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Hybrid Multi-Criteria Simulation Model for Power Plant Optimal Performance and Control

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***Abstract*—** *Thermal power plant performance depends strongly on coupled control variables whose effects extend simultaneously to power output, fuel use, heat rate, efficiency, emissions, and operating economics. This study develops a hybrid multi-criteria simulation model by reorganizing a simulation-based Digital Twin into an integrated engineering decision-support framework. The model combines first-principles representations of the boiler, steam turbine, condenser and feedwater pump with deterministic one-second time-step simulation, fourth-order Runge–Kutta integration, metaheuristic optimization modules based on Particle Swarm Optimization and Genetic Algorithm concepts, and technical, environmental, economic and grid-related performance criteria. A 24 h operating cycle generated 86,400 time-stamped simulation states. Reported output ranged from 147.9 to 217.5 MW, with an average of 190.4 MW. Mean thermal efficiency and heat rate were 41.8% and 8,608 kJ/kWh, respectively, while total generated energy was 4,568.5 MWh. The simulation consumed 378.0 t of fuel and emitted 1,039.5 t of* CO_2*, corresponding to approximately 0.228 kg* CO_2*/kWh. Total revenue and gross operating profit were \$296,953.27 and \$43,315.27 over the simulated day. Computational validation maintained per-step energy-balance error at or below 0.01%, and the thesis reports benchmark deviation below 1.5% over the stated load range. The principal contribution is the integration of plant-wide thermodynamic simulation with multi-domain performance assessment and an optimization-ready control layer. Because the source study does not report complete optimizer hyperparameters, convergence histories or final optimized decision vectors, no quantified PSO-versus-GA improvement is claimed. The framework is therefore positioned as a validated computational test bed for plant performance and control studies rather than a field-deployed Digital Twin.*

Keywords*— *Digital Twin; thermal power plant; heat rate; thermodynamic modelling; multi-criteria assessment; Particle Swarm Optimization; Genetic Algorithm; decision support.

I. INTRODUCTION

Electricity demand is increasing as industrial production, electrification, cooling loads and data-centre activity expand. The International Energy Agency projects continued strong global electricity-demand growth through 2027 [1]. Although low-emission generation is expanding rapidly, conventional thermal units remain operationally important in many power systems because they can provide dispatchable generation, reserve capacity and load-following support. Their continuing role places sustained pressure on operators to improve heat rate, reduce fuel consumption and emissions, preserve equipment reliability and maintain acceptable grid response.

A steam-based thermal power plant is a tightly coupled energy-conversion system. Combustion in the boiler determines steam generation, turbine inlet conditions influence shaft work, condenser pressure affects expansion and cycle efficiency, and feedwater pumping closes the Rankine cycle. Fuel flow, excess air, feedwater flow, steam pressure, steam temperature, turbine admission, and cooling-water conditions therefore cannot be treated as independent control variables. A set-point that improves one local indicator may worsen another plant-wide objective. For example, higher fuel flow may increase gross output while raising total fuel burn and carbon emissions; lower-load operation can reduce absolute fuel use while increasing heat rate and cost per unit electricity. The control problem is consequently multi-variable and multi-criteria rather than a sequence of isolated component adjustments [14], [15].

Digital Twin research addresses this integration problem by linking a virtual representation to the physical or operational state of an engineering asset. General Digital Twin literature emphasizes model fidelity, bidirectional information flow and decision support [3], [4], while recent reviews show rapidly growing application across the power-generation sector [2]. In thermal power plants, Digital Twin studies have been used for plant-performance optimization [5], web-based representation and interaction [6], collaborative condition monitoring [7], turbine control-stage monitoring [8] and turbine-system energy-efficiency optimization [9]. These studies demonstrate technical feasibility but also show a recurring fragmentation of scope: some emphasize platform architecture, some concentrate on one subsystem, and others optimize a narrow efficiency metric without integrating technical, environmental and economic consequences.

The research underlying this article addresses that fragmentation through a simulation-based plant-wide framework. Four thermodynamic subsystems—boiler, steam turbine, condenser and feedwater pump—are linked to a time-resolved simulation engine and a decision layer that evaluates power output, thermal efficiency, heat rate, fuel consumption, carbon emissions, revenue, operating cost, availability, reliability and selected grid indicators. Metaheuristic search is represented through Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) modules. Here, the term hybrid refers to the integration of first-principles component modelling, deterministic dynamic simulation, metaheuristic search logic and multi-domain performance criteria. It does not imply a newly derived PSO–GA fusion operator.

The article is deliberately more conservative than the thesis wherever the evidence is incomplete. The underlying work is computational: no live plant sensors were connected, no hardware-in-the-loop testing was conducted, and no field deployment was performed. In addition, the thesis defines the PSO/GA optimization layer but does not report sufficient optimizer hyperparameters, convergence traces, final optimized control vectors or baseline-versus-optimized comparisons to support a numerical claim of optimization gain. The strongest defensible contribution is therefore an integrated simulation and performance-evaluation framework that is optimization-ready and internally validated. This distinction is central to interpreting the results and to defining the next work required for an industrial Digital Twin.

