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Optimization of Gas Turbine Operational Parameters Using Machine Learning

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Abstract. *Cogeneration gas turbines are vital for power generation and steam production in industrial grids. Current dispatch methods rely on numerical calculations that often misalign with real-time turbine capabilities, resulting in fuel inefficiency and suboptimal steam output. This study aims to develop a data-driven optimization model using machine learning to accurately predict gas turbine performance and improve dispatch decisions in a multi-unit cogeneration plant. An Artificial Neural Network based on a Multi-Layer Perceptron (ANN-MLP) was trained using high-frequency operational data from four gas turbine units (2024). The model was validated and used to rank unit capabilities under efficient baseload conditions, followed by constraint-based load allocation. The ANN-MLP model achieved a prediction error of less than 2% and reduced the average deviation from dispatcher recommendations by approximately 7%. This alignment is projected to save about 20,230 MMSCF of fuel annually and increase steam production by 2,521 BCEWPD. Integrating ANN-based prediction with optimization improves dispatch accuracy, enhances fuel efficiency, and boosts steam output in cogeneration systems. The proposed approach offers a scalable, data-informed framework for real-time turbine dispatch, supporting operational sustainability, cost reduction, and extended equipment life in industrial power plants.*

Keywords: *Gas Turbine, ANN–MLP, Optimization, Dispatch, Cogeneration.*

INTRODUCTION

To support widely dispersed production facilities, Rokan's oil-field power system in Riau runs many plants with a cogeneration capacity of about 530 MW and a peak demand of about 410 MW (Zhang et al., 2021; Tan et al., 2020). To maintain steam-flood operations, the power plant uses five gas turbine generators (about 90 MW total) and Heat Recovery Steam Generators for steam and power (Sari et al., 2022). Gas availability, fuel consumption, and total demand are used in numerical computations to determine the daily load allocation (Wang & Li, 2023). Field data demonstrates ongoing discrepancies between suggested set-points and real-time unit capabilities, which results in inefficient fuel use and less-than-ideal steam production (Yang et al., 2020; Jones et al., 2022). Aligning unit set-points with dynamic capabilities under ambient and aging impacts requires a data-driven strategy (Rao & Singh, 2021; Liu et al., 2021).

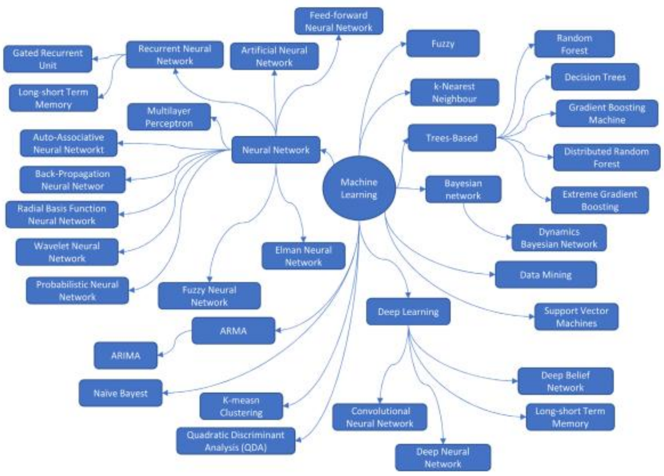

Figure 1. Machine Learning Algorithm Mindmap (Dalzochio et al., 2020)

Previous research has demonstrated the effectiveness of machine learning techniques in modeling and optimizing gas turbine performance (Du et al., 2022; Esfahanian et al., 2024; Kim, 2024; Liu & Karimi, 2020; Yao et al., 2025). For instance, artificial neural networks (ANNs), particularly Multi-Layer Perceptron (MLP) models, have been widely applied to capture nonlinear relationships between operational parameters—such as inlet air temperature, compressor discharge pressure, and exhaust temperature—and performance outputs like power output and efficiency. Liu and Karimi (2020) developed an ANN-based high-dimensional model representation (HDMR) that reproduced turbine performance curves with less than 2% error. Similarly, Chen et al. (2023) compared various machine learning models, including support vector machines (SVM), Gaussian process regression (GPR), and MLP, for auxiliary system optimization in gas turbines, finding that MLP achieved the lowest prediction error at 1.82%. Beyond static modeling, reinforcement learning (RL) has also been explored for sequential decision-making in energy systems. Zheng et al. (2023) applied a multi-stage deep reinforcement learning framework to integrated energy systems, improving dispatch decisions and reducing operational costs. Despite these advances, few studies have integrated high-accuracy ANN predictions with constraint-based dispatch optimization in cogeneration settings, where simultaneous electricity and steam production must be balanced under variable ambient conditions and equipment aging.

