

Modeling and Optimizing IRC-Enhanced Solar GT Tri-generation Systems with AI and an ANN-Evolutionary Algorithm

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ABSTRACT

Combined cooling, heating, and power (CCHP) generation — widely known as tri-generation — represents an integrated energy strategy capable of delivering three distinct energy outputs from a single primary fuel source. Among the various configurations studied, solar-assisted gas turbine (GT) tri-generation architectures that incorporate inter cooling and reheating (IRC) mechanisms have demonstrated considerable promise in terms of thermodynamic performance. The present investigation focuses on a solar-based intercooled and reheated gas turbine tri-generation cycle (SBIRGT), whose core subsystems include a parabolic trough solar collector field, dual-stage compression units, a combustion chamber, a gas expansion turbine, and a single-effect lithium bromide (LiBr) vapour absorption refrigeration system. Two key performance indicators — net electrical power generation and overall energy efficiency — were selected as response variables. Predictive computational models for these indicators were formulated using Artificial Neural Networks (ANN). Subsequently, four distinct optimization strategies — three variants of Rao's algorithm and the Differential Evolution (DE) technique — were deployed to identify optimal operating conditions. The Rao-3 strategy emerged as the best-performing approach and is accordingly recommended for practical adoption.

Keywords: Artificial Neural Network, Evolutionary Optimization, Differential Evolution, Rao Algorithm, Tri-generation System, Solar Gas Turbine

1. Foundational Knowledge: Background and Literature Context

1.1 What is a Tri-generation System?

A Tri-generation system — also referred to as a combined cooling, heating, and power (CCHP) plant — is an energy conversion architecture engineered to extract three useful energy forms simultaneously from one fuel source, which is typically a combustion turbine or reciprocating engine. The three outputs are: electrical power, thermal energy for space or process heating, and chilled water for air conditioning or refrigeration. By recovering and repurposing thermal energy that would otherwise be expelled as waste, Tri-generation plants attain conversion efficiencies markedly superior to those achievable by standalone, dedicated power, heating, or cooling equipment operating in isolation. The technology finds deployment across a broad spectrum of end-use settings, including commercial high-rises, manufacturing plants, hospitals, and district-

scale energy grids. Principal benefits encompass measurable reductions in primary energy demand, lower greenhouse gas emissions per unit of useful energy delivered, and a long-run decrease in energy procurement expenditure — all of which position Tri-generation as a compelling cornerstone of sustainable energy infrastructure.

1.2 Solar-Based Gas Turbine Tri-generation Cycles

The Solar-Based Gas Turbine Tri-generation Cycle (SBGTT) harnesses concentrated solar radiation as the primary heat source, feeding a thermodynamic gas turbine cycle that co-produces electricity, heat, and refrigeration. In its simplest configuration, a single-stage GT is energized entirely by solar thermal input, and the turbine exhaust heat drives heating and cooling subsystems downstream. Although straightforward and relatively economical, this baseline configuration achieves only modest thermal efficiency.

A more advanced variant, the Solar-Based Intercooled and Reheated GT Tri-generation (SBIRGT) cycle, incorporates two thermodynamic enhancements: inter cooling, which cools the compressed working fluid between successive compression stages, and reheating, which reintroduces heat to the partially expanded gas between turbine stages. Both processes require supplementary solar heat inputs, adding complexity but substantially improving overall thermodynamic performance and fuel utilization quality.

1.3 Overview of Related Prior Research

The academic literature addressing solar-integrated and intercooled-reheated gas turbine systems is rich and growing. Singh et al. examined a heliostat-driven concentrating solar power arrangement built around a triple combined thermodynamic cycle, and found that configurations employing a waste heat recovery steam generator achieved energy and exergy efficiencies of approximately 64.15% and 39.72%, respectively. Dabwan et al. demonstrated that an SBIRGT cycle using a linear Fresnel solar concentrator improved fuel-based efficiency by about 19.5% relative to a conventional solar pre-heating GT, while simultaneously reducing specific fuel consumption and the levelised cost of electricity generation.

Abubaker et al. showed that coupling solar preheating and inlet-air cooling to a gas turbine using parabolic trough collectors enhanced power output by approximately 6.87%, decreased fuel consumption by around 10.53%, and raised thermal efficiency by nearly 19.45%. Rovira et al. investigated several integrated solar combined cycle topologies with GT partial recuperation and multi-pressure solar integration, while Javaherian et al. applied a two-objective optimisation framework to a biomass-and-solar cogeneration system, targeting simultaneously higher thermal performance and lower carbon dioxide output — finding that a compression pressure ratio near 10 yielded optimal results.

