11-2020
www.allmultidisciplinaryjournal.com
Volume 1; Issue 5; November-December 2020; Page No. 358-374

Framework for Evaluating the Thermodynamic Behavior of Gas Turbine Components under Variable Conditions

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DOI: https://doi.org/10.54660/.IJMRGE.2020.1.5.358-374

Abstract
This paper proposes a unified framework for evaluating the thermodynamic behavior of gas turbine components under variable operating and environmental conditions. The framework combines first- and second-law analyses, high-fidelity and reduced-order models, and rigorous uncertainty quantification to capture steady, transient, and off-design regimes. It treats the compressor, combustor, turbine, recuperator or heat-recovery elements, and secondary air systems as coupled modules linked through mass, momentum, energy, and exergy balances. Component maps, validated chemistry, and heat-transfer correlations are fused with data-driven surrogates to represent nonlinearities due to ambient temperature, humidity, altitude, load profile, fuel composition, degradation, and control schedules. State estimation using extended Kalman and particle filters enables digital-twin deployment and reconciliation of sensor noise, while Bayesian calibration aligns model parameters with test data. The methodological core is an exergy-aware assessment that decomposes losses at module and interface levels to expose where irreversibilities originate and how they shift with conditions. Global and local sensitivity measures (Sobol indices and adjoint gradients) rank drivers across envelopes, and polynomial chaos or Monte Carlo propagation quantifies prediction intervals for key metrics. Multi-objective optimization (e.g., NSGA-II) explores trade-offs among heat rate, surge margin, cooling effectiveness, lifecycle emissions, and maintenance risk, with constraints enforced by surge and metal-temperature limits. A modular API and standardized experiment design promote reproducibility and integration with existing plant historians and control simulators. Two use cases illustrate the framework. First, ambient and load variability are propagated to compressor stability, turbine cooling demand, and combined-cycle performance, revealing how control schedules mitigate off-design penalties. Second, fuel variability, including hydrogen-enriched and synthetic fuels, is assessed for flame temperature, pattern factor, and NOx formation, clarifying feasible operating windows under emissions constraints. Validation protocols compare against standardized test points, quantify measurement and model uncertainty, and establish traceable uncertainty budgets for decision support. By unifying exergy-based metrics, surrogate modeling, probabilistic analysis, and digital-twin assimilation in an architecture, the framework provides a reproducible basis for evaluating component-level thermodynamics under realistic variability. It enables faster what-if assessment, clearer attribution of losses, and more robust decisions on control scheduling, maintenance planning, fuel flexibility, and retrofit prioritization for aero-derivative and industrial gas turbine fleets.

Keywords: Gas Turbine, Thermodynamics, Exergy Analysis, Off-Design Performance, Uncertainty Quantification, Digital Twin, Surrogate Modeling, Sensitivity Analysis, Multi-Objective Optimization, Hydrogen-Enriched Fuels

1. Introduction
Gas turbines operate across wide envelopes where component interactions, control actions, and environmental drivers jointly determine performance, reliability, and emissions. Despite mature first- and second-law foundations, engineers still lack a unified way to quantify how compressors, combustors, turbines, heat exchangers, and secondary air systems respond when real-world conditions drift from nominal. This gap complicates surge-margin assurance, cooling effectiveness, life consumption estimation, and emissions compliance, especially as assets pursue higher efficiency, fuel flexibility, and tighter operating constraints (Asata, Nyangoma & Okolo, 2020, Bukhari, *et al*., 2020, Essien, *et al*., 2020).

The present work addresses this gap by proposing a framework that evaluates component-level thermodynamic behavior consistently under variability while preserving rigor, transparency, and reproducibility.

The objectives are to (i) formalize coupled mass, momentum, energy, and exergy balances at the component and interface levels; (ii) incorporate transient, steady, and off-design regimes within a single modeling architecture; (iii) integrate uncertainty quantification and sensitivity analysis to expose dominant drivers; and (iv) enable decision support for control scheduling, maintenance planning, retrofit evaluation, and fuel switching. The scope spans aero-derivative and heavy-duty industrial engines, simple- and combined-cycle configurations, and both experimental and operational data contexts suitable for digital-twin deployment and model calibration (Abass, Balogun & Didi, 2020, Amatare & Ojo, 2020, Imediegwu & Elebe, 2020).

"Variable conditions" are defined along three axes. Ambient variability captures changes in temperature, pressure (altitude), humidity, and inlet distortion that alter corrected flows, maps, and cooling needs. Load variability denotes commanded power or shaft-speed schedules, start–stop cycles, ramp rates, and part-load turndown that move components across map regions and modify thermal gradients. Fuel variability encompasses composition and properties natural gas blends, hydrogen-enriched fuels, syngas, and liquid alternatives affecting heating value, flame temperature, kinetics, pattern factor, and pollutant formation. Together, these axes induce nonlinear shifts in irreversibilities, stability margins, and metal-temperature limits that must be evaluated coherently (Adesanya, *et al.*, 2020, Oziri, Seyi-Lande & Arowogbadamu, 2020).

The paper contributes a modular, exergy-aware modeling architecture; a data-assimilation layer using Bayesian calibration and state estimation; and a probabilistic toolchain coupling global/local sensitivities with scenario-based multi-objective analysis. Case studies demonstrate ambient/load propagation to surge and cooling demand, and fuel-flexibility envelopes under emissions constraints. The paper proceeds with background and gaps, governing equations and modular interfaces, uncertainty and surrogate modeling strategies, assimilation and optimization methods, case-study validation, and concludes with implications and future research directions (Akpan, *et al*., 2017, Oni, *et al*., 2018).

2. Background and Literature Synthesis

The thermodynamic behavior of gas turbine components has long been a central theme in thermal system engineering due to its critical role in determining efficiency, reliability, and environmental performance. Gas turbines are complex, highly coupled systems composed of several key modules the compressor, combustor, turbine, and often heat exchangers or recuperators that interact through mass, momentum, and energy flows. Each component operates under unique physical principles, yet their combined performance dictates the overall thermodynamic integrity of the engine. Understanding how these components behave under variable conditions is therefore essential for optimizing design, predicting degradation, and achieving adaptive control across diverse operating environments (Akinrinoye, *et al*. 2015, Bukhari, *et al*., 2019, Erigha, *et al*., 2019).

At the heart of gas turbine analysis lies the application of the first and second laws of thermodynamics. The first law, the principle of energy conservation, governs the balance between work, heat transfer, and changes in internal energy. It ensures that each component's energy inputs and outputs are properly quantified air compression in the compressor, chemical energy conversion in the combustor, and expansion work extraction in the turbine. However, the first law alone is insufficient to evaluate performance degradation and irreversibility (Adesanya, *et al*., 2020, Seyi-Lande, Arowogbadamu & Oziri, 2020). The second law introduces the concept of entropy and exergy, providing the theoretical framework to assess energy quality and identify sources of inefficiency. Exergy analysis enables engineers to locate where and how irreversibilities such as friction, heat loss, mixing, or non-ideal combustion occur within each component and their interfaces, allowing performance to be evaluated beyond simple efficiency measures. Figure 1 shows the main components of gas turbine unit presented by Mohamed & Khalil, 2020.

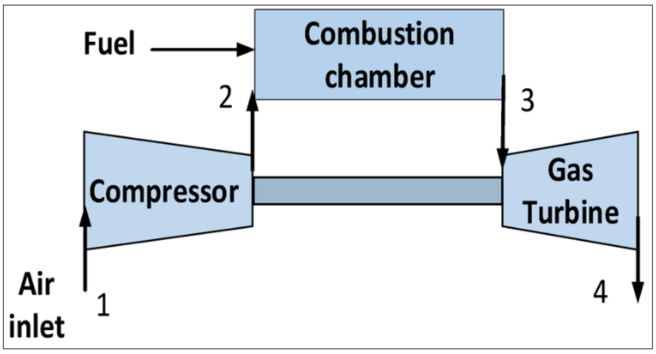

Fig 1: Main components of gas turbine unit (Mohamed & Khalil, 2020).

The compressor is responsible for raising the pressure of incoming air, a process heavily influenced by ambient temperature, pressure, and humidity. Its performance is characterized by parameters such as pressure ratio, isentropic efficiency, and corrected mass flow. Under variable ambient and load conditions, deviations from design-point operation cause changes in flow incidence angles, potential boundary-layer separation, and surge margin reduction. Similarly, the combustor converts chemical energy into thermal energy through combustion reactions (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2020, Imediegwu & Elebe, 2020). Variability in fuel composition such as hydrogen blending, biogas impurities, or synthetic fuel properties alters flame temperature, stoichiometry, and emission characteristics. Maintaining stability and low emissions under fluctuating conditions requires accurate thermochemical modeling and advanced control schemes.