TABLE 1
POSITIONING OF THE PRESENT FRAMEWORK RELATIVE TO REPRESENTATIVE DIGITAL TWIN STUDIES

Study	System boundary	Primary approach	Validation/result emphasis	Relevance to present work
Xu et al. [5]	Plant-level coal-fired unit	Physics-based Digital Twin and techno-economic optimization	Plant-wide performance/economics; calibrated against operating data	Demonstrates value of integrated plant model; current study extends multi-criteria KPI set
Yu et al. [8]	Steam-turbine control stage	Hybrid mechanism/data model	330 MW and 1000 MW cases; average errors within ~1%	High-fidelity subsystem monitoring; not full plant multi-domain evaluation
Lei et al. [6]	Thermal power plant platform	Web-based Digital Twin architecture	Case demonstration	Strong architecture/interaction focus; limited heat-rate/economic optimization detail
Ghita et al. [7]	Thermal plant condition monitoring	Hybrid twin architecture	Collaborative condition-monitoring framework	Monitoring-oriented; plant-wide optimization not central
Chen et al. [9]	Steam-turbine system	Mechanism/data hybrid Digital Twin	Reported relative efficiency improvements of 0.35% and 0.14% for selected optimization actions	Quantified subsystem optimization; narrower system boundary than present framework
Present study	Boiler–turbine–condenser–pump system	First-principles simulation with PSO/GA-ready optimization layer	Energy balance ≤0.01% per step; reported benchmark deviation <1.5%	Integrates technical, environmental, economic and grid-related KPIs; field validation remains future work

II. MATERIALS AND METHODS

2.1 Research Design and System Boundary

A simulation-based engineering design was adopted to permit controlled variation of plant operating parameters without exposing a physical unit to experimental risk. The simulated plant consists of a boiler, steam turbine, condenser, and feedwater pump. The plant layer receives fuel, air, feedwater and cooling-water inputs; the virtual layer evaluates component thermodynamics; the simulation layer advances the model at one-second intervals; the performance layer computes key performance indicators (KPIs); and the decision layer compares candidate operating states against technical, environmental and economic objectives.

The architecture contains six interacting functions: physical-plant representation, data/state handling, virtual thermodynamic modelling, time-step simulation, optimization, and decision support. Validation is not treated as a final post-processing step but as a parallel function that checks model consistency during execution. Figure 1 redraws the architecture described in the thesis in a compact journal form.

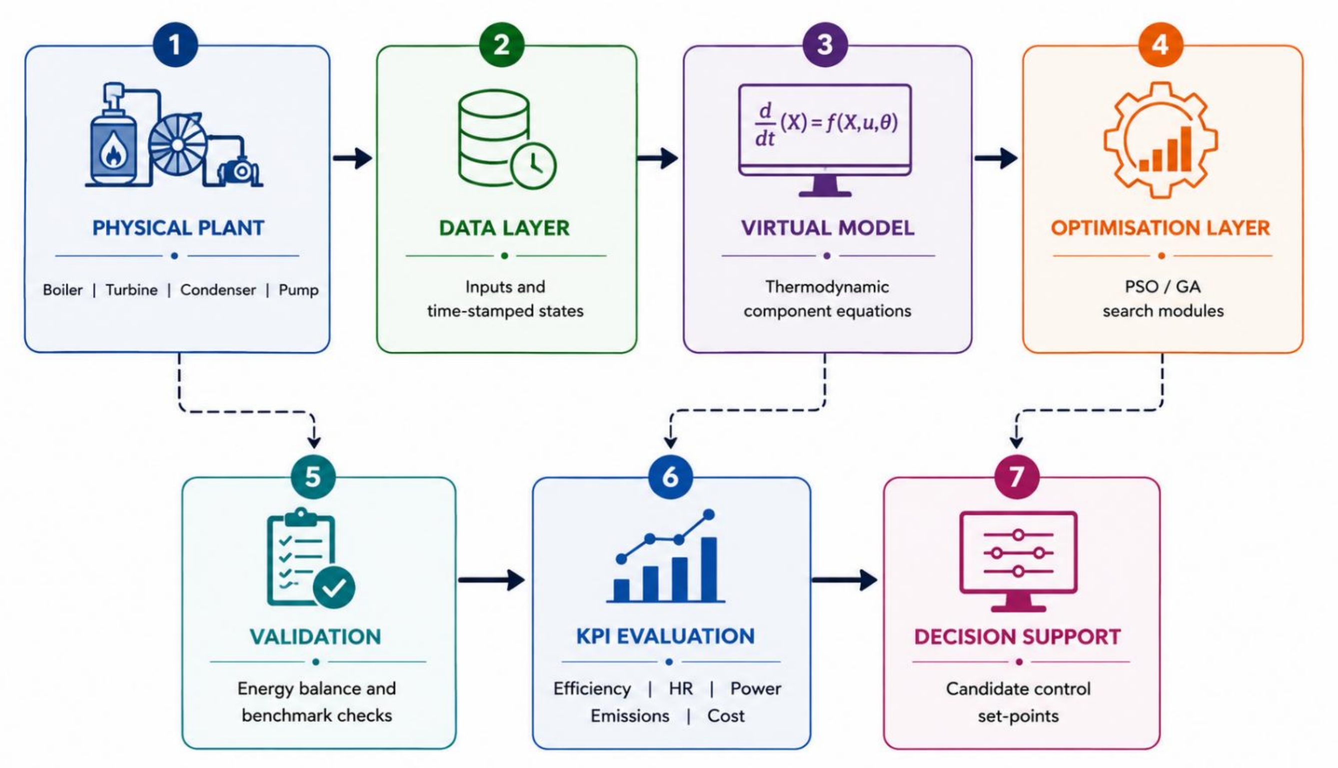

FIGURE 1: Integrated architecture of the simulation-based Digital Twin and multi-criteria decision layer

TABLE 2
PRINCIPAL CONTROL VARIABLES AND OPERATING RANGES REPRESENTED IN THE DIGITAL TWIN.

