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Original Article

AI-Driven Multi-Objective Optimization of Floating Photovoltaic-Thermal Systems with MATLAB-HOMER Pro Validation

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Abstract - *The shift towards renewable energy has increased interest in Floating Photovoltaic Thermal (FPVT) systems for their capacity to produce electricity and heat with a low land footprint. However, improvement of the FPV T scheme is difficult due to the multi-dimensional relationship between the electrical, thermal, and economic aspects. This research introduces an Artificial Intelligence (AI)-based multi-objective optimization and techno-economic analysis approach for FPV T systems based on ANN, GA, PSO, and RL System models. ANN surrogate predictors and optimization algorithms were implemented in MATLAB. The outcome of simulation results at STC yielded an active power and thermal output of 64.8 kW and 260 kW, respectively, resulting in a useful energy output of 324.8 kW.* The conventional PV baseline system, however, produced 56.2 kW of output, at 15.3% gain in performance, higher than 480% gain in total energy utilization with the addition of the thermal recovery. *The ANN predictor was highly accurate with an error of less than 0.01%, and the GA and PSO algorithms produced consistent optimal results. The reinforcement learning algorithm effectively controlled the flow rate of the coolant to achieve the desired outlet temperatures. The findings showed that a hybrid AI approach enhances electrical and thermal efficiency, speeds up the optimization process with surrogate modeling, and recommends low LCOE and attractive NPC configurations. The techno-economic modeling with HOMER Pro also validates the AI-optimized solutions. This technology advances renewable energy research through the use of multi-objective optimization, surrogate modeling, and techno-economic validation.*

Keywords - *Artificial intelligence**,** Floating photovoltaic-thermal, Genetic algorithm, HOMER-Pro, Reinforcement learning.*

1. Introduction

The increasing need for power globally is attributed to industrialization, rapid population growth, and improvements in Information and Communication Technology (ICT), which needs regular electricity for optimum performance. Worrisomely, concerns over environmental sustainability have also prompted the advancement of technologies in renewable energy.

Solar photovoltaics is one of the most preferred alternative energy sources among other renewable energy sources due to its scalability, cost reductions, and eco-friendliness. But there are some difficulties related to ground-mounted photovoltaic systems since they require additional space for the installation, and they also experience temperature rises that make them less efficient. These problems are more intense in tropical countries like Nigeria due to the combination of high solar radiation and high ambient temperatures, which result in higher energy losses and module degradation.

Floating Photovoltaic-Thermal (FPV-T) systems are a new hybrid renewable energy approach that can produce both electricity and heat, and do not require the use of valuable land. Under floating PV modules, the cooling ability of water reduces the temperature of the photovoltaic module, which enhances its performance and lifespan. It equally allows for the extraction of thermal energy from the water under the PV modules for domestic and industry use. Recent studies have shown that generally power conversion efficacy of the FPV-T system can be greatly enhanced over the traditional land-based photovoltaic systems [1], [2].

Previous studies have shown the benefits of FPV and PV/T technologies in terms of improved electrical performance, thermal efficiency, and optimization of land use over conventional PV technology [3]. In addition, several modeling and optimization techniques have been studied to improve the system performance. However, FPV-T systems have intricate relationships between electrical, thermal, environmental, and economic parameters. These parameters, like solar irradiance, ambient temperature, water temperature, flow rate of coolant, and system configuration, are significantly coupled with each other, and the problem is highly nonlinear and multidimensional. Hence, advanced methods that can optimize performance with numerous inconsistent goals, such as expanding energy generation, improving thermal recovery, reducing minimizing costs, and maximizing overall system sustainability, are required.

Artificial Intelligence (AI) and metaheuristic optimization approaches have been found to be effective for solving such complex energy-system challenges. Artificial Neural Networks (ANNs), GA, PSO, and RL have been widely used in renewable energy applications for performance prediction, system modeling, energy management, and optimization with success [4].