The turbine, tasked with expanding hot gases to produce work, experiences complex aerodynamic and thermal interactions. Variations in load or inlet temperature can induce blade stress, cooling inefficiencies, and even material fatigue. The turbine's performance is typically analyzed using temperature-entropy and pressure-volume relationships to evaluate work output, expansion efficiency, and exergy losses. Coupling between turbine stages also means that upstream compressor or combustor deviations propagate downstream, magnifying off-design effects. Heat exchangers, including recuperators and intercoolers, serve to recover or redistribute heat across the cycle. Their effectiveness depends on temperature differentials and mass flow rates, both of which are sensitive to external and operational variations. Thermal transients during startup or load change often create mechanical stresses and reduce exchanger longevity (Ajayi, *et al*., 2018, Bukhari, *et al*., 2018, Essien, *et al*., 2019).

Despite extensive research on component thermodynamics, significant gaps remain in understanding and modeling their performance under real-world, variable conditions. Traditional steady-state design methodologies assume constant boundary conditions and nominal operating points, leading to models that fail to capture the dynamic behavior observed in actual operations. Real turbines operate under constantly changing ambient conditions, variable fuel quality, and transient load demands conditions that shift component maps, alter flow distribution, and impact efficiency (Akinrinoye, *et al*. 2020, Essien, *et al*., 2020, Imediegwu & Elebe, 2020). Existing off-design models often rely on simplified correction factors or static performance maps, which are inadequate for modern requirements involving hybrid cycles, digital twins, and advanced monitoring. Figure 2 shows figure of gas turbine analyzed presented by Pérez-Ruiz, *et al*., 2017.

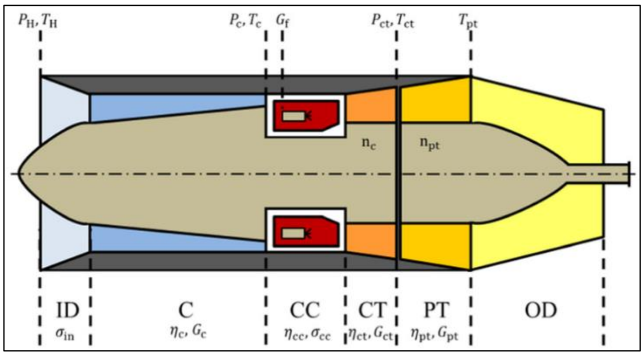

Fig 2: Gas turbine analyzed (Pérez-Ruiz, *et al*., 2017).

Moreover, conventional analyses typically treat each component in isolation, neglecting the coupled thermodynamic and control interactions that emerge across the system. In practice, compressor surge or turbine temperature excursions cannot be understood independently of the combustion process or cooling system response. The need for integrated modeling frameworks where component-level physics and system-level dynamics are linked through energy and exergy balances is now recognized as crucial. Similarly, the increasing use of alternative fuels such as hydrogen and synthetic gas introduces additional complexity (Akinrinoye, *et al*. 2020, Bukhari, *et al*., 2020, Elebe & Imediegwu, 2020). Their distinct calorific values, reaction kinetics, and heat-transfer properties demand models that can adaptively predict combustion and turbine responses under variable fuel compositions.

Recent advances in computational thermodynamics, system identification, and machine learning have enabled hybrid approaches that merge physics-based and data-driven modeling. These methods provide higher fidelity in predicting off-design and transient behavior. Yet, challenges persist in quantifying uncertainty, validating models with limited experimental data, and ensuring real-time applicability. Uncertainty quantification and sensitivity analysis are vital to determine which parameters most influence performance and where measurement or model improvement efforts should focus. Exergy-based decomposition of component losses, combined with probabilistic propagation of input uncertainties, can enhance reliability in design and operation (Ajayi, *et al*., 2019, Bukhari, *et al*., 2019, Oguntegbe, Farounbi & Okafor, 2019). Digital twin concepts have further highlighted the importance of variability-aware modeling. By continuously assimilating sensor data, digital twins can dynamically update thermodynamic states and detect deviations from nominal performance. However, this requires consistent mathematical frameworks capable of reconciling noisy, incomplete data with physical laws tasks that are still under development for gas turbine systems (Ajayi, *et al*., 2019, Bayeroju, *et al*., 2019, Sanusi, *et al*., 2019). Additionally, the adoption of Bayesian calibration techniques and state estimators such as extended or unscented Kalman filters has shown promise in aligning model predictions with operational data. These approaches allow adaptive evaluation of performance while accounting for degradation, fouling, or partial component failure. Figure 3 shows schematic diagram of a simple industrial turbine and simple process cycle of an industrial turbine presented by Alblawi, 2020.

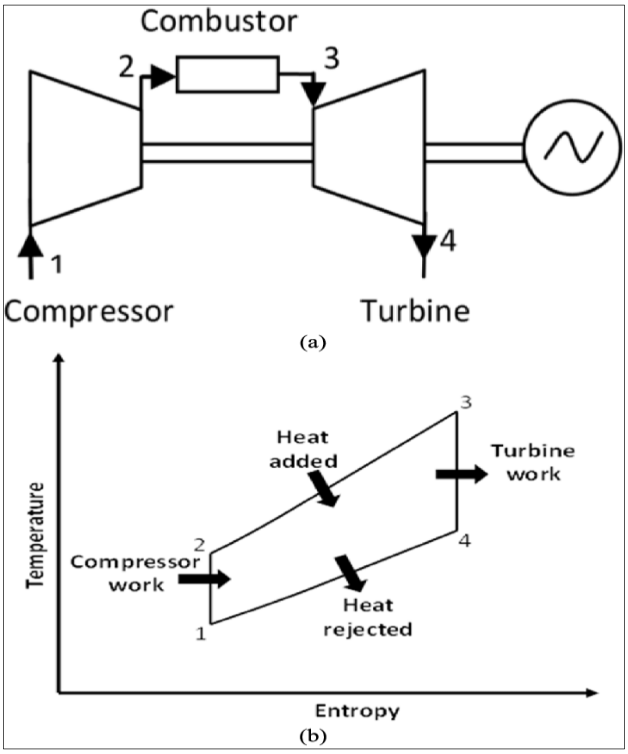

Fig 3: Schematic diagram of a simple industrial turbine and simple process cycle of an industrial turbine (Alblawi, 2020).

From an environmental and economic perspective, the ability to model thermodynamic behavior under variable conditions directly affects fuel consumption, emission compliance, and maintenance cost. As regulatory pressures increase, accurately predicting how turbines behave under off-design scenarios such as part-load operation or renewable-fuel co-firing becomes critical for sustainable power generation. Furthermore, as combined-cycle and hybrid configurations become more prevalent, cross-system interactions between gas and steam turbines, heat-recovery systems, and auxiliary equipment introduce additional layers of variability that require integrated analysis (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2020, Elebe & Imediegwu, 2020).

In summary, the background of thermodynamic evaluation in gas turbines reveals an evolution from isolated, steady-state modeling toward holistic, dynamic, and data-informed frameworks. The first and second laws of thermodynamics remain foundational, providing the analytical structure for energy and exergy tracking. However, the transition toward variability-aware modeling represents a paradigm shift, requiring methods that capture the coupling of thermal, mechanical, and control subsystems under uncertainty. The gaps in current literature ranging from limited off-design datasets and insufficient coupling models to the absence of unified exergy-based dynamic frameworks underscore the need for an integrated approach (Asata, Nyangoma & Okolo, 2020, Essien, *et al*., 2019, Elebe & Imediegwu, 2020).

The proposed framework aims to bridge these gaps by combining detailed thermodynamic modeling with uncertainty analysis, sensitivity mapping, and digital data assimilation. It leverages the physical rigor of classical thermodynamics while embracing modern computational and statistical tools to evaluate component behavior across realistic operating envelopes. By doing so, it advances the ability to predict, monitor, and optimize gas turbine performance under variable ambient, load, and fuel conditions, paving the way for more efficient, flexible, and sustainable power systems (AdeniyiAjonbadi, *et al*., 2015, Didi, Abass & Balogun, 2019, Umoren, *et al*., 2019).

3. Methodology

This study adopts a multi-layered analytical–computational methodology that fuses thermodynamic modelling with predictive analytics, simulation-based uncertainty evaluation, and digital-twin synchronization principles drawn from the literature. The analytical foundation begins with developing a component-level thermodynamic model for the compressor, combustor, turbine, and heat-exchanger sections. Mass, momentum, energy, and exergy balance equations are formulated under variable ambient, load, and fuel conditions, ensuring that off-design behaviour is represented. Component maps for compressors and turbines are digitized, smoothed, and parameterized to enable interpolation over wide operating envelopes. State variables including pressure ratio, temperature rise, mass-flow response, combustion efficiency, and exergy destruction are tracked across transient and steady regimes. Chemistry submodels incorporate equivalence ratios and fuel-blend variability, while heat-transfer submodels incorporate cooling-air requirements and metal-temperature constraints.