Control variable	Range used in thesis	Engineering role
Fuel flow rate	1.0–20.0 kg/s	Fuel-energy input and steam generation
Excess-air factor, λ	1.05–1.40	Combustion completeness and flue-gas loss
Feedwater flow rate	50–200 kg/s (nominal)	Boiler inventory and steam-generation balance
Steam pressure	40–160 bar (nominal)	Turbine expansion and cycle efficiency
Steam temperature	300–600 °C	Turbine work and material-temperature limit
Turbine speed	80–105% rated (nominal)	Rotational stability and synchronization
Main steam valve opening	0–100%	Steam admission to the turbine
Cooling-water flow rate	100–500 kg/s (nominal)	Condenser heat rejection and back pressure

2.2 Thermodynamic Formulation

The component models are based on steady-flow mass and energy balances. Thermodynamic properties were reported as being evaluated with IAPWS-IF97 water and steam formulations [13], which are intended for industrial steam-property calculations. For a general open control volume, the governing balances are:

$$\Sigma\, \dot{m}_{in} = \Sigma\, \dot{m}_{out} \tag{1}$$

$$Q - W = \Sigma\, \dot{m}_{out}\, h_{out} - \Sigma\, \dot{m}_{in}\, h_{in} \tag{2}$$

where $\dot{m}$ is mass flow rate, $\dot{Q}$ is heat-transfer rate, $\dot{W}$ is work rate, and h is specific enthalpy. Kinetic and potential-energy terms are omitted in the source formulation.

2.2.1 Boiler Model

The boiler model relates fuel input, excess air, and feedwater enthalpy to steam production. The source model expresses combustion efficiency as a function of excess-air factor λ and calculates the steam-generation rate from the overall boiler efficiency, fuel flow, lower heating value and feedwater-to-steam enthalpy rise:

$$\eta_{comb} = 0.88\, exp\left[-\frac{(\lambda - 1.20)^2}{0.16}\right] \tag{3}$$

$$\dot{m}_{steam} = \frac{\eta_{boiler}\, \dot{m}_{fuel}\, LHV}{(h_{steam} - h_{fw})} \tag{4}$$

The original thesis contains a separate fuel-energy-input equation object whose right-hand side is incomplete in the supplied document. To avoid inventing a missing term, that truncated equation is not reproduced as an independent numbered relation here. Fuel heat-input rate $\dot{Q}$_fuel is retained as the model variable used in the efficiency calculation.

2.2.2 Turbine, Condenser and Feedwater-Pump Models

The turbine converts the available steam enthalpy drop into electrical power. Isentropic efficiency corrects the ideal enthalpy drop, after which generator efficiency and main-steam-valve opening scale the electrical output:

$$\Delta h_{actual} = \eta_{is}\, (h_{in} - h_{out}, s) \tag{5}$$

$$\dot{W}_{elec} = \dot{m}_{steam}\, \Delta h_{actual}\, \eta_{gen} \left(\frac{V_{open}}{100}\right) \tag{6}$$

Condenser heat rejection is evaluated with the logarithmic mean temperature difference (LMTD) method:

$$LMTD = \left(\frac{\Delta T^1 - \Delta T^2}{\ln\left(\frac{\Delta T^1}{\Delta T^2}\right)}\right) \tag{7}$$

$$\dot{Q}_{cond} = U\, A \cdot LMTD \tag{8}$$

For the feedwater pump, the source model applies the speed affinity law to pump head and uses the conventional hydraulic-power relation:

$$H = H_{rated} \left(\frac{N}{N_{rated}}\right)^2 \tag{9}$$

$$P_{shaft} = \frac{\rho\, g\, H\, Q}{\eta_{pump}} \tag{10}$$

2.2.3 Plant-Level Performance and Environmental/Economic Models

Net power is obtained after auxiliary demand is deducted from gross electrical output. Thermal efficiency and heat rate are then evaluated as mutually consistent cycle indicators:

$$\dot{W}_{net} = \dot{W}_{elec} - \dot{W}_{aux} \tag{11}$$

$$\eta_{net} = \left(\frac{\dot{W}_{net}}{\dot{Q}_{fuel}}\right) \times 100 \tag{12}$$

$$HR = \frac{3600}{(\frac{\eta_{net}}{100})} \quad [kJ/kWh] \tag{13}$$

The carbon model applies a fuel-specific emission factor, while revenue and gross operating profit are calculated from generated energy and the fixed price/cost assumptions used for the 24 h case:

$$\dot{m}_{CO_2} = \dot{m}_{fuel} \cdot EF_{CO_2} \tag{14}$$

$$evenue = E_{generated} \times electricity\ price \tag{15}$$

$$Gross\ profit = Revenue - fuel\ cost - O\&M\ cost \tag{16}$$

The thesis reports a value of \$55.52/MWh as a levelized cost of electricity. Numerically, the reported value equals the 24 h operating cost divided by generated energy. Because capital recovery, financing, asset life, and lifetime generation are not modelled, the present article refers to this quantity as operating cost intensity rather than a full life-cycle LCOE.

2.3 Simulation Procedure

The Digital Twin was implemented as a deterministic computational model using a pure-function structure: identical input states produce identical model outputs. A 24 h operating cycle was executed at a fixed one-second time step, generating 86,400 time-stamped states. The source methodology specifies a fourth-order Runge–Kutta integration scheme for time advancement. At each step, the solver evaluates the component states, calculates plant KPIs, performs the energy-balance check, and stores the resulting snapshot for trend analysis and decision support.