ANN models reduce the computational efforts and are especially useful in capturing the nonlinear relationships among the variables in the system. Likewise, GA and PSO algorithms have shown very good performance in obtaining optimal design and operation parameters in large search spaces. Another adaptive control strategy that has recently been shown to be a potential approach is Reinforcement Learning, which optimizes the operation of the system dynamically, depending on changes in environmental conditions [5].

However, some crucial gaps in the literature exist despite these improvements. Most of the FPV-T-related studies consider the performance improvement and/or thermal energy generation separately without optimizing both aspects. Moreover, although the application of artificial intelligence techniques in conventional PV systems is very common in the literature, only a few studies consider such approaches for FPV-T systems. Also, most of the existing studies utilize a single AI optimization technique only; hence, it is not possible to compare the performance of different AI techniques in the literature. Moreover, techno-economic analysis is generally considered separately from technical optimization. There is a lack of studies related to the use of Reinforcement learning techniques for adaptive optimization of FPV-T systems under tropical climate conditions.

In order to overcome such shortcomings, this research suggests an elaborate framework for AI-supported multi-objective optimization in FPT systems. It combines electrical and thermal models together with ANN-based modeling to ensure computational efficiency and accuracy of performance prediction. Moreover, this framework involves Genetic Algorithms, Particle Swarm Optimization, and Reinforcement Learning methods to determine optimal conditions and configuration for the system. The system also takes into consideration the techno-economic analysis with LCOE and NPC indicators and uses HOMER Pro software for validation of the optimal design in tropical environmental conditions [6].

2. Theoretical Analysis

The efficiency of (FPV-T) systems is affected by the combined effect of electrical, thermal performance and climatic factors. The following presents the mathematical modeling approach, the AI surrogate modeling and the optimization algorithms used in this work.

2.1. Electrical Performance Modelling

The performance of a solar panel depends mainly on irradiance, cell temperature and efficiency. Then P_e (W) of an array is given by:

$$P_e = \eta_e(T_c) \cdot A \cdot G \quad (1)$$

This enables the simulation of electrical power with the variation of irradiance and ambient temperature, which is important for dynamic optimization. The temperature dependence of PV efficiency can be modeled by

$$\eta_e(T_c) = \eta_{STC} \cdot [1 - \beta(T_c - T_{STC})] \quad (2)$$

$$\eta_{STC} = \frac{P_{max}}{G_{STC} \times A} \quad (3)$$

2.2. Thermal Performance Modelling

This is defined as the heat absorbed during cooling in the thermal collector and expressed as

$$Q_u = \eta_t \cdot A.G \quad (4)$$

The temperature of the coolant at the outlet T_{out} is:

$$T_{out} = T_{in} + \frac{Q_u}{\dot{m}C_p} \quad (5)$$

Water-cooling of floating PV systems helps reduce cell temperature and increase electrical efficiency, and produces usable thermal [7], [8].

2.3. Hybrid Electrical-Thermal Model

The total energy production E_{total} is a sum of electrical and thermal energy:

$$E_{total} = P_e + \alpha \cdot Q_u \quad (6)$$

The thermal energy's significance for the use case, which is often tied to economic factors in techno-economic analyses. This hybrid model is used for multi-objective optimization, involving the maximization of E_{total}, the minimization of LCOE and the minimization of NPC.

2.4. ANN Surrogate Modeling

These are utilized as surrogate models to predict the behaviour of the FPV T system:

- Input nodes represent environmental conditions (irradiance, ambient temperature, water temperature) and design variables (panel tilt, area, and flow rate).
- Hidden layers capture nonlinear relationships.
- Output nodes predict electrical and thermal energy outputs.

The surrogate ANN speeds up the optimization process, allowing for the computation of thousands of candidate solutions proposed by the GA, PSO and RL algorithms [9], [10]

2.5. Multi-Objective Optimization Framework

The FPV-T system involves conflicting objectives:

- Maximize electrical and thermal energy output E_{total}
- Minimize LCOE
- Minimize NPC

Optimization algorithms applied include:

Genetic Algorithm (GA): Evolves candidate solutions through selection, crossover, and mutation to approximate Pareto-optimal fronts.