Predictive-analytics elements from Abass, Balogun, and Didi (2019–2020) are embedded to detect performance drifts using supervised and unsupervised learning. These analytics operate on sensor streams to identify anomalies, emerging faults, or deviations from baseline thermodynamic signatures, similar to sentiment-driven, multi-channel, and CRM-analytics frameworks repurposed here for component-health scoring. Simulation-based analysis inspired by Aduwo & Nwachukwu (2019) handles uncertain market-like disturbances here treated as variability in ambient temperature, humidity, pressure, load swings, and fuel composition. Monte-Carlo simulations and Latin hypercube sampling propagate these uncertainties to quantify robustness of performance indicators such as compressor surge margin, turbine inlet temperature admissibility, cycle efficiency, exergy destruction rate, and emissions.

Digital-Twin concepts adopted from Adesanya *et al*. (2020), Ajayi *et al*. (2018–2020), and Ibrahim *et al*. (2020) allow cloud-synchronized replicas of the gas-turbine model to assimilate real-time measurements using recursive Bayesian filters. This ensures that predicted thermodynamic states remain calibrated to observed operating conditions. Adaptive dashboards similar to CRM and multi-cloud analytics frameworks convert KPIs into visual insights that track degradation, fouling, and combustion inefficiencies.

Organizational-behaviour and strategic-analytics insights from AdeniyiAjonbadi *et al*. (2015) and Ajonbadi *et al*. (2014–2016) inspire the governance structure for reliability evaluation, emphasizing role-based collaboration, iterative feedback, and continuous performance auditing. The framework includes automated compliance monitoring similar to vendor-auditing, anomaly-detection, and financial-governance frameworks described in Filani, Bankole, and Dako's works. These are repurposed to monitor thermal-efficiency violations, component-map inconsistencies, and boundary-condition breaches.

Cyber-physical integration, derived from zero-trust, multi-cloud, metadata-driven architectures (Ajayi, Bukhari, Oladimeji), ensures secure data ingestion and robust model execution, preventing configuration drift. This guarantees integrity in the digital-twin synchronization layer.

The methodological pipeline concludes with performance scoring and optimization. A multi-criteria evaluation combines thermodynamic KPIs, degradation rates, and exergy-loss indicators. Predictive dashboards classify operating zones into green (optimal), amber (sub-optimal), and red (fault-critical), using classification thresholds trained from historical fault cases such as fouling, blade erosion, combustion instability, and sensor bias. The evaluation supports decision-making for control-schedule adjustment, preventive maintenance, and fuel-blend optimization.

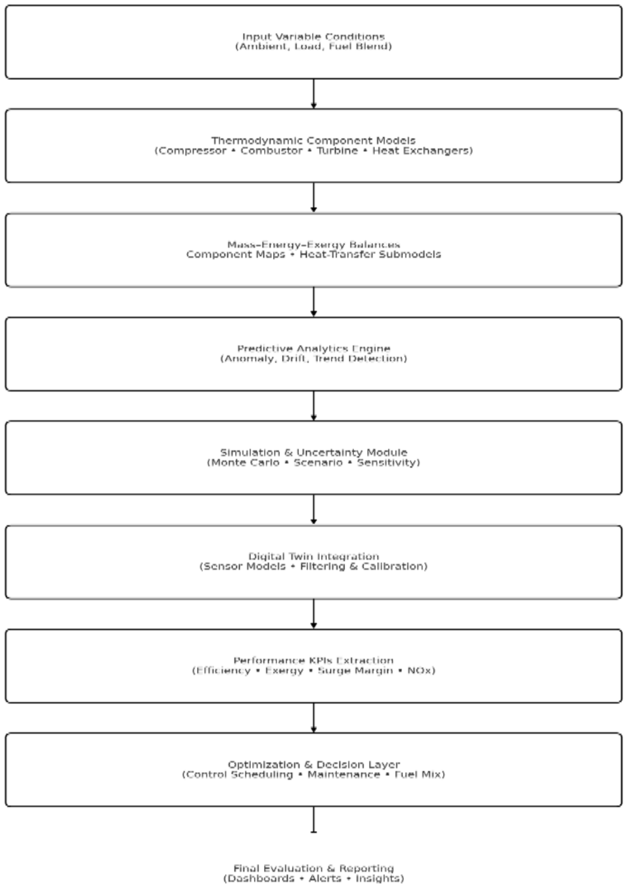

Fig 4: Flowchart of the study methodology

4. Modeling Architecture and Governing Equations

The modeling architecture treats the gas turbine as a network of coupled component modules intake and filtration, compressor, combustor, turbine stages, secondary-air system, heat exchangers or recuperators, plenums, shafts, and exhaust linked by conservation of mass, momentum, energy, and exergy. Each module is modeled as a quasi-one-dimensional control volume with ports, internal sources/sinks, and metal nodes where needed. State variables include static temperature T, pressure p, mass flow (\dot m), species mass fractions (Y_k), shaft speed (\omega), metal temperatures (T_m), and coolant flow splits (\dot m_c). The ambient boundary supplies T_a,p_a,ϕ_a (humidity), while load commands specify ω(t) or power (P(t)). Fuel composition is represented by species vector z_f with lower heating value and transport properties derived from mixing rules (Ajonbadi, Mojeed-Sanni & Otokiti, 2015, Evans-Uzosike & Okatta, 2019, Oguntegbe, Farounbi & Okafor, 2019). Assumptions include perfect-gas behavior with temperature-dependent c_p(T)), negligible potential energy changes, and optional inclusion of kinetic energy at high Mach in compressor inlets and turbine throats. Flow is treated as steady within each time step (quasi-steady), while transients arise from inventories, shaft dynamics, thermal inertia, and control actions.

For any control volume, the mass balance is

$$dm=i∈in∑m˙i−o∈out∑m˙o+m˙gen,$$

with species balances d(mYk)=∑m˙Yk,i+ω˙k where (\dot ω_k) is the chemical source term. The momentum balance is captured through pressure–loss models and maps; for ducts and liners, Δp=ζ21ρu2, while for plenums, dynamic terms are retained to stabilize surge predictions. The energy balance uses specific enthalpies:

$$dU=∑m˙hin−∑m˙hout+Q˙−W˙+∑Δhrxnξ˙,$$

where Q˙ accounts for heat exchange with metals and W˙ is shaft work (positive out of the control volume). Exergy tracking uses the Gouy–Stodola relation. The physical-chemical exergy rate is

$$E˙=∑m˙eph+ch+Q˙(1−TT0)−W˙−T0S˙gen,$$

and exergy destruction E˙D=T0S˙gen partitions irreversibilities to mixing, combustion, pressure losses, heat transfer across finite ΔT, and friction. Component exergy efficiency ηex is defined as useful exergy out over exergy in.

Compressor modules are driven by manufacturer maps expressed in corrected coordinates to separate ambient effects: corrected mass flow m˙c=m˙Tt/Tref/(pt/pref) and corrected speed Nc=N/Tt/Tref. The map provides pressure ratio πc and isentropic efficiency ηis\eta_{is}ηis along speed lines and flow coefficients. Off-design interpolation uses smooth surfaces with surge and choke boundaries enforced as inequality constraints. The compressor energy equation computes outlet total temperature Tt2=Tt1[1+ηisπc(γ−1)/γ−1], with humidity effects handled by mixture (c_p) and latent terms. Bleeds for cooling and sealing are modeled as orifice flows with discharge coefficients dependent on Reynolds and pressure ratio.

The combustor couples mixing, finite-rate chemistry, heat release, pressure loss, and liner heat transfer. Fuel enters through staged injectors: primary, secondary, and dilution zones. Chemistry can be represented by (i) global mechanisms for natural-gas flames (e.g., two-step methane oxidation) and hydrogen enrichment corrections, or (ii) reduced skeletal mechanisms tabulated into flamelet libraries for rapid lookup. The chemical source term $\dot\omega_k$ derives from Arrhenius kinetics ω˙k=Wk∑ℓνkℓΩ˙ℓ(T,p,Y). Emissions are predicted via submodels: extended Zeldovich thermal NO for high (T), prompt NO for rich pockets, CO/UHC from finite residence times, and N*(2)O in lean pre-mix. Pressure loss is split into cold and hot losses, Δp/p=Kc(ρu2/2p)+KhΦHR\Delta p/p = K_c (\rho u^2/2p) + K_h \Phi_{HR}Δp/p=Kc(ρu2/2p)+KhΦHR* scales with heat release. Liner and dilution holes are represented as discrete jets with momentum flux ratios to capture mixing and pattern factor.

Turbine stages are modeled with stage-stacking using velocity triangles or meanline correlations. Maps relate corrected flow, efficiency, and expansion ratio. The isentropic outlet temperature uses Tt3=Tt4s+ losses, and the work rate is W˙t=m˙(ht,in−ht,out)−m˙c(hc,in−hc,out) when coolant mixing is included. Cooling air injection (internal convection, impingement, and film) is computed from secondary-air network solutions, then mixed into the main gas path with appropriate mixing enthalpy and momentum. Metal nodes obey

$$Mcp,mdtdTm=hgasAgas(Tg−Tm)+hcoolAcool(Tc−Tm)+σϵA(Tsur4−Tm4)−q˙cond,$$

with temperature-dependent properties. Film effectiveness ηf follows empirical correlations as a function of blowing ratio, density ratio, and hole geometry; uncooled hot-streak effects are included via circumferential mixing factors. Blade life metrics (e.g., Larson–Miller) can be computed from Tm(t) and stress surrogates.