The hourly profile used for presentation in the thesis represents a load-following day. Output falls during the early-morning low-demand period, increases through the morning, remains high around the daytime peak and then declines toward late evening. This imposed profile provides a useful test of the framework across part-load and high-load operating regions, although it is not a measured dispatch trace from a named physical power station.

2.4 Optimization and Multi-Criteria Objective

PSO and GA are incorporated as alternative metaheuristic search mechanisms for selecting candidate control vectors within the operating bounds in Table 2. PSO represents each candidate operating point as a particle that is updated using personal-best and global-best information [16]. GA represents a candidate set-point vector as a chromosome and applies selection, crossover, mutation, and elitism [17]. Both methods are appropriate in principle for coupled nonlinear search spaces where gradients are unavailable or inconvenient [18].

The thesis defines multiple objectives: maximize efficiency and power output, minimize heat rate, fuel consumption and emissions, and maximize gross operating profit. These objectives are condensed into a weighted multi-criteria function:

$$F(x) = w^1\eta_{net} - w_2HR - w_3(CO_2\,intensity) + w_4(Profit) \tag{17}$$

where x is the control vector and w_1–w_4 represent operating priorities. The source document does not state the numerical weights, PSO particle count, inertia/acceleration coefficients, GA population size, mutation/crossover rates, stopping criteria, random seeds or final optimized decision vectors. Accordingly, the optimization layer is treated as a defined search architecture, but the present article does not fabricate a numerical comparison of PSO and GA or claim a quantified optimization gain.

2.5 Validation and Evaluation Criteria

Computational validation consisted of (i) a first-law energy-balance check applied at every simulation step and (ii) comparison with published subcritical drum-boiler performance maps. The thesis reports an energy-balance error not exceeding 0.01% per time step and absolute benchmark deviation below 1.5% across the stated 40–105% maximum-continuous-rating load range. These checks support numerical and thermodynamic consistency, but they do not constitute field validation against synchronized sensor data. Performance evaluation used power output, thermal efficiency, heat rate, fuel consumption, CO_2 emission, revenue, gross profit, availability, reliability and selected grid-related indicators.

III. RESULTS AND DISCUSSION

3.1 Twenty-Four-Hour Technical Performance

TABLE 3
PRINCIPAL RESULTS FROM THE 24 h DIGITAL TWIN SIMULATION

Performance indicator	Reported value
Peak / minimum power output	217.5 / 147.9 MW
Average power output	190.4 MW
Average thermal efficiency	41.80%
Average heat rate	8,608 kJ/kWh
Average fuel flow	4.375 kg/s
Total energy generated	4,568.5 MWh
Total fuel burned	378.0 t
Total CO_2 emitted	1,039.5 t
Carbon intensity	≈0.228 kg CO_2/kWh
Total revenue	$296,953.27
Gross operating profit	$43,315.27
Operating cost intensity	$55.52/MWh
Availability/reliability	94.8% / 96.6%

The simulation completed the full 24 h cycle with output ranging from 147.9 MW at 03:00 to 217.5 MW at 10:00, 11:00 and 17:00. Mean output was 190.4 MW. Figure 2 shows that fuel flow follows the imposed loading pattern closely, increasing from 3.40 kg/s at the minimum load point to 5.00 kg/s at peak output. The correspondence is expected for a fuel-fired unit, but the relevant performance question is not whether fuel flow rises with output; it is whether the incremental fuel produces electricity at an acceptable heat rate and efficiency.

At low load, the plant must absorb fixed and part-load losses over a smaller electrical output. As the unit approaches the higher-load region represented in the simulation, heat rate falls, and thermal efficiency improves. This behaviour is consistent with established Rankine-cycle and thermal-plant performance principles [14], [15] and with power-plant studies showing efficiency penalties during deep load reduction [5], [10].