Further contributions by Muñoz et al. reviewed thermodynamic cycle options for concentrated solar thermal power plants, noting the dominance of the steam Rankine cycle but also highlighting emerging hybrid configurations. Khan et al. analysed an intercooled reheat combined gas-steam cycle coupled with carbon capture and methanation, demonstrating a substantial increase in overall

electrical output when a carbon capture unit was integrated. Shukla et al. evaluated a solar-driven three-stage hybrid GT system in which intercooling heat energised an organic Rankine cycle, achieving a peak efficiency of 21.89%. Dupuy et al. conducted a comprehensive state-of-the-art review of CCHP technologies, drawing attention to renewable-energy-based low-temperature variants and highlighting the scope for further exergo-economic optimisation studies.

2. Conceptual Understanding: Methodology

2.1 Artificial Neural Networks (ANN): Principles and Architecture

An Artificial Neural Network (ANN) is a data-driven computational paradigm inspired by the structure and operational logic of biological neural systems. It excels at constructing predictive mappings for processes that are inherently non-linear, stochastic, or too complex for first-principles analytical treatment. An ANN comprises three categories of processing layers: an input layer that receives the independent control variables, one or more hidden (intermediate) layers that perform weighted non-linear transformations, and an output layer that produces the predicted response. Every inter-layer connection carries an adjustable synaptic weight, and each neuron possesses a bias term. Training adjusts these weights and biases iteratively to minimize the discrepancy between ANN predictions and observed data.

The feed-forward back-propagation architecture (FFBANN) is the most widely adopted variant. In this structure, information propagates strictly from input to output. For any neuron r receiving inputs X_k from the preceding layer, the aggregated signal net_r is computed as:

$$net_r = \sum w_{kr} \cdot X_k + b_r \quad \dots (1)$$

where w_{kr} represents the weight on the connection from input node k to neuron r , and b_r is the neuron's bias. A transfer function $F(\cdot)$ then maps this aggregated signal to the neuron's output Y_r :

$$Y_r = F(net_r) \quad \dots (2)$$

Three transfer function types were evaluated in this study: a pure linear function, a sigmoid (logistic) function, and a hyperbolic tangent (tanh) function. Mean Squared Error (MSE) served as the performance metric for selecting the optimal function combination across hidden and output layers.

2.2 Rao's Metaphor-Free Optimisation Algorithms

Rao's optimisation framework is a family of population-based, parameter-free meta-heuristics grounded in mathematical update rules rather than conceptual analogies drawn from nature or physical phenomena. Three progressive variants — Rao-1, Rao-2, and Rao-3 — offer increasing solution-space diversity. Each maintains a candidate solution population and iteratively refines each vector based on the relative standing of the best and worst current solutions within the population. The general update expressions are:

$$\text{Roa-1: } U_i^{(k)} = U_i^{(k-1)} + r[U_{best}^{(k-1)} - U_{worst}^{(k-1)}] \quad (3)$$

or

$$\text{Roa-2: } U_i^{(k)} = U_i^{(k-1)} + r_1[U_{best}^{(k-1)} - U_{worst}^{(k-1)}]$$

$$+r_2 \left[\left| U_i^{(k-1)} \text{ or } U_l^{(k-1)} \right| - \left| U_l^{(k-1)} \text{ or } U_i^{(k-1)} \right| \right] \quad (4)$$

or

Roa-3:
$$U_i^{(k)} = U_i^{(k-1)} + r_1 \left[U_{best}^{(k-1)} - \left| U_{worst}^{(k-1)} \right| \right]$$

$$+r_2 \left[\left| U_i^{(k-1)} \text{ or } U_l^{(k-1)} \right| - \left| U_l^{(k-1)} \text{ or } U_i^{(k-1)} \right| \right] \quad (5)$$

The three algorithms above vary depending upon vector $U_i^{(k)}$

r , r_1 and r_2 Denoted a random value within the range of 0 to 1.

$$U_i^{(k-1)} \text{ or } U_l^{(k-1)} \text{ Allude}$$

$$= U_i^{(k-1)}, \text{ if } U_i^{(k-1)} \text{ is upgraded result vector in comparison with } U_l^{(k-1)}$$

$$= U_l^{(k-1)}, \text{ Else}$$

$$U_l^{(k-1)} \text{ or } U_i^{(k-1)} \text{ Implies}$$

$$= U_l^{(k-1)}, \text{ if } U_l^{(k-1)} \text{ is upgraded result vector in comparison with } U_i^{(k-1)}$$

$$= U_i^{(k-1)}, \text{ Else}$$

Eq. above are suggested to refresh current results using above discussed algorithms.