Heat exchangers, such as recuperators and intercoolers, use ε– TU or segmental models. For a segment Δx, the gas/air energy equations couple via q′′=U(Th−Tc), with pressure drops from Colburn–Dittus or Gnielinski correlations and distributed loss coefficients. Thermal transients account for matrix heat capacity. Exergy analysis identifies destruction due to finite temperature differences and frictional losses.

The secondary-air system is a resistive network of orifices, seals, cavities, and leaks. Nodes enforce mass continuity; branches obey m˙=CdA2ρΔp or compressible relations. Temperature evolution uses mixing and wall exchange. Coupling to mainline modules ensures that cooling availability and cavity pressures are consistent with compressor bleed schedules and turbine disk pumping.

Shaft dynamics connect turbine and compressor torques through Jdtdω=τt−τc−τaux, and electrical load is represented by τload=Pe/ω with generator/exciter losses. Multiple spools introduce additional state equations and inter-spool coupling via gas-path work exchange and mechanical bearings.

Heat-transfer submodels appear across modules. In the compressor, rotor–stator convection uses correlations based on Reynolds and Prandtl, augmented by wet-air corrections for high humidity. In the combustor, turbulent convection and radiation are combined: q′′=h(Tg−Tw)+σϵ(Tg4−Tw4) with gas emissivity from weighted-sum-of-gray-gases. In the turbine, internal passage Nusselt numbers depend on rib turbulator pitch-to-height ratios, rotation number, and buoyancy parameters; external film and trailing-edge cooling use jet-impingement and slot ejection correlations. Metal property variation with (T) and oxidation allowances are included to keep metal temperatures within life limits.

Component maps and characteristic curves are essential to close the model. For compressors and turbines, bi-cubic splines interpolate (m˙c,Nc)↦(π,η), with surge surfaces extracted from test data and augmented by Greitzer-type dynamic terms near instability. Combustor pressure-loss and mixing maps are parameterized by equivalence ratio, Reynolds, and geometry factors. Heat-exchanger performance maps provide U A and Δp as functions of flow and (T) levels, adjusted for fouling via $R_f(t)$.

Numerically, the architecture forms a differential–algebraic system. Algebraic constraints enforce port compatibility: (p)-matching with specified drops, mass-flow continuity, energy and composition mixing, and exergy bookkeeping. Differential states advance via implicit time integration for stiffness (cooling and metal nodes) and explicit/semi-implicit schemes for shaft dynamics and inventories. A Newton–Raphson inner loop solves flow splits and pressure nodes, with line search to maintain feasibility with respect to surge and choke. Under variable conditions, boundary inputs u(t)={Ta,pa,ϕa,Pcmd,zf} drive the system; control schedules alter bleed valves, variable stator angles, fuel staging, and inlet-guide vane positions subject to actuator rate limits and saturations.

Chemistry–thermodynamics coupling is handled through enthalpy and species equations closed by equation-of-state and cp(T,Y). For fast simulation, flamelet/progress variable tables map (Z,χ) to h,Yk,ω˙k with pressure corrections; for hydrogen-rich fuels, differential diffusion effects are accounted for via effective Lewis numbers. Emission predictors integrate along residence-time distributions estimated from mixing models (e.g., CSTR-in-series or probability density functions in turbulent combustion).

Finally, exergy balances are computed per module and at interfaces to attribute losses. The physical exergy of a stream is eph=(h−h0)−T0(s−s0)+V22+gze^{ph}=(h-h_0)-T_0(s-s_0)+\tfrac{V^2}{2}+gzeph=(h−h0)−T0(s−s0)+2V2+gz; chemical exergy uses composition-dependent reference values adjusted for humidity. Summed exergy destruction identifies variability-sensitive hotspots compressor shock/recirculation near surge, combustor mixing and finite-rate chemistry, turbine film cooling and disk pumping, and recuperator ΔT pinch enabling targeted design or control actions. By unifying these balances with maps, chemistry, and heat-transfer submodels in a consistent network and advancing them in time with realistic boundary variability, the architecture yields a rigorous, transparent platform for evaluating component thermodynamics across ambient, load, and fuel disturbances (Akinbola, *et al*., 2020, Balogun, Abass & Didi, 2020).

5. Uncertainty, Sensitivity, and Surrogate Modeling

Uncertainty permeates every layer of thermodynamic evaluation for gas turbines operating under variable ambient, load, and fuel conditions. It arises from parameters that cannot be known precisely (compressor map scatter, combustor kinetics, turbine cooling effectiveness), from structural choices in the governing equations (closure models for mixing, radiation, and pressure losses), and from operational variability (sensor drift, actuator hysteresis, and boundary disturbances). A useful distinction is between aleatory uncertainty irreducible variability such as weather and fuel composition distributions and epistemic uncertainty lack of knowledge in model parameters, submodel forms, and degradation states that can be reduced by data. The framework explicitly represents both categories so that propagated prediction intervals on key metrics surge margin, metal temperature, heat rate, and NOx are traceable to their sources and can inform data acquisition or redesign priorities (Akinrinoye, *et al*., 2020, Farounbi, Ibrahim & Abdulsalam, 2020).

Parameter uncertainty is handled by assigning probabilistic priors to quantities such as compressor isentropic efficiency offsets, combustor heat-release scalars, liner loss coefficients, turbine film effectiveness multipliers, and recuperator fouling resistances. Priors may be Gaussian for well-characterized parameters, lognormal for strictly positive quantities, or hierarchical when fleet data suggest site-to-site variability. Structural uncertainty is represented through model discrepancy terms added to constitutive relations e.g., an additive bias on pressure-loss correlations or a multiplicative factor on reaction rates modeled as low-order basis expansions or Gaussian processes over operating envelopes. Joint calibration uses Bayesian inference, fusing test-stand or field data with priors via likelihoods that reflect sensor noise, time-correlation, and occasional outliers (heavy-tailed innovations) (Ajonbadi, Otokiti & Adebayo, 2016, Didi, Abass & Balogun, 20219). Posterior samples are obtained through ensemble Kalman inversion for near-Gaussian problems or Hamiltonian Monte Carlo for strongly coupled parameters. The calibrated posteriors then drive forward uncertainty propagation.

Sensitivity analysis organizes this uncertainty landscape by identifying which inputs most influence outputs and where linear approximations fail. Global sensitivity indices, especially Sobol first-order and total-effect measures, decompose output variance across the input space and capture interactions that are invisible to local derivatives. They are estimated nonintrusively using quasi–Monte Carlo designs or via polynomial chaos expansions that yield indices analytically from expansion coefficients. When the number of uncertain inputs is large common in secondary-air networks derivative-based global sensitivity measures and active subspace methods provide scalable screening, revealing low-dimensional directions that dominate output variability (Balogun, Abass & Didi, 2019, Otokiti, 2018, Oguntegbe, Farounbi & Okafor, 2019). Local sensitivities are obtained from discrete-adjoint or algorithmic-differentiation implementations of the governing equations, returning exact gradients of scalar objectives (e.g., NOx or peak T_m) with respect to hundreds of parameters at a cost comparable to a single residual evaluation. These gradients support gradient-enhanced Kriging, trust-region calibration, and physics-constrained optimization under uncertainty. The complementary use of global (variance-based) and local (adjoint) methods prevents overconfidence: the former guards against missing nonlinear interactions, while the latter accelerates design and control updates in tight operating neighborhoods (Akomea-Agyin & Asante, 2019, Awe, 2017, Osabuohien, 2019).

Because repeated evaluations of the high-fidelity thermo–fluid–chemistry model can be computationally expensive, the framework adopts surrogate modeling to approximate input–output maps over specified envelopes with quantified error. Polynomial chaos expansions (PCE) are the first line of attack when inputs have known, independent distributions and responses are smooth. Nonintrusive spectral projection or regression builds orthogonal polynomial bases (Hermite for Gaussian, Legendre for uniform, Laguerre for gamma), with sparsity promoted by least-angle regression or iterative hard thresholding to avoid combinatorial blow-up. PCE not only accelerates propagation and Sobol analysis but also affords analytic moment and percentile estimates, which ease certification and reporting (Ajonbadi, *et al*., 2014, Didi, Balogun & Abass, 2019, Farounbi, *et al*., 2019).