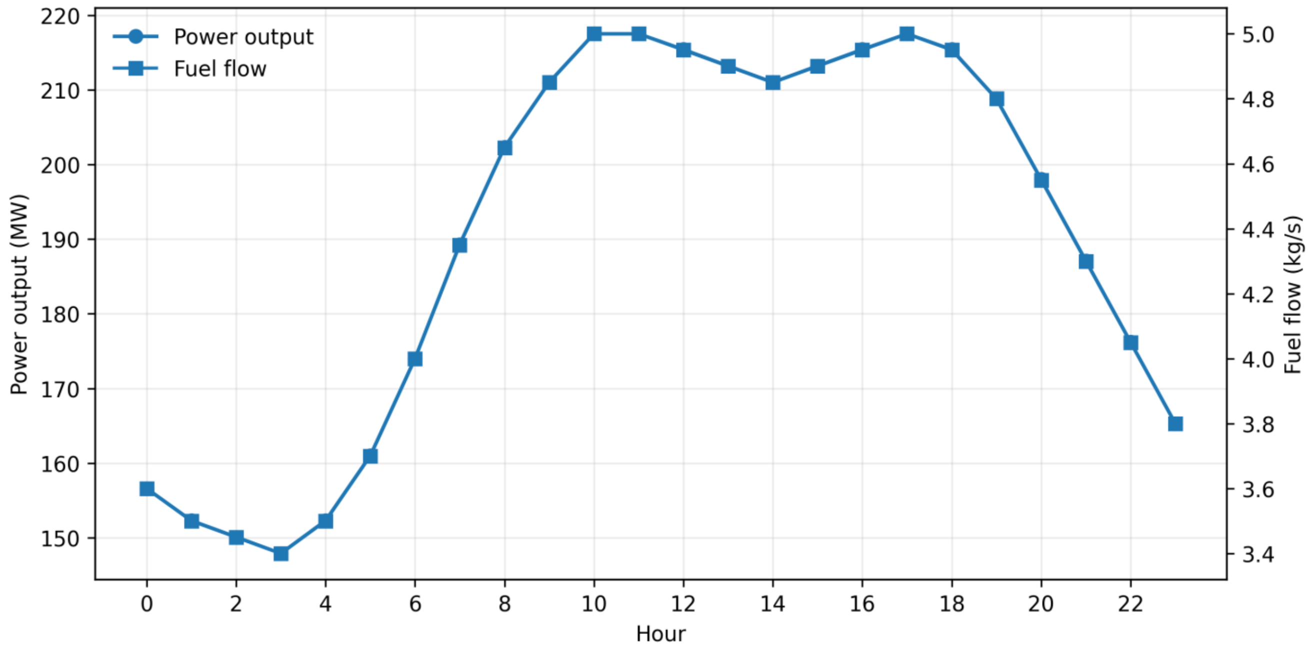

FIGURE 2: Hourly power output and fuel-flow profile over the simulated 24 h operating cycle

3.2 Heat Rate and Thermal Efficiency

Heat rate reached its maximum of 8,763 kJ/kWh at the 03:00 minimum-load condition and fell to 8,511 kJ/kWh during the high-load periods. Thermal efficiency varied from approximately 41.1% to 42.3% and moved inversely to heat rate, as shown in Fig. 3. The 24 h averages were 8,608 kJ/kWh and 41.8%. The inverse trends provide an internal thermodynamic cross-check because the source formulation defines heat rate from net efficiency through Eq. (13).

The magnitude of variation is modest compared with the change in electrical output, indicating that the simulated plant remains within a relatively efficient operating envelope even while following the daily load profile. The result also illustrates why heat-rate minimization should not be treated as a turbine-only problem. The heat rate is affected by fuel conversion in the boiler, steam conditions at the turbine, condenser back pressure, feedwater-pump demand and auxiliary load. A plant-wide model is therefore structurally better suited to evaluating competing set-points than an isolated component model, even when the component model itself is highly accurate.

The present results should not be interpreted as proof that PSO or GA reduced heat rate by a specific amount. The thesis does not provide a baseline simulation and a separate optimized simulation with identical boundary conditions. The numerical evidence instead demonstrates that the Digital Twin can resolve the expected load–efficiency–heat-rate relationships and can calculate the objective variables required by an optimizer.

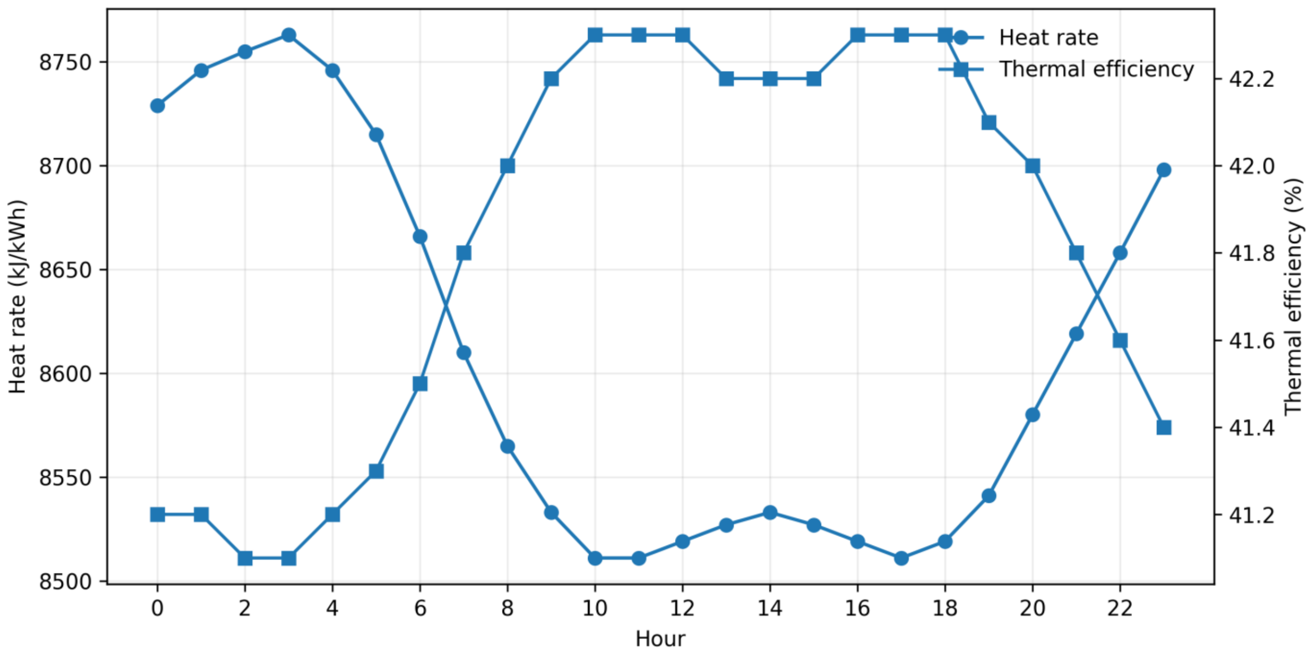

FIGURE 3: Inverse relationship between hourly heat rate and thermal efficiency

3.3 Fuel Use and Environmental Performance

Average fuel flow was 4.375 kg/s, giving a reported 24 h fuel burn of 378.0 t. Total CO_2 emission was 1,039.5 t. Dividing the reported daily CO_2 total by generated energy gives a carbon intensity of approximately 0.228 kg CO_2/kWh. The hourly CO_2 rate increased from 33.66 t/h at minimum load to 49.50 t/h at peak load. Figure 4 shows the strong positive relationship between electrical output and total hourly CO_2 release within the simulated operating range.