This study aims to address this research gap by developing an ANN–MLP model to predict real-time gas turbine capabilities and integrate these predictions into a constraint-based load allocation framework. The specific objectives are: (1) to train an accurate ANN–MLP model using historical operational data from multiple gas turbine units; (2) to rank units based on predicted capability under efficient baseload conditions; and (3) to optimize load distribution in alignment with dynamic system demand and unit constraints. The benefits of this approach include measurable fuel savings, increased steam production, reduced thermal stress on turbine components, and enhanced overall plant reliability. By bridging machine learning prediction with operational dispatch, this research offers a practical, scalable solution for improving the efficiency and sustainability of cogeneration power plants.

MATERIALS AND METHODS

Inlet air temperature, compressor discharge pressure/temperature, fuel gas pressures, multiple wheelspace temperatures, exhaust average temperature (TTXM), control references (FSRN, FSRT), and generator output (DWATT) are among the minute-level PLC sensor records for CDGT Units 1–4 (January–December 2024). Cleaning, outlier elimination, and baseload-efficient filtering (FSRT < FSRN) include pre-processing. Training and testing are split 80/20. Model: Adam optimizer, learning-rate scheduling, ANN–MLP with five hidden layers (ReLU). RMSE, MAE, MAPE, and temporal cross-validation-like splits are metrics used to evaluate generalization. Unit capability rankings are produced by the trained model, which also provides information for an optimization that respects per-unit constraints and system demand.

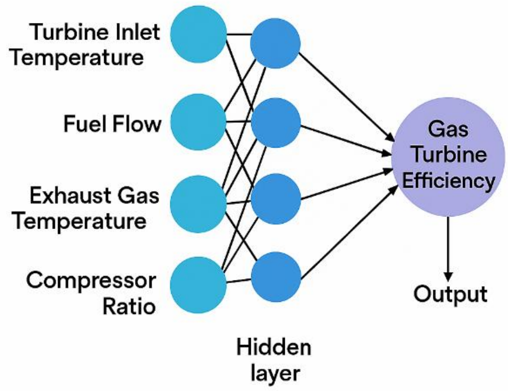

Figure 2. Model ANN-MLP Turbin Gas Efficiency
Source: Liu & Karimi (2020)

After filtering and cleaning, the training set comprises ~38k samples and testing ~9.6k samples. The chosen ANN–MLP achieves test RMSE ≈ 0.069 and MAPE ≈ 0.27%, with validation accuracies up to ~98%. January 2025 predictions rank CDGT1 and CDGT2 highest (~20.4 and ~20.3 MW), followed by CDGT4 and CDGT3. Under a 74.5 MW demand, the solver-based split is approximately (19.38, 19.37, 18.37, 17.38) MW for Units 1–4, respectively, aligning set-points with estimated real-time capability.

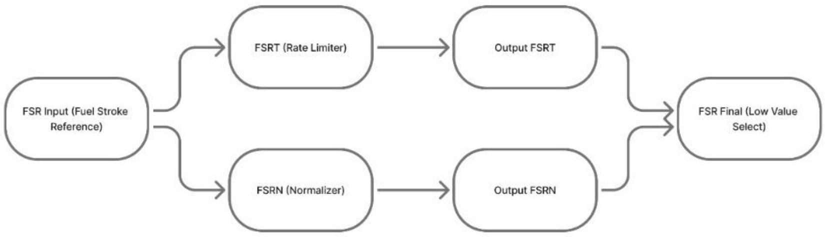

Figure 3. logic diagram FSRN and FSRT (General Electric)
Source: Adapted from General Electric (2000), Speedtronic Mark VI Control System Guidebook

Based on the results of machine learning training data and from the formula above, the performance of each unit will be found. After finding the rank of each unit, Maximization is carried out for load distribution with the following mathematical functions.
$Z=X1+X2+X3+X4$
$X1>X2>X3>X4$
$X1,X2,X3,X4>15$. Where Z is load required by the system (MW), X(i) is Rank (i).