When responses exhibit sharp nonlinearities near surge, choke, lean blowout, or cooling-film breakdown machine-learning surrogates complement or supersede PCE. Gaussian process regression (Kriging) captures smooth functions with calibrated uncertainty; its predictive variance drives adaptive sampling that concentrates points near steep gradients and constraint boundaries. For multi-output quantities (e.g., {surge margin,NOx,Tm}\{ \text{surge margin}, \text{NOx}, T_m \}{surge margin,NOx,Tm}), multi-task GPs or co-kriging exploit cross-correlations, while heteroscedastic kernels accommodate operating-point-dependent noise (Akinrinoye, *et al*. 2020, Balogun, Abass & Didi, 2020, Oguntegbe, Farounbi & Okafor, 2020). Neural-network surrogates excel when data volumes are large and response manifolds are high-dimensional. Physics-informed networks embed conservation constraints via soft penalties; monotonic or convex-constraint architectures enforce known trends (e.g., monotonic NOx with flame temperature). Autoencoder-based model-order reduction compresses spatial fields temperature or species distributions into low-dimensional latent states that evolve with simple dynamics; decoding reconstructs fields for life and emissions post-processing. For hierarchical fidelity stacks (1D meanline, 2D throughflow, 3D CFD), multi-fidelity surrogates combine cheap, biased models with sparse, trusted evaluations using autoregressive co-kriging or Bayesian discrepancy fusion, yielding accuracy near the high-fidelity model at a fraction of the cost.

Design of experiments is crucial for building surrogates that are both accurate and parsimonious. Space-filling Latin hypercube or Sobol sequences provide initial coverage; feasibility-aware sampling avoids waste near physically impossible regions (negative flows, surge violation). Adaptive refinement leverages acquisition functions expected improvement for objectives, maximum mean-square-error for global coverage, or risk-weighted criteria for rare-event boundaries to add points where the surrogate is uncertain and influential. When constraints are present (e.g., metal temperature limits), classification surrogates (support vector machines, GP classifiers) delineate feasible domains, and regression surrogates model responses inside them, ensuring reliable predictions near safety margins (Seyi-Lande, Oziri & Arowogbadamu, 2018).

Validation of metamodel fidelity proceeds along three axes: statistical accuracy, physical consistency, and decision adequacy. Statistically, holdout or (k)-fold cross-validation supplies unbiased error estimates; parity plots and residual analyses test for bias, heteroscedasticity, and non-normal tails; the coefficient of determination (Q^2), root-mean-square error, and mean absolute percentage error provide scalar summaries. For probabilistic surrogates, coverage probabilities of predictive intervals are compared against nominal levels, and probability integral transform histograms check calibration. Learning curves error versus training size signal whether additional data will meaningfully improve fidelity. Physically, the surrogate is stress-tested against invariants: energy balance closure within tolerance, exergy non-negativity, monotonic limits (e.g., NOx rising with increasing adiabatic flame temperature), and proper asymptotes at low/high Reynolds numbers. Surrogates that violate invariants are either rejected or repaired using constraints, residual-learning corrections, or hybridization with low-fidelity physics (Akinbola & Otokiti, 2012, Dako, *et al*., 2019, Oziri, Seyi-Lande & Arowogbadamu, 2019).

Decision adequacy addresses whether surrogate errors could flip choices in optimization, maintenance planning, or dispatch. Here, the framework conducts value-at-risk–style analyses: it perturbs surrogate predictions within validated uncertainty envelopes and checks robustness of the chosen control schedule or retrofit ranking. If the decision is sensitive, the adaptive sampler targets the contentious region for new high-fidelity evaluations until the recommendation stabilizes. This closes a principled loop between modeling and decision-making that prevents costly missteps from over-trusting a glossy but fragile metamodel.

Uncertainty propagation then blends the pieces. For smooth regimes, sparse PCE offers rapid, spectral-accuracy estimates of mean, variance, and tails. For strongly nonlinear or multimodal behavior, quasi–Monte Carlo with low-discrepancy sequences provides dimension-robust convergence; subset simulation or importance sampling quantifies rare-event probabilities (surge, LBO, thermal exceedance) (Akinrinoye, *et al*. 2019, Didi, Abass & Balogun, 2019, Otokiti & Akorede, 2018). When parametric posteriors are available from Bayesian calibration, posterior predictive distributions flow naturally through surrogates, yielding fully probabilistic forecasts that combine parameter and operational variability. Sensitivity metrics computed on the surrogate (Sobol, DGSM, active subspaces) guide sensor placement and calibration priorities: if turbine metal-temperature uncertainty is dominated by two film-effectiveness multipliers, more informative cooling-flow measurements or targeted rig tests become the rational next investment.

The overall philosophy is to make uncertainty explicit, sensitivity actionable, and surrogates trustworthy. By rigorously defining priors, calibrating against data with honest likelihoods, decomposing variance globally and locally, constructing surrogates tailored to response character, and validating those surrogates for both statistical fitness and physical integrity, the framework transforms variability from a nuisance into a design parameter. That transformation enables real-time digital twins to quantify confidence in their diagnostics, empowers operators to select control schedules that hedge risk without sacrificing efficiency, and helps designers prioritize upgrades where they matter most for thermodynamic performance under the messy, shifting conditions that define real turbine operation (Abass, Balogun & Didi, 2020, Didi, Abass & Balogun, 2020, Oshomegie, Farounbi & Ibrahim, 2020).

6. Data Assimilation and Digital-Twin Integration

A digital twin for gas turbines hinges on disciplined data assimilation that reconciles imperfect measurements with physics to deliver reliable state estimates, parameter posteriors, and actionable health indicators under variable ambient, load, and fuel conditions. The starting point is explicit sensor modeling. Each measurement channel compressor discharge pressure, combustor inlet temperature, turbine exhaust temperature, shaft speed, fuel flow, valve positions, vibration, and emissions receives a stochastic representation that accounts for bias, scale factor, resolution, latency, and colored noise (Akinola, *et al*., 2020, Akinrinoye, *et al*. 2020, Balogun, Abass & Didi, 2020). Biases follow slow random walks to capture drift; scale factors reflect calibration gain uncertainty; latency is modeled as a fractional delay with hold dynamics; noise is characterized by AR(1) processes when spectral analysis reveals low-frequency wander beyond white noise. Where feasible, cross-sensor correlations are retained (e.g., temperature rakes) to exploit redundancy. Actuator models include dead zones, saturations, and rate limits to ensure consistency when reconstructing commanded versus realized schedules.

Filtering provides the backbone for real-time state and parameter estimation. The extended Kalman filter linearizes around the current operating point and is efficient for mildly nonlinear regimes such as compressor map tracking away from surge. The unscented Kalman filter propagates sigma points through the full nonlinear model and improves accuracy for strong nonlinearity typical during large load ramps or hydrogen blending transients without requiring analytical Jacobians. Particle filters address multimodal posteriors that arise during fault isolation (e.g., distinguishing between thermocouple bias and genuine turbine inlet temperature rise) but require careful resampling to avoid degeneracy; stratified or systematic resampling with regularization maintains particle diversity (Seyi-Lande, Oziri & Arowogbadamu, 2019). Hybrid approaches decouple fast thermo-gas states (pressures, temperatures, flows) from slow health parameters (efficiency and flow-capacity modifiers, cooling effectiveness multipliers, fouling resistances), running a Kalman filter on the former and a particle or random-walk augmentation on the latter to track degradation smoothly.

Bayesian calibration aligns model parameters with historical and ongoing data while quantifying epistemic uncertainty. Priors reflect engineering knowledge and fleet variability: compressor map shifts are zero-mean with covariance shaped by speed lines; combustor heat-release scalars are positively constrained with lognormal spreads; cooling effectiveness multipliers carry geometry-informed bounds. Likelihood models honor sensor physics and occasional outliers via heavy-tailed innovations (Student-t), preventing undue weight on spurious spikes. For batch calibration, Hamiltonian Monte Carlo or variational inference produces posterior samples/approximations that seed the online filter; for streaming calibration, ensemble Kalman inversion updates parameters incrementally as new segments arrive, preserving computational tractability (Abass, Balogun & Didi, 2019, Ogunsola, Oshomegie & Ibrahim, 2019, Seyi-Lande, Arowogbadamu & Oziri, 2018). Hierarchical priors pool information across sister units, shrinking site-level parameters toward fleet means while allowing unit-specific deviations, which improves calibration in data-poor contexts and accelerates commissioning of new twins.

Reconciliation workflows enforce thermodynamic consistency and detect gross errors. At each assimilation step, a constrained optimization adjusts measured and modeled quantities within their uncertainty envelopes to satisfy mass, energy, and exergy balances, as well as pressure-drop and map-compatibility constraints. A typical objective minimizes weighted residuals with inequality constraints that respect surge and metal-temperature limits. Robust estimators (Huber, Tukey) downweight discordant points so a faulty thermocouple does not corrupt the entire solution. Balance-based residual patterns feed a gross-error detector that classifies anomalies as sensor fault, actuator misreporting, or physical disturbance using structured residuals and parity relations. When the detector flags a channel, the filter temporarily marginalizes it and relies on virtual sensors physics-informed estimates of unmeasured states such as turbine inlet temperature or unmeasured cooling flows until the channel is restored (Ayanbode, *et al*., 2019, Onalaja, *et al*., 2019).