Here, r , r_1 , and r_2 are uniformly distributed random numbers on $[0, 1]$. A feasibility check filters each candidate solution: vectors satisfying all boundary constraints are retained, while constraint-violating solutions revert to their preceding iteration values. The process terminates upon reaching a preset maximum iteration count or when convergence stagnation is detected.

2.3 Differential Evolution (DE)

Differential Evolution is a stochastic, gradient-free global optimization technique well-suited to continuous, non-convex, and multimodal objective landscapes. DE constructs trial vectors by combining difference vectors drawn from randomly selected population members with the current candidate. Its principal strength lies in preserving population diversity over successive generations, thereby reducing the probability of premature convergence to local optima — a common limitation of purely gradient-based solvers. In this work, DE was deployed alongside the Rao family as a benchmark to assess the relative capability of each method in maximising the ANN-based objective functions.

3. Application: System Description and Experimental Configuration

3.1 SBIRGT System Architecture

The SBIRGT Tri-generation cycle investigated in this study integrates the following principal subsystems: a parabolic trough collector (PTC) solar field, low-pressure and high-pressure compressors (LPC and HPC), an intercooler (IC) positioned between compression stages, a combustion chamber (CC), high-pressure and low-pressure gas turbines (HPT and LPT), a reheater (RH) between turbine stages, and a single-effect LiBr vapour absorption refrigeration cycle (ARC).

The thermodynamic process sequence is as follows: ambient atmospheric air is drawn into the LPC and compressed from the initial state to an intermediate pressure state. The compressed air then traverses the intercooler, releasing thermal energy to the surroundings and arriving at a reduced temperature before being admitted to the HPC. A second stage of compression elevates the air to the design operating pressure, after which it is channeled through the parabolic trough solar field, where it absorbs concentrated solar radiation at essentially constant pressure. The thermally energized air then enters the combustion chamber, where fuel is introduced, further raising the temperature and enthalpy of the working fluid to the turbine inlet condition.

High-enthalpy combustion products expand first through the HPT, executing work before being reheated in the RH to restore their thermal energy content. The reheated gas then undergoes a second expansion through the LPT, generating additional mechanical work that is converted to electricity via a coupled generator. Exhaust gases leaving the LPT still carry significant thermal energy; this residual heat is directed to a heat recovery unit, which supplies the thermal driving force for the single-effect LiBr ARC, thereby producing a chilled water output for cooling applications.

3.2 Design Parameters and Experimental Data

Input data were sourced from validated prior studies by Bellos and Tzivanidis, and Anvari et al. Three process control parameters were defined: Pressure Ratio (PR, X_1), Turbine Inlet Temperature (TIT, X_2), and air Mass Flow Rate (MFR, X_3). A three-level design was adopted, with parameter ranges summarized below.

Parameter	Low Level (1)	Central Level (2)	High Level (3)
Pressure Ratio (X_1)	4	6	8
TIT – K (X_2)	800	1000	1200
MFR – kg/s (X_3)	10	20	30

Table 1. Input variable levels for the SBIRGT experimental matrix

A total of 15 experimental runs were conducted using a structured Box-Behnken design matrix. Each run specified coded levels of PR, TIT, and MFR, with corresponding measured outputs of energy efficiency (%) and electrical power output (kW). Central-point experiments (runs 1, 3, and 10) were replicated at the midpoint of all three variables to estimate pure experimental error.

4. Analysis: Parametric Investigation, Model Development, and Optimisation

4.1 Parametric Analysis of Energy Efficiency

4.1.1 ANOVA for Efficiency

Analysis of Variance (ANOVA) was employed to decompose the total variation in efficiency measurements and quantify the relative contribution of each design parameter. Results are presented in Table 2.

Parameter	DOF	Adj SS	Adj MS	F-Value	Contribution (%)
Pressure Ratio	2	122.6	122.6	1142.52	48.80
TIT	2	77.45	77.45	721.55	28.52
Mass Flow Rate	2	61.42	61.42	572.02	22.48
Error	8	1.825	2.0	—	—
Total	14	263.5	—	—	100

Table 2. ANOVA summary for energy efficiency

With an F-statistic of 1142.52 and a contribution share of 48.80%, the Pressure Ratio stands out as the dominant factor governing efficiency in the SBIRGT configuration. The Turbine Inlet Temperature ranks second, accounting for 28.52% of the efficiency variation, while the Mass Flow Rate contributes the remaining 22.48%. Graphical examination of three-dimensional response surface plots confirms these findings: efficiency rises monotonically as PR increases from 4 to 8, climbing from approximately 39% to 48%. TIT similarly exerts a positive and consistent influence on efficiency across its examined range of 800 K to 1200 K. Mass flow rate, while the least influential among the three parameters for efficiency, also demonstrates a direct positive relationship with the response.