This relationship highlights a distinction that is often lost when environmental and thermodynamic metrics are separated. Higher load can improve heat rate and lower the emission intensity per unit electricity while still increasing the absolute emission rate because more fuel is burned. An operating objective that minimizes heat rate alone therefore does not necessarily minimize total emissions, just as an objective that minimizes fuel flow alone may simply reduce generation. The multi-criteria formulation is useful precisely because it forces the decision layer to distinguish intensity metrics from absolute totals and to balance output, efficiency, emissions and economic value.

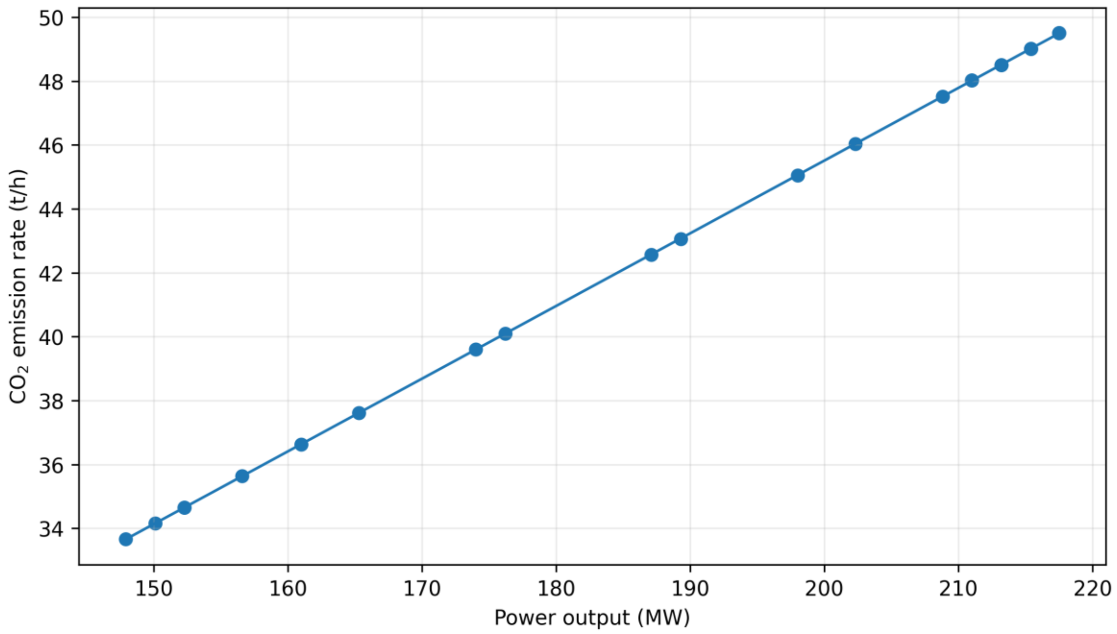

FIGURE 4: Relationship between hourly power output and CO_2 emission rate in the simulation

3.4 Economic Performance

The 24 h simulation reported revenue of $296,953.27, fuel cost of $207,900 and total operating cost of $253,638, leaving a gross operating profit of $43,315.27. The resulting operating cost intensity is $55.52/MWh. Figure 5 summarizes these quantities. The hourly economic pattern follows generation because revenue is calculated from energy produced under a fixed electricity-price assumption, while fuel and operating costs increase with load.

The economic layer is useful for scenario comparison but is not a market model. Fuel price, electricity price and operating-cost assumptions were fixed across the 24 h period, and the thesis does not provide price uncertainty, start-up cost, degradation cost, capital cost or ancillary-service revenue. Consequently, the reported profit should be interpreted as an internally consistent operating scenario rather than a prediction of realized plant profitability. The same limitation is why the $55.52/MWh quantity is reported here as operating cost intensity rather than life-cycle LCOE.