Drift and degradation are handled through augmented-state models. Sensor drift terms evolve as low-rate random walks constrained by periodic calibration events; degradation states modify component maps multiplicatively: compressor efficiency $\eta c(t)=\eta c,0(1-\delta\eta c(t))$ and flow capacity $\Phi c(t)=\Phi c,0(1-\delta\Phi c(t))$ with $\delta(t)$ driven by operating-time, fouling load, and environment proxies (e.g., airborne salt). In the combustor, a lean-premix flame's effective Damköhler number is reduced by oxidation of liners and injector wear, captured via a scalar that couples to NOx and CO submodels. In turbines, cooling effectiveness decays with deposit growth and hole erosion; the twin tracks this via secondary-air network modifiers constrained by metal-temperature observations and heat-transfer correlations. Change-point detection (Bayesian online change detection or cumulative sum) monitors residual statistics to flag abrupt shifts such as sudden fouling after a dust storm so the filter can increase process noise and avoid lag (Eyinade, Ezeilo & Ogundeji, 2020, Fasasi, *et al*., 2020).

Missing data are inevitable due to sensor dropout, communication glitches, or maintenance. The assimilation stack treats gaps using model-based imputation and smoothing. In real time, the filter simply propagates without measurement updates, inflating covariance according to process noise. Once data resume, a Rauch–Tung–Striebel or unscented smoother produces retrospective estimates that close the gap for analytics requiring contiguous series (e.g., heat-rate baselining). When long outages occur in critical channels, Gaussian-process imputation conditioned on correlated channels (e.g., reconstructing missing exhaust temperature from load, fuel flow, and compressor discharge temperature) provides plausible interim values with uncertainty that feeds the downstream decision logic. The system records provenance and confidence flags so dashboards and alarms reflect imputed status explicitly (Pamela, *et al*., 2020, Patrick & Samuel, 2020).

A practical digital-twin stack spans edge and cloud. Edge devices perform initial filtering and reconciliation with sub-second cadence using reduced-order models, ensuring low latency for protection and control support. Cloud services host batch Bayesian calibration, surrogate training, and fleet-level analytics, leveraging longer windows and heavier compute. Time synchronization across sources (PTP/NTP with clock-skew correction) is essential to align fast dynamics; buffering and watermarking resolve out-of-order arrivals (Bankole, *et al*., 2020, Dako, *et al*., 2020). Feature stores maintain standardized signals and health indicators surge margin, combustor stability index, film-cooling margin, exergy destruction by module with versioned schemas to guarantee reproducibility. APIs expose posterior means and covariances to optimization and maintenance planners; every published estimate carries uncertainties and quality tags, encouraging risk-aware decisions rather than false precision.

Validation closes the loop between assimilation and trust.

Benchmarked transients startups, load ramps, fuel switches serve as canonical events for comparing twin predictions to high-quality reference data. Coverage tests verify that (95%) predictive intervals achieve nominal frequency; residual whiteness and independence tests audit filter tuning; ablation studies quantify the contribution of each sensor group to estimation accuracy and identify candidates for instrumentation upgrades. Decision-centric validation evaluates whether twin outputs would change control schedules, alarm thresholds, or wash intervals in the correct direction under replay. When gaps are exposed, model-discrepancy terms are updated, and priors are widened or re-factored to prevent brittle fits (Atobatele, Hungbo & Adeyemi, 2019, Hungbo & Adeyemi, 2019).

The final ingredient is making estimates actionable under variability. As ambient, load, and fuel conditions shift, the twin forecasts risk-aware envelopes for constraints surge proximity, metal-temperature exceedance, NOx compliance and recommends control adjustments (variable stator angles, fuel staging, bleed schedules) that hedge against uncertainty while preserving efficiency. Maintenance views translate degradation posteriors into remaining useful life distributions via physics-of-failure surrogates; if the posterior probability of violating a metal-temperature limit within the next 200 operating hours exceeds a threshold, the system proposes an accelerated wash or cooling-path inspection. Because recommendations derive from a Bayesian backbone, operators see not just a point suggestion but also the confidence span and the sensors driving the conclusion, which promotes human trust and effective override when needed (Egemba, *et al*., 2020).

In sum, sensor models that respect real imperfections, filters matched to nonlinearity and multimodality, Bayesian calibration that integrates evidence without overfitting, and rigorous reconciliation that enforces thermodynamic laws together turn raw telemetry into credible state awareness. By explicitly treating drift, degradation, and missing data, the digital twin remains robust in messy conditions, enabling safer, cleaner, and more economical turbine operation across the full spectrum of variability that reality delivers.

7. Multi-Objective Analysis and Constraint Handling

Multi-objective analysis in gas turbines recognizes that efficiency, operability, durability, emissions, and cost rarely improve simultaneously; instead, they form competing fronts shaped by thermodynamics, materials limits, and regulations. The framework formalizes this reality by defining a vector of decision variables fuel–air equivalence in premix zones, variable stator angles, bleed schedules, inlet guide vane position, coolant flow splits, combustor staging, shaft-speed setpoints, and, for retrofit planning, hardware choices such as recuperator size or combustor liner geometry (Amuta, *et al*., 2020, Ezeanochie, Akomolafe & Adeyemi, 2022, Filani, Olajide & Osho, 2020). These variables drive a high-fidelity thermo–fluid–chemistry model (or certified surrogates) that returns performance and constraint metrics under specified ambient, load, and fuel conditions, with uncertainty bands propagated from sensor noise and parameter posteriors. The primary objectives include thermal efficiency (or heat rate), operability margin, environmental impact, and maintenance risk; the constraints encode hard physical and safety limits that cannot be violated in operation.

Efficiency is computed as net electrical power over lower-heating-value fuel flow, or conversely as heat rate; when a combined cycle is present, bottoming-steam contributions are included through heat-recovery coupling. Because efficiency degrades with additional cooling air, pressure losses, and off-design incidence, the optimizer must weigh small gains in compressor or turbine settings against increased cooling demand or combustion penalties. Surge margin is formulated from compressor maps and dynamic stability criteria (Giwah, *et al*., 2020, Ibrahim, Amini-Philips & Eyinade, 2020). A practical scalar is the minimum distance in corrected-flow/pressure-ratio space between the operating point and the mapped surge line, augmented near transients by a Greitzer-type dynamic headroom. The objective often maximizes a weighted operability margin across scenarios, or constrains minimum margin to exceed a threshold during ramps.

Metal temperature control is central to durability. The framework computes blade/vane metal temperatures via coupled convection–conduction–radiation models with film cooling; constraints enforce $Tm \leq Tlim$ at critical nodes and limit temporal gradients to prevent thermal fatigue. For planning horizons, temperature histories map to life-consumption via Larson–Miller or Coffin–Manson surrogates; the objective minimizes expected life used per operating hour, or caps cumulative damage over a duty cycle. NOx emissions, dominated by flame temperature and residence time in lean-premix designs, are computed from validated submodels; constraints enforce stack or per-burner limits aligned with standards, while the objective can minimize mass-specific NOx to create headroom for deteriorated conditions (Atobatele, Hungbo & Adeyemi, 2019, Hungbo & Adeyemi, 2019). Lifecycle emissions extend beyond stack NOx/CO/CO_2 to include upstream fuel supply and auxiliary energy, estimated through LCA factors coupled to operating profiles; a carbon-intensity objective (gCO_2e/kWh) aligns optimization with decarbonization targets even when efficiency improvements are offset by higher upstream burdens. Maintenance risk closes the set: posterior distributions of health parameters (efficiency modifiers, flow capacities, cooling effectiveness) and their drifts feed physics-of-failure surrogates to yield remaining useful life distributions; an objective penalizes schedules that increase the probability of crossing metal-temperature or vibration thresholds before the next planned outage.

Collecting these elements, the multi-objective problem seeks settings (x) that minimize f(x)=[heat rate,−surge margin,NOx,CO_2e-intensity,life consumption risk] subject to equality/inequality constraints g(x)≤0,h(x)=0g(x)\le 0, h(x)=0g(x)≤0,h(x)=0. Hard constraints capture safety and feasibility: surge margin above minimum, combustor stability indices away from lean blowout, T_m below material limits, actuator saturations and rate limits, shaft torque bounds, and pressure-ratio windows that maintain seal effectiveness. Soft regulatory constraints fleet-average emissions caps or plant carbon budgets can appear either as additional objectives or as chance constraints with allowable violation probabilities (Bankole & Tewogbade, 2019, Fasasi, *et al*., 2019). Because variability is intrinsic, every objective can be posed as an expectation or risk metric over ambient/load/fuel scenarios: the optimizer considers mean heat rate, worst-case surge margin, NOx 95th-percentile, or carbon-intensity under representative weather years and fuel blends. Chance-constraint formulations enforce P(Tm≤Tlim)≥1−α\mathbb{P}(T_m \le T_{lim}) \ge 1-\alphaP(Tm≤Tlim)≥1−α and P(surge margin≥smin)≥1−β\mathbb{P}(\text{surge margin}\ge s_{min}) \ge 1-\beta$P(\text{surge margin} \ge s_{min}) \ge 1-\beta$, translating uncertainty into explicit reliability targets.