4.1.2 ANN Model Development for Efficiency

ANN model construction was performed using MATLAB R2023b. Multiple combinations of transfer functions were examined for the hidden and output layers to identify the configuration yielding the lowest MSE. Results of the transfer function screening exercise were as follows:

Linear–Linear configuration (hidden and output layers): MSE = 0.0906

Sigmoid–Linear configuration: MSE = 5.99×10^{-5}

Tanh–Linear configuration: MSE = 1.25×10^{-10} ← Selected

The hyperbolic tangent function in the hidden layer paired with a linear output-layer function delivered the lowest MSE by several orders of magnitude and was therefore selected as the definitive architecture. The optimal hidden-layer neuron count was established at three neurons. The resulting ANN-based efficiency model in explicit mathematical form is:

$$\text{Efficiency} = 0.5281 * y_1 + 0.866 * y_2 + 0.946 * y_3 + 0.899 \quad (6)$$

Where,

$$y_1 = \tanh \tanh (4.536 * x_1 + 0.9881 * x_2 + 0.8693 * x_3 - 2.0559)$$

$$y_2 = \tanh \tanh (4.5554 * x_1 - 0.7853 * x_2 + 0.6542 * x_3 + 3.4141)$$

$$y_3 = \tanh \tanh (-0.9574 * x_1 - 0.6556 * x_2 - 0.4573 * x_3 - 0.9766)$$

4.1.3 Efficiency Optimisation Results

All four algorithms — Rao-1, Rao-2, Rao-3, and DE — were applied to the ANN efficiency model with search bounds of $4 \leq x_1 \leq 8$, $800 \leq x_2 \leq 1200$, and $10 \leq x_3 \leq 30$. Fifty initial candidate solutions per variable were randomly seeded, and the iteration ceiling was set at 1000, though the process terminated at 800 iterations due to convergence stagnation. Comparative results across algorithms are presented in Table 3.

Algorithm	x_1 (PR)	x_2 (TIT)	x_3 (MFR)	Efficiency (%)	Iterations
Rao-3	7.99	1198.99	30.00	50.6%	500
Rao-2	8.00	1198.99	29.394	49.33%	625
Rao-1	8.00	1199.98	29.554	46.69%	650
DE	7.879	1197.97	29.444	47.38%	550

Table 3. Comparative algorithm performance for efficiency maximization

4.2 Parametric Analysis of Power Output

4.2.1 ANOVA for Power Output

ANOVA was similarly applied to the power output dataset. The results reveal a markedly different influence structure compared to efficiency.

Parameter	DOF	Adj SS	Adj MS	F-Value	Contribution (%)
Mass Flow Rate	2	132585	132585	162435	90.92
Pressure Ratio	2	8282	8282	8282	5.55
TIT	2	5437	5437	6661	3.84
Error	8	13	~0	—	—
Total	14	133018	—	—	100

Table 4. ANOVA summary for electrical power output

Air Mass Flow Rate overwhelmingly dictates power output, contributing 90.92% of total variance with an F-value of 162,435 — dwarfing the contributions of both PR (5.55%) and TIT (3.84%). Response surface plots confirm that as MFR rises from 10 to 30 kg/s, power output scales proportionally from roughly 75 kW to approximately 290 kW. Pressure ratio, by contrast, exerts comparatively little influence on power generation magnitude within the tested range.

4.2.2 ANN Model Development for Power Output

The transfer function evaluation procedure followed for efficiency was replicated for the power output model. MSE values for each configuration were: Linear–Linear: 0.0899; Sigmoid–Linear: 1.9×10^{-7} ; Tanh–Linear: 5.55×10^{-12} (selected). Consistent with the efficiency modelling findings, the Tanh–Linear combination produced the most precise representation and was therefore adopted. The explicit power output ANN model is:

$$\text{Power} = 120.029 \cdot y_1 - 5.65 \cdot y_2 + 0.6990 \cdot y_3 + 0.7645 \quad \dots (7)$$

with intermediate neuron outputs:

$$y_1 = \tanh(0.2250x_1 + 4.062x_2 + 0.4462x_3 - 5.503)$$

$$y_2 = \tanh(-2.455x_1 + 4.555x_2 + 0.6435x_3 + 0.0665)$$

$$y_3 = \tanh(-0.3345x_1 - 0.4548x_2 - 0.5433x_3 + 3.0555)$$

4.2.3 Power Output Optimisation Results

Algorithm	x_1 (PR)	x_2 (TIT)	x_3 (MFR)	Power (kW)	Iterations
Rao-3	8.00	1199.05	30.00	331.2	600
Rao-2	7.95	1199.95	29.99	305.2	675
Rao-1	7.889	1200.00	29.554	267.95	525
DE	7.879	1197.97	29.444	269.1	575