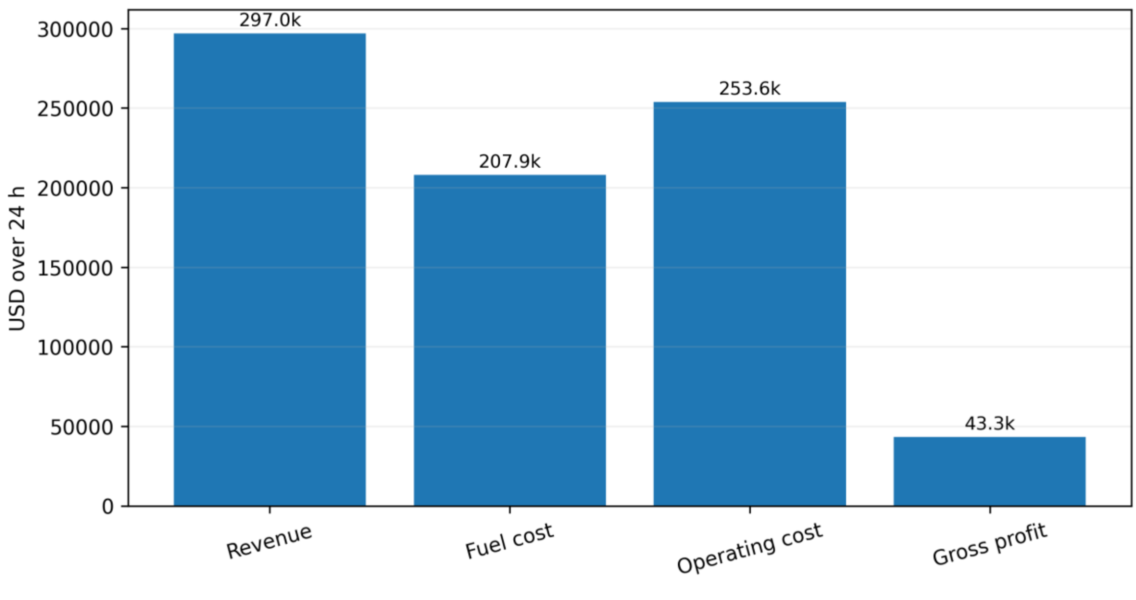

FIGURE 5: Twenty-four-hour economic summary from the simulated operating case

3.5 Grid-Related Indicators and Computational Validation

TABLE 4
OPERATIONAL, GRID-RELATED AND VALIDATION INDICATORS REPORTED BY THE SIMULATION

Indicator	Simulation result	Target/basis	Assessment
Grid frequency	50.02 Hz	50.00 ± 0.20 Hz	Within stated limit
Terminal voltage	11.05 kV	11.0 ± 0.5 kV	Within stated limit
Power factor	0.964 lag	≥0.95	Within stated target
Grid stability margin	13.00%	≥10%	Above stated target
Frequency response time	2.80 s	≤10 s	Within stated limit
Availability	94.80%	High-availability target	Reported acceptable
Reliability	96.60%	High-reliability target	Reported acceptable
Energy-balance error	≤0.01% per step	Internal tolerance	Pass
Benchmark deviation	<1.5%	40–105% MCR range	Reported acceptable

The simulated frequency, terminal voltage, power factor and grid-stability margin remained within the limits stated in the thesis. These results show that the imposed operating trajectory did not produce an internally flagged grid-control violation within the model. They should not be interpreted as a full electromechanical grid-stability study because the paper does not model network topology, generator swing dynamics, fault events, or system-wide frequency response.

The strongest validation evidence is the repeated energy-balance check. Maintaining an error at or below 0.01% per simulation step indicates that the numerical implementation preserves the model's first-law balance to the specified tolerance. The reported benchmark deviation below 1.5% provides an additional computational comparison. These checks are meaningful for model verification and benchmark validation, but a Digital Twin intended for operational deployment would still require calibration and validation against synchronized plant measurements under multiple loads, ambient conditions and equipment-health states.

3.6 Engineering Interpretation and Comparison with Prior Work

The framework occupies a useful middle ground between subsystem Digital Twins and fully integrated industrial twins. Compared with turbine-centered studies such as Yu et al. [8] and Chen et al. [9], it expands the system boundary to include boiler, condenser and feedwater-pump interactions and calculates economic and environmental KPIs in the same workflow. Compared with architecture-oriented studies such as Lei et al. [6] and Ghita et al. [7], it provides a complete 24 h numerical operating profile and explicit thermodynamic performance measures. Xu et al. [5] remains a particularly relevant benchmark because that work also uses plant-level Digital Twin modelling for performance and economic optimization; the present framework adds a different multi-criteria structure but does not yet match the plant-data calibration depth reported by Xu et al.

For control engineering, the key implication is that a candidate set point should be evaluated against a vector of outcomes rather than a single process variable. A fuel or valve adjustment can be screened simultaneously for net power, heat rate, efficiency, CO_2 intensity and profit before it is recommended. This is a credible role for the current model because it is advisory and simulation based. Automatic implementation of recommended set-points would require additional safeguards, real-time state estimation, uncertainty handling, actuator constraints and a validated closed-loop controller.

The results also sharpen the research gap. The limitation is not simply that existing plants lack more dashboards. The harder problem is constructing a sufficiently faithful model, connecting it to trustworthy data, defining objectives that do not conflict destructively, validating the model across the operating envelope, and then proving that the optimizer improves performance without violating safety or equipment constraints. The present study establishes the simulation and KPI foundation for that sequence, but it does not complete the final industrial-control steps.

IV. LIMITATIONS AND FUTURE DEVELOPMENT

The principal limitation is the absence of plant-data synchronization. The Digital Twin is implemented entirely in a computational environment; it does not ingest live sensor data from an operating thermal unit, and no hardware-in-the-loop or field trial is reported. The quality of the outputs therefore depends on the assumed component parameters, property calculations, efficiency correlations, boundary conditions, and imposed load profile.

Reproducibility of the optimization layer is also incomplete. The thesis does not report numerical values for the multi-criteria weights, PSO particle count, inertia and acceleration coefficients, GA population size, crossover and mutation rates, termination criteria, random seed or replication procedure. It also does not provide optimizer convergence histories, final decision vectors or a baseline-versus-optimized KPI table. These omissions prevent a rigorous comparison of PSO and GA performance and should be addressed before submission to a high-impact optimization or control journal.

Several model constants also require fuller reporting for independent reproduction, including the lower heating value used in the simulation, overall boiler and generator efficiencies, condenser U and A values, pump efficiency, auxiliary-power relationship, CO_2 emission factor, electricity price, fuel-price assumption and O&M coefficients. In addition, the source fuel-energy equation object is truncated in the thesis document. These details should be verified against the original simulation code and added to the manuscript's supplementary material or model-parameter table.