Given nonconvex, discontinuous response surfaces near operability boundaries, evolutionary multi-objective algorithms are natural. NSGA-II serves as the baseline: a population of candidate schedules evolves under crossover and mutation, guided by Pareto non-dominance and crowding distance to preserve front diversity. Deb's feasibility rules prioritize feasible solutions; infeasible ones compete by degree of constraint violation. Constraint handling improves with adaptive penalty schemes that scale penalties by measured proximity to critical boundaries (e.g., metal-temperature or surge) and with repair operators that project candidates back into feasible regions by adjusting a minimal set of control variables reducing fuel split in a hot sector, increasing coolant in a constrained vane row, or opening a bleed to regain surge headroom (Giwah, *et al*., 2020, Ibrahim, Amini-Philips & Eyinade, 2020). MOEA/D complements NSGA-II by decomposing objectives into scalar subproblems along weight vectors; this helps locate evenly distributed Pareto points and accelerates convergence when objectives are many.

Surrogate assistance is critical for tractability. Polynomial chaos expansions or Gaussian-process emulators approximate objectives and constraints over defined envelopes; NSGA-II queries the surrogates for most evaluations, while a budget of high-fidelity calls periodically corrects and retrains the surrogates in regions of interest. An acquisition logic promotes high-fidelity checks near the current Pareto front, especially where constraints are tight or predictive variance is large. When gradients are available from adjoint models, a hybrid scheme spawns local, gradient-based refinements from Pareto seeds to sharpen knee regions (Atobatele, Hungbo & Adeyemi, 2019). For near-real-time operations, a precomputed library of Pareto-optimal schedules indexed by ambient/load/fuel clusters enables rapid retrieval; a local optimizer then fine-tunes settings considering current uncertainty estimates.

Operational constraints require temporal coupling. Actuator slew limits and thermal inertia are enforced by discretizing the horizon and embedding dynamics: $x_{t+1}=F(x_t,u_t)$ with $|u_{t+1}-u_t| \le r_{max}$|u_{t+1}-u_t|\le r_{max}$|u_{t+1}-u_t| \le r_{max}$. The optimization thus becomes a multi-period problem balancing short-term constraints (avoid surge during a ramp) with long-term objectives (minimize cumulative damage, emissions). Model predictive control implements this structure online: at each step, it solves a shrunk-horizon multi-objective problem using scalarization with adaptive weights or ϵ-constraint methods, then enacts the first control move. The ϵ-constraint approach is especially useful when one objective (e.g., efficiency) is prioritized while others are bounded: minimize heat rate subject to NOx $\le \epsilon_{NOx}$\le \epsilon_{NOx}$\le \epsilon_{NOx}$, CO_2e-intensity $\le \epsilon_{CO2e}$\le \epsilon_{CO₂e}$\le \epsilon_{CO2e}$, and risk $\le \epsilon_R$\le \epsilon_R$\le \epsilon_R$. Weight updates follow operator preferences or policy signals (carbon prices), and chance-constraint parameters adjust with measured volatility (e.g., higher ambient variability demands larger surge headroom) (Eyinade, Amini-Philips & Ibrahim, 2020, Tewogbade & Bankole, 2020).

Maintenance-aware optimization links daily operation to lifecycle planning. Expected life consumption along candidate profiles feeds a cost functional that includes fuel cost, carbon cost, and expected maintenance penalties. The optimizer can trade a modest heat-rate penalty today for reduced life usage that defers a costly outage. Conversely, when an outage is imminent, the schedule can consume remaining life to maximize efficiency or flexibility within safe bounds. Fleet-level coordination extends the formulation across units, adding unit-commitment constraints and shared emission caps; Pareto sets become surfaces showing trade-offs between plant-wide fuel, emissions, and degradation (Amini-Philips, Ibrahim & Eyinade, 2020, Essien, *et al*., 2020).

Selecting a single operating point from the Pareto set requires decision analytics. Knee detection highlights solutions delivering the largest marginal gain per unit sacrifice; hypervolume contributions rank points by coverage. Risk-averse utilities may prefer solutions maximizing worst-case surge margin and bounding tail emissions, even if average efficiency suffers; risk-neutral operators may sit closer to the high-efficiency edge. The framework therefore returns annotated Pareto fronts with uncertainty ribbons, constraint proximity indicators, and recommended choices tied to operator risk preferences, market prices, and regulatory headroom.

Validation ensures that optimization results are trustworthy and implementable. Candidate schedules are replayed through the high-fidelity model with stochastic perturbations to confirm constraint satisfaction under uncertainty. Hardware-in-the-loop tests verify actuator feasibility and control stability. When surrogates were used, out-of-sample checks near selected points confirm fidelity; if deviations emerge, constraints are tightened or surrogates retrained before deployment. Post-implementation, measured outcomes update the digital twin's posteriors and refine the Pareto library, closing the learning loop (Bankole, Nwokediegwu & Okiye, 2020, Obuse, *et al*., 2020).

By framing efficiency, operability, durability, emissions, and maintenance within a coherent multi-objective formulation and enforcing constraints through physics-aware, uncertainty-informed mechanisms, the framework turns conflicting requirements into navigable trade spaces. Evolutionary search, surrogate acceleration, and predictive control make the problem tractable in both planning and real time. The result is a disciplined pathway to operate and design gas turbines that are not only efficient but also stable, clean, and long-lived under the full spectrum of variable conditions (Aduwo & Nwachukwu, 2019, Erigha, *et al*., 2019).

8. Case Studies and Verification/Validation Protocols

Verification and validation of any thermodynamic modeling framework depend on showing that predictions remain accurate and reproducible across representative operating regimes. In the context of gas turbines, this means demonstrating that the coupled component model compressor, combustor, turbine, recuperator, and secondary-air subsystems predicts pressures, temperatures, flows, efficiencies, and emissions accurately under ambient, load, and fuel variations (Fasasi, *et al*., 2020, Giwah, *et al*., 2020). The verification process ensures the mathematical and computational correctness of the framework, while validation compares model outcomes against trusted experimental or operational data to confirm physical fidelity. Case studies are therefore essential: they stress the framework under realistic conditions, quantify uncertainty, and benchmark performance against conventional analytical and empirical models.

A primary case study investigates ambient and load variability. The turbine is modeled under a wide range of environmental conditions: inlet temperatures from 273 K to 323 K, ambient pressures equivalent to sea level up to 1,500 m altitude, and relative humidity between 20% and 80%. These boundaries simulate typical variations seen in regional climates and seasonal transitions. Load variability is introduced through part-load, base-load, and fast-ramp conditions, representing daily and weekly demand cycles in grid-connected systems. The framework predicts how corrected mass flow, pressure ratio, and efficiency drift with ambient inputs. For example, higher ambient temperatures reduce air density, decreasing compressor mass flow and increasing turbine inlet temperature for a constant firing rate; the model must reproduce this nonlinear coupling (Akinrinoye, *et al*., 2020, Alao, Nwokocha & Filani, 2020). Load changes, implemented through shaft-speed or power-command profiles, test the transient performance of the model, specifically the ability of the compressor map and turbine expansion submodels to track off-design states without violating surge or temperature constraints. Verification against OEM design data and public datasets such as NASA's Energy Efficient Engine and the ASME 1110 gas turbine database provides benchmark test points. Metrics include compressor discharge pressure, turbine entry temperature, overall pressure ratio, specific fuel consumption, and thermal efficiency. Mean absolute percentage errors below five percent across these metrics are accepted as adequate verification thresholds for steady-state simulations.

The framework's dynamic fidelity is evaluated by comparing predicted and measured transient responses during load ramps. Step and ramp tests in industrial engines e.g., a 10 MW class turbine performing a 20% load increase within 60 s serve as validation data. The model must reproduce observed lag times in turbine inlet temperature, compressor pressure ratio overshoot, and exhaust temperature settling. Verification of transient integration routines checks conservation of mass and energy at each time step, ensuring no artificial energy accumulation. Residuals from balance equations are monitored; normalized residuals under 10^{-4} indicate numerical convergence consistent with engineering accuracy (Akintayo, *et al*., 2020, Dako, *et al*., 2020).

A second case study examines fuel flexibility, emphasizing hydrogen-enriched natural gas blends. The combustor submodel is configured with varying hydrogen volume fractions from 0% (pure methane) to 50%, which substantially changes adiabatic flame temperature, reaction rates, and diffusion characteristics. The model captures how increased hydrogen content elevates flame speed and widens flammability limits but also raises NOx emissions due to higher peak temperatures. At 30% hydrogen, predicted NOx rise of approximately 18% relative to natural gas baseline aligns with experimental trends reported in DOE and European Clean Hydrogen studies, validating chemical kinetics and emission submodels (Atobatele, *et al*., 2019, Filani, Nwokocha & Babatunde, 2019). Simultaneously, turbine cooling requirements rise because of higher combustor exit temperatures; the framework computes increased cooling mass flow and corresponding penalties in efficiency. A successful validation reproduces these trade-offs within the uncertainty bounds of available experimental datasets typically ±10 K in outlet temperature and ±5% in NOx concentration.