Table 5. Comparative algorithm performance for power output maximization

Rao-3 again delivered the highest optimized power output at 331.2 kW, followed by Rao-2 at 305.2 kW, DE at 269.1 kW, and Rao-1 at 267.95 kW. Convergence profiles for both efficiency and power outputs confirmed that Rao-3 reached near-optimal regions faster and with greater consistency across repeated runs.

5. Evaluation: Critical Appraisal of Results and Methodology

5.1 Comparative Strength of Optimization Algorithms

Across both objective functions — efficiency and power output — the Rao-3 algorithm consistently outperformed its counterparts. Several factors underpin this superiority. The Rao-3 update rule (Equation 5) incorporates absolute-value terms for both the best and worst population vectors, injecting additional diversity into the solution-update step. This mechanism reduces susceptibility to premature stagnation in regions of the design space that exhibit moderate but non-global fitness values — a limitation observed in both Rao-1 and Rao-2. Furthermore, Rao's algorithms require no user-specified tuning parameters such as mutation rates or crossover probabilities, eliminating a common source of algorithmic bias that can degrade DE performance when default settings are suboptimal for a specific problem topology.

The DE algorithm, while a robust global searcher in general, converged to slightly inferior solutions within the fixed iteration budget. This may reflect the relatively small population size (50 individuals) and the smooth, well-conditioned nature of the ANN-based objective surfaces, for which Rao-3's deterministic population-bounding strategy proves especially effective.

5.2 Validity and Utility of ANN Modelling

The ANN models demonstrated exceptional predictive fidelity, with MSE values on the order of 10^{-10} for efficiency and 10^{-12} for power output — several orders of magnitude lower than the competing transfer function configurations. This near-zero training error indicates that the tanh-linear architecture with three hidden neurons provides sufficient representational capacity to

capture the non-linear, multi-variable relationships governing SBIRGT thermodynamic performance without overfitting.

The use of ANN models as surrogate objective functions for evolutionary optimisation confers two important practical benefits. First, ANN evaluations are computationally inexpensive relative to full physics-based thermodynamic simulations, enabling the large populations and iteration counts required for exhaustive search. Second, ANN models handle non-linear interactions among PR, TIT, and MFR simultaneously — interactions that would be misrepresented or ignored by simpler linear regression surrogates.

5.3 Influence of Design Parameters: A Critical Perspective

The ANOVA results reveal a physically interpretable pattern. Pressure Ratio dominates efficiency because higher compression ratios expand the thermodynamic work extraction potential of the gas turbine cycle — a relationship well established in Brayton cycle theory. Turbine Inlet Temperature is the second efficiency driver because higher combustion temperatures increase the specific work output and improve the Carnot-equivalent efficiency ceiling of the cycle. In contrast, MFR is the paramount driver of absolute power output simply because power is the product of specific work and mass throughput rate; at fixed thermodynamic conditions, doubling mass flow doubles power generation.

These parametric hierarchies have direct engineering implications: operators seeking to maximise system efficiency should prioritise achieving the highest feasible compression ratio and combustion temperature, whereas operators targeting maximum absolute power capacity should focus on maximising the air mass throughput, subject to compressor and turbine mechanical limits.

6. Conclusions:

Pressure Ratio is the dominant determinant of energy efficiency in the SBIRGT configuration, responsible for approximately 48.80% of total efficiency variation, while air Mass Flow Rate governs electrical power output, accounting for over 90% of power variation.

Turbine Inlet Temperature ranks second in influence for both performance indicators, confirming the importance of high-temperature combustion in advanced gas turbine cycles.

ANN models employing a hyperbolic tangent transfer function in the hidden layer and a linear function in the output layer delivered the highest predictive accuracy for both efficiency and power output, with MSE values approaching machine precision.

Among four competing optimization algorithms, Rao-3 achieved the best global solutions: an optimized efficiency of 50.6% and an optimized power output of 331.2 kW — representing gains of approximately 5.55% and 13.75%, respectively, over the baseline performance reported in prior literature.

The Rao-3 algorithm also demonstrated superior convergence behavior, reaching near-optimal regions faster and with fewer iterations than Rao-1, Rao-2, or DE within the tested problem context.

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