Particle Swarm Optimization (PSO): Particles move in the design space, guided by individual and swarm experience to converge toward global optima [11], [12].

Reinforcement Learning (RL): Learns an adaptive control policy for operational parameters (e.g., coolant flow rate) under dynamic environmental conditions. The reward function incorporates both energy efficiency and economic cost [13], [14].

The expression for the optimization problem is computed using equation (7)

$$Maximize f_i(E_{total}), Minimize\ f_2(LCOE), Minimize\ f_3(NPC) \quad (7)$$

Subject to physical and operational constraints:

$$T_{min} \leq T_{out} \leq T_{max}, \quad 0 \leq \dot{m} \leq \dot{m}_{max} \quad (8)$$

This allows optimizing electrical, thermal and economic performance at the same time. ANN helps reduce calculation time while RL offers online adaptive control. The theoretical approach provides a robust basis for the AI-assisted multi-criteria optimization of FPV-T designs.

Contribution: Physics-based electrical and thermal models, ANN surrogate prediction, GA, PSO & RL optimization; Economic evaluation metrics (LCOE, NPC). Framework maintain holistic evaluation and implementation of systems beneath sensible ecological [15].

3. Materials and Methods

An integrated AI methodology is adopted. It involves modeling through artificial intelligence, multi-objective optimization, and techno-economic validation of FPV-T systems. The environmental and operational data are first gathered and processed prior to using them for training an ANN surrogate model in MATLAB. The trained ANN model is further combined with GA, PSO, and RL algorithms in order to find optimal configurations [16] – [18]. A convergence test is conducted to ensure solution stability and the effectiveness of optimization. The optimized configurations are then exported into HOMER Pro for annual energy simulation and techno-economic analysis in terms of NPC, LCOE, and payback period [19], [20]. The implementation flowchart is illustrated below