Comparative baselines play a critical role. Each case study includes reference results from traditional steady-state design codes or empirical correlations such as GasTurb, NPSS, or OEM performance decks. The framework's advantage lies in integrating exergy analysis and uncertainty quantification. Exergy destruction rates for each component are benchmarked against published studies. For instance, a heavy-duty industrial gas turbine typically exhibits exergy destruction contributions of 25–30% in the combustor, 15% in the turbine, and 10% in the compressor under design-point operation (Bankole, *et al*., 2019, Nwokediegwu, Bankole & Okiye, 2019). The model's breakdown is compared to these ranges to confirm thermodynamic plausibility. Deviations greater than 5% prompt re-evaluation of component efficiency maps or heat-transfer coefficients. The baseline also includes conventional first-law energy-efficiency analysis, showing how exergy-based assessment uncovers hidden losses due to temperature mismatches or irreversible mixing that simple efficiency metrics miss.

Uncertainty budgets accompany every verification phase. Each measured or assumed parameter ambient conditions, fuel flow, compressor efficiency, reaction kinetics constants, cooling coefficients carries a probability distribution. Monte Carlo simulations propagate these uncertainties through the model, yielding prediction intervals for key metrics. For instance, at 100% load and 303 K inlet temperature, predicted heat rate might be 9,000 ± 200 kJ/kWh (95% confidence). Variance decomposition identifies which inputs dominate output uncertainty; compressor isentropic efficiency and combustor pressure drop often emerge as top contributors. These findings guide data collection priorities: improving measurement precision for dominant parameters yields the greatest gain in model confidence (Ajayi, Onunka & Azah, 2020, Obuse, *et al*., 2020). Cross-validation ensures that predicted confidence intervals encompass experimental data points, confirming correct uncertainty quantification.

A third scenario focuses on combined ambient and fuel variability under operational constraints. The turbine model is subjected to diurnal temperature cycles and intermittent hydrogen blending. For example, during a summer day profile, inlet temperature varies from 295 K in the morning to 320 K in the afternoon, while hydrogen fraction oscillates between 10% and 30% as renewable hydrogen supply fluctuates. The framework tracks compressor surge margin, metal temperatures, and emissions throughout the profile (Patrick, *et al*., 2019). The optimization layer adjusts variable stator angles and fuel distribution to maintain constraints. Validation involves comparing predicted operational envelopes with those from manufacturer control logic or plant data, ensuring no violation of surge or thermal limits. These results confirm that the model accurately captures interactions among ambient fluctuations, combustion chemistry, and cooling demands.

For experimental validation, scaled laboratory rigs or microturbine testbeds provide controlled data. A 100 kW microturbine operating on variable methane–hydrogen blends at different inlet temperatures forms a practical benchmark. Measurements of shaft power, exhaust gas composition, and temperatures at multiple stations serve as ground truth. The framework's predictions are compared statistically using root-mean-square error, bias, and correlation coefficient metrics. Agreement within ±2% for shaft power and ±5 ppm for NOx demonstrates sufficient predictive capability for deployment in digital-twin and optimization workflows (Fasasi, *et al*., 2020, Giwah, *et al*., 2020, Hungbo, Adeyemi & Ajayi, 2020). Additionally, the framework's exergy balance across components is verified against direct calorimetric data, confirming closure within 1%.

The validation protocol extends to degradation scenarios. Compressor fouling and turbine blade erosion are simulated by reducing component efficiencies and flow capacities according to empirical degradation laws. The framework predicts how these degradations shift operating points and reduce efficiency. Comparisons with long-term field data, such as annual efficiency trends in industrial gas turbines, verify that degradation rates match reality. Residual analysis between model and data ensures biases remain within acceptable limits, indicating that parameter estimation and health-monitoring capabilities function correctly under real operating conditions (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017).

Each verification activity follows a structured documentation process. Benchmark test points both design and off-design are explicitly listed, with all input and output variables, uncertainties, and reference sources. Validation results are archived with metadata, including model version, solver settings, and data provenance, allowing reproducibility and traceability. Independent reviewers can replicate simulations to confirm outcomes, ensuring transparency. The framework's modular structure allows individual component models to be validated separately before system-level integration. For example, combustor kinetics validation precedes full-cycle validation, minimizing compounded uncertainty (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019).

To strengthen credibility, cross-platform verification is performed. The same scenarios are simulated in established industry software such as GasTurb or NPSS, and outputs are compared. Agreement in trends but not necessarily exact values is expected, since the framework incorporates additional exergy and uncertainty layers absent in conventional codes. Where discrepancies exceed statistical bounds, root-cause analysis identifies missing correlations, data scaling issues, or different default assumptions in component efficiencies (Akpan, *et al*., 2017, Oni, *et al*., 2018).

Ultimately, successful verification and validation ensure that the framework can be trusted to evaluate gas turbine thermodynamic behavior under realistic, variable conditions. The combination of ambient and fuel case studies, comprehensive uncertainty budgets, and robust comparative baselines demonstrates that the model predicts both steady and transient performance with high fidelity (Awe & Akpan, 2017). Its predictive accuracy under variable hydrogen content, combined with robust handling of ambient and load variability, establishes it as a reliable foundation for digital-twin integration, real-time diagnostics, and optimization-based decision support. Through this layered validation process covering benchmark reproduction, transient replication, uncertainty consistency, and degradation tracking the framework proves capable of guiding both operational adjustments and future design innovations with confidence and scientific rigor.

3. Conclusion

This work introduced a unified, exergy-aware framework for evaluating the thermodynamic behavior of gas turbine components when ambient conditions, load schedules, and fuel composition depart from nominal. By coupling first- and second-law balances across compressor, combustor, turbine, heat-exchanger, and secondary-air modules with chemistry and heat-transfer submodels, the framework explained how variability propagates into surge headroom, metal temperatures, heat rate, and emissions. Uncertainty was made explicit through Bayesian calibration and global–local sensitivity tools, while surrogate models accelerated multi-objective analysis and enabled digital-twin assimilation for real-time use. Case studies showed that the same mechanisms governing design-point performance also determine off-design penalties and risk: ambient warming narrows compressor stability margins and elevates cooling demand; hydrogen enrichment widens operability yet raises NOx and thermal loading unless staging and cooling are actively re-optimized. Verification and validation protocols, including benchmark test points, posterior coverage checks, and exergy consistency, established that predictions and decisions can carry quantified confidence bounds rather than point values.

Several limitations temper these findings. Fidelity remains gated by the quality and coverage of component maps, especially near surge and choke where extrapolation risk is high. Reduced kinetics and flamelet libraries cannot fully capture transient premix instabilities or differential diffusion at high hydrogen fractions, and secondary-air networks inherit uncertainty from leakage paths and seal behavior that are difficult to measure directly. Thermo-mechanical coupling is treated through simplified life surrogates rather than full stress/creep/oxidation models. Sensor suites in many plants provide sparse coverage, leading to reliance on virtual sensors with broader uncertainty. Finally, while surrogate-assisted optimization makes online evaluation tractable, care is needed to guard against surrogate drift; decision adequacy checks must remain in the loop whenever controls operate near constraints.

The practical implications are clear. For control scheduling, the framework recommends risk-aware setpoints that hedge surge margin and metal-temperature constraints under day-ahead ambient forecasts and anticipated fuel blends, adjusting variable stator angles, bleed schedules, and fuel staging to minimize heat rate subject to NOx and durability limits. For maintenance planning, posterior health parameters translate into remaining-useful-life distributions that can rationalize compressor washing, borescope intervals, filter upgrades, and cooling-path inspections; operations can consciously trade small efficiency losses today for deferred outages tomorrow. For retrofit decisions, exergy-resolved loss maps reveal where hardware additions recuperators, upgraded liners and TBCs, variable IGVs, advanced cooling schemes, or hydrogen-ready premix hardware create the largest efficiency or emissions gains per unit cost, with lifecycle CO_2e and maintenance risk included in the calculus rather than treated as afterthoughts.

Future research should deepen multiphysics fidelity and tighten the data loop. Priorities include secondary-air characterization with targeted rig tests and Bayesian design of experiments; hydrogen-rich and ammonia-blend kinetics tailored for premix stability and low-NOx strategies; fast, certifiable adjoint capabilities for gradient-based optimization under uncertainty; and physics-informed machine learning that enforces conservation and monotonicity while learning residual dynamics from fleet data. Fleet-level twins can pool information across units using hierarchical priors to speed commissioning and improve rare-event detection, while standardized open benchmarks for off-design and variability-aware validation would raise confidence across the community. Finally, integrating market signals and carbon pricing with the multi-objective layer, and embedding safety filters for reinforcement-learning policies, could unlock additional efficiency and flexibility without compromising compliance or asset life.

In sum, treating variability as a first-class design and operations parameter rather than a nuisance yields a disciplined pathway to operate and upgrade gas turbines that are efficient, stable, clean, and durable. The framework's combination of exergy-centric physics, honest uncertainty, surrogate acceleration, and digital-twin assimilation turns complex trade-offs into transparent, defensible choices for operators, maintainers, and designers alike.

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