RESULTS AND DISCUSSION

The optimized split reduces average deviation relative to dispatcher recommendations by ~7%. Sensitivity analyses indicate robustness under moderate ambient changes, with annual re-training advised to capture aging effects and drift. The approach is extensible to include additional objectives (e.g., steam maximization) and constraints (e.g., maintenance windows, fatigue states) for plant-wide optimization.

Table 1. Predicted MW vs Dispatch recommendation

Unit	Predicted (MW)	Dispatcher Recommendation (MW)	Delta (MW)
CDGT 1	19,38	20,3	0,92
CDGT 2	19,37	17	-2,37
CDGT 4	18,37	18,6	0,23
CDGT 3	17,38	18,6	1,22
Total	74,5	74,5	0

Source: Model predictions and dispatcher records from Rokan power plant (2024)

Fuel savings and steam: Based on historical deviations, the aligned dispatch yields estimated savings of ~20,230 MMSCF/year and an incremental steam output of ~2,521 BCEWPD, supporting cogeneration targets. Thermal stress reduction: Load balancing against real-time capability mitigates exhaust-temperature excursions and limiter activations (FSRT), reducing thermal shock risk and extending component life. Reliability & cost: More consistent compliance with demand reduces overload risk on aging units, lowers unplanned outages, and improves O&M cost profiles. Sustainability: Efficiency gains translate into lower emissions per MWh and improved energy-use intensity across the field operations.

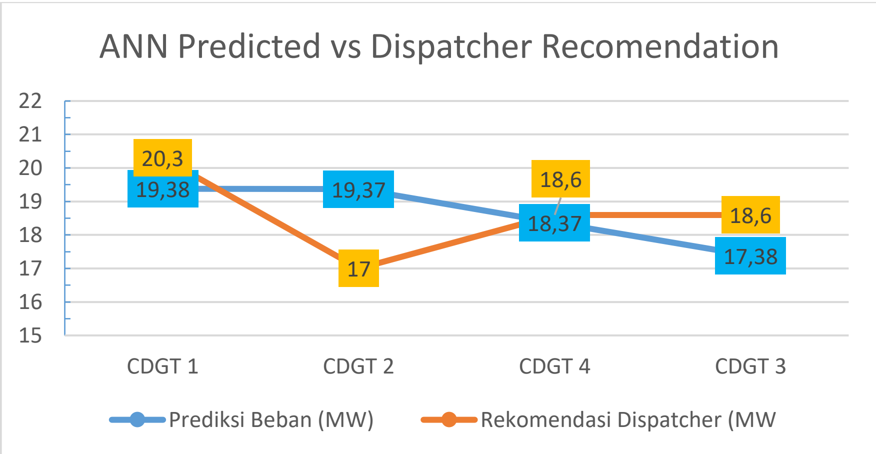

Figure 4. Predicted MW vs Dispatch recomendation

Source: Analysis based on CDGT unit data (January–December 2024)

CONCLUSION

A combined ANN–MLP and constraint-based dispatch framework aligns unit set-points with dynamic capability at CDPP, achieving <2% prediction error and practical fuel/steam benefits. The modeling process with the Artificial Neural Network using Multi Layer Preceptron with more hidden layers results in better prediction accuracy. The results of the ANN-MLP model's prediction of MW output produce an error below 2%. With the ANN-MLP Model, the MW output prediction of each unit is obtained which can be used as the basis for the loading of each unit. The use of the ANN Model can increase steam productivity by 2,500 BCEWPD or 7%. The expanded literature review situates our approach among ANN, GA, HDMR, and RL advances. Future work should integrate fatigue/maintenance states, ambient corrections, and steam-production coupling into a unified optimization that balances reliability, efficiency, and cost.

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