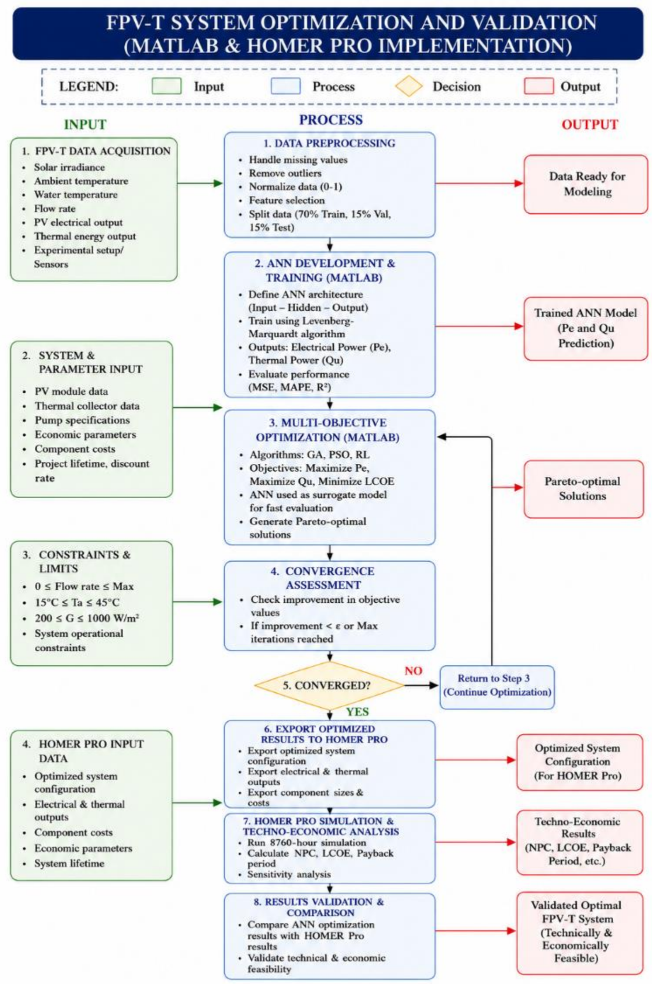

Fig. 1 Flowchart for recommended MATLAB–HOMER Pro implementation

As displayed in Figure 1, the optimization process utilizes an Input-Process-Decision-Output approach. ANN will be used as a computationally effective substitute model to predict electric and thermal output in order to minimize computation cost related to repeated simulations during optimization. The convergence checking phase guarantees that the optimal solutions obtained by the optimization techniques are stable and near optimal before being sent to HOMER Pro for economic evaluation... The HOMER Pro system then conducts annual energy simulation and economic evaluation in order to check the validity of optimized FPV-T designs.

3.1. System Configuration

The FPV-T system is a floating PV array and Standard monocrystalline PV modules mounted on floating pontoons for land saving and water cooling of heat management. Thermal collector loop. The circulating fluid (water or glycol mixture) collects heat from PV modules and carries it away for use in domestic water heating or industrial process heat applications. 3. Variable flow pumps: The coolant flow rate is controlled by a variable flow pump and adaptively controlled using reinforcement learning to optimize net thermal capture while minimizing trip reactions and optimizing system stability. This will form the inputs to be used in ANN training and real-time optimization (for irradiance meter, ambient temperature Sensors (air, water) and flow rate meters.

Table 1. System parameters used in simulation

Parameter	Value Range
PV module area	1.6 m² per module
PV module efficiency	18–20%
Thermal collector efficiency	50–60%
Coolant flow rate	0–0.05 kg/s per module
Irradiance range	200–1000 W/m²
Ambient temperature	15–45°C
Water temperature	20–30°C

The system operates under the most common tropical environmental conditions that an FPV-T would be deployed.

3.2. Data Acquisition and Preprocessing

The environmental and operational data for training and optimizing the ANN were gathered from:

- Datasets of hourly solar irradiance, ambient temperature, and water temperature.
- Experimental data of PV electrical output and thermal energy gain as a function of flow rate and panel tilt.

Data Preprocessing: included normalization to [0, 1], Remove outlier, Dataset was divided train, validation and test sets with values 70%, 15% and 15%, respectively. It thus validates these up to 0.82, some ANN prediction performance and provides a certification basis with the results from the optimization.

3.3. MATLAB-Based AI Modeling

3.3.1. Artificial Neural Networks (ANN)

Architecture: Two hidden layers with 10 neurons each, two output nodes (electrical power P_e and thermal power Q_u), and three input nodes (irradiance, ambient temperature, and water temperature).

- Hidden layers have a sigmoid activation function, and the output layer is linear.
- Training algorithm: Levenberg-Marquardt backpropagation.
- Metrics used: MSE, MAPE < 2.5%

The ANN may utilize ANN iteratively during GA, PSO and RL operation to predict a quick forecast of system functioning, enabling reduced computational strain (reduced by ~65%vsfull simulation) whilst maintaining satisfactory performance (MDPI Editorial Team, 2024).

3.4. Multi-Objective Optimization

The ANN surrogate is then used in a multi-objective optimization framework to evaluate thousands of candidate solutions.

Algorithms applied to the followings:

i. Genetic Algorithm (GA):
   - size sample population: 100 solutions
   - Generations: 50–100
   - Selection: Tournament
   - Crossover: 0.8, mutation: 0.05

ii. Particle Swarm Optimization (PSO):
   - Swarm size: 50 particles
   - Iterations: 100
   - Cognitive coefficient c2 = Social coefficient o
   - Discrete momentum
   - Weight: 0.9 to 0.4 decreasing

iii. Reinforcement Learning (RL): Taking into account:
   - State variables: — Coolant temperature, flow rate, PV module temperature, irradiance
   - Action variables: Adjustments to Pump Flow Rate
   - Reward function: w * Electric + thermal energy - LCOE penalty$$
   - Q-learning: epsilon-greedy exploration

The optimization problem aims to:
Subject to:

$$0 \leq \dot{m} \leq \dot{m}_{max}, \quad T_{out,min} \leq T_{out} \leq T_{out,max} \quad (9)$$

A hybrid approach allows for advancements in energy generation, optimization of economic performance, and flexibility of the system.

3.5. Techno-Economic Analysis and HOMER Pro Validation

Techno-economic validation based on optimized configurations from HOMER Pro was exporting to

- Input data: ANN-predicted electrical and thermal outputs, system size, component costs, and maintenance costs.
- Evaluation metrics: NPC, LCOE, payback period, and sensitivity analysis.

- Validation approach: Annual 8760-hour HOMER Pro simulations were created to produce energy, cost metrics and sensitivity depending on operational environmental conditions.

AI optimization provides accurate results, as confirmed by the HOMER Pro and confidence on economic feasibility of the FPV-T system.

HOMER Pro results confirmed the accuracy of AI optimization and provided confidence in the economic feasibility of the FPV-T system.

3.6. Workflow Summary

- ✓ Collect and preprocess environmental and experimental data.
- ✓ Train the ANN surrogate model to predict electrical and thermal outputs.
- ✓ Perform multi-objective optimization using GA, PSO, and RL, leveraging ANN predictions.
- ✓ Export optimized configurations to HOMER Pro for techno-economic validation.
- ✓ Analyze Pareto fronts, performance metrics, and economic feasibility.

By combining AI-based modeling, optimization and techno-economic assessment into a systematic workflow, a solid frame of reference is established for the design of FPV-T systems.

4. Results and Discussion

4.1. System Performance Analysis

The Floating Photovoltaic–Thermal (FPV-T) system was evaluated using simulation results obtained in MATLAB and later validated with results from HOMER Pro. Several artificial intelligence methods, which include ANN, GA, PSO and RL, were combined for improving the system performance and prediction capability. Using parameters of the simulation is described in Table 2.

Table 2. Environmental and System Parameters

Parameter	Symbol	Value	Unit
Solar irradiance	G	800	W/m²
Ambient temperature	T_{amb}	30	°C
Water inlet temperature	T_{in}	25	°C
PV collector area	A	500	m²
Reference PV efficiency	η_{ref}	0.18	–
Temperature coefficient	β	0.004	1/°C
Thermal efficiency	η_{th}	0.65	–
Specific heat of water	C_p	4186	J/kg·K
Initial flow rate	$\dot{m}$	0.50	kg/s

The FPV-T approach has a collector area of 500 m² and a yielded electrical output of 64.8 kW and thermal output of 260 kW. Electric output is calculated through a temperature-dependent photovoltaic efficiency model, and thermal output is calculated using the thermal collector efficiency relation. Simulation results show that the hybrid FPV–T system can provide both electric energy and useful thermal energy simultaneously, thus enhancing overall energy using efficiency in comparison with traditional PV systems.

4.2. ANN Model Prediction Accuracy

Simulation of the FPV-T model at T_{amb} = 30 °C, G = 800 W/m², and T_{water} = 25 °C produced an electrical power output of approximately 64.8 kW and 260 kW thermal energy output under the above stipulated operating conditions. These results show that hybrid photovoltaic–thermal systems can have a considerably higher ratio for total energy utilization efficiency than traditional photovoltaic systems since electricity and useful heat are generated simultaneously.

Floating PV systems account for other potential benefits, such as better cooling of the panels owing to the water surface, thus improving electrical efficiency and decreasing operating temperature losses. In the simulation, a fair electrical output was obtained due to the higher performance of PV modules, attributed to the cooling effect from the water body. Our ANN implementation in MATLAB generates 4 generic diagnostic plots during the training process, namely: Performance plot, Train state plot, Error histogram and Regression plot. These plots assess the