Future work should therefore proceed in three stages. First, complete parameter disclosure and optimizer reporting should establish numerical reproducibility and quantify the Pareto trade-offs between heat rate, emissions and profit. Second, the virtual model should be calibrated against historical operating data and then validated on unseen load periods. Third, live plant connectivity can be introduced through a secure data interface, followed by hardware-in-the-loop testing and, only after safety validation, supervisory or Model Predictive Control integration.

V. CONCLUSION

A hybrid multi-criteria simulation model for thermal power plant performance and control was developed from the underlying Master's research. The model integrates first-principles representations of the boiler, steam turbine, condenser and feedwater pump with one-second deterministic simulation, plant-wide KPI calculation, computational validation and an optimization-ready decision layer based on PSO and GA concepts. Over the 24 h case, the simulated plant produced 147.9–217.5 MW with an average thermal efficiency of 41.8% and average heat rate of 8,608 kJ/kWh. Reported daily generation was 4,568.5 MWh, with 378.0 t of fuel consumption and 1,039.5 t of CO_2 emissions. Revenue and gross operating profit were $296,953.27 and $43,315.27, respectively.

The main contribution is not a claimed new optimizer or an industrially deployed Digital Twin. It is the integration of thermodynamic, environmental, economic and operational criteria within a single simulation workflow in which control choices can be evaluated before implementation. Energy-balance error at or below 0.01% per step and the reported benchmark deviation below 1.5% support computational consistency, while the absence of plant-data validation defines the present boundary of confidence. The framework is therefore suitable as a research test bed and decision-support prototype. Its progression to a field-grade Digital Twin requires complete optimization reporting, parameter disclosure, sensor-based calibration, uncertainty analysis and staged closed-loop validation.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] International Energy Agency. (2025). *Electricity 2025: Analysis and forecast to 2027*. IEA. https://www.iea.org/reports/electricity-2025

[2] Shahmoradi, S., Hosseini Imani, M., Mazza, A., & Pons, E. (2025). Applications of the digital twin and the related technologies within the power generation sector: A systematic literature review. *Energies*, *18*(21), Article 5627. https://doi.org/10.3390/en18215627

[3] Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405-2415. https://doi.org/10.1109/TII.2018.2873186

[4] Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, *8*, 108952-108971. https://doi.org/10.1109/ACCESS.2020.2998358

[5] Xu, B., Wang, J., Wang, X., Liang, Z., Cui, L., Liu, X., & Ku, A. Y. (2019). A case study of digital-twin-modelling analysis on power-plant-performance optimizations. *Clean Energy*, *3*(3), 227-234. https://doi.org/10.1093/ce/zkz025

[6] Lei, Z., Zhou, H., Hu, W., Liu, G.-P., Guan, S., & Feng, X. (2022). Toward a web-based digital twin thermal power plant. *IEEE Transactions on Industrial Informatics*, *18*(3), 1716-1725. https://doi.org/10.1109/TII.2021.3086149

[7] Ghita, M., Siham, B., Hicham, M., & Amine, M. (2022). HT-TPP: A hybrid twin architecture for thermal power plant collaborative condition monitoring. *Energies*, *15*(15), Article 5383. https://doi.org/10.3390/en15155383

[8] Yu, J., Liu, P., & Li, Z. (2020). Hybrid modelling and digital twin development of a steam turbine control stage for online performance monitoring. *Renewable and Sustainable Energy Reviews*, *133*, Article 110077. https://doi.org/10.1016/j.rser.2020.110077

[9] Chen, C., Liu, M., Li, M., Wang, Y., Wang, C., & Yan, J. (2024). Digital twin modeling and operation optimization of the steam turbine system of thermal power plants. *Energy*, *290*, Article 129969. https://doi.org/10.1016/j.energy.2023.129969

[10] Wang, Z., Liu, M., & Yan, J. (2021). Flexibility and efficiency co-enhancement of thermal power plant by control strategy improvement considering time varying and detailed boiler heat storage characteristics. *Energy*, *232*, Article 121048. https://doi.org/10.1016/j.energy.2021.121048

[11] Dapkute, A., Siozinys, V., Jonaitis, M., Kaminickas, M., & Siozinys, M. (2024). Enhancing industrial process control: Integrating intelligent digital twin technology with proportional-integral-derivative regulators. *Machines*, *12*(5), Article 319. https://doi.org/10.3390/machines12050319

[12] Ersan, M., & Irmak, E. (2024). Development and integration of a digital twin model for a real hydroelectric power plant. *Sensors*, *24*(13), Article 4174. https://doi.org/10.3390/s24134174

[13] International Association for the Properties of Water and Steam. (2012). *Revised release on the IAPWS Industrial Formulation 1997 for the thermodynamic properties of water and steam* (R7-97). https://www.iapws.org/relguide/IF97-Rev.html

[14] Moran, M. J., Shapiro, H. N., Boettner, D. D., & Bailey, M. B. (2018). *Fundamentals of engineering thermodynamics* (9th ed.). Wiley.

[15] Çengel, Y. A., & Boles, M. A. (2019). *Thermodynamics: An engineering approach* (9th ed.). McGraw-Hill Education.

[16] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of the IEEE International Conference on Neural Networks* (Vol. 4, pp. 1942-1948). Perth, Australia. https://doi.org/10.1109/ICNN.1995.488968

[17] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182-197. https://doi.org/10.1109/4235.996017

[18] Nocedal, J., & Wright, S. J. (2006). *Numerical optimization* (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-40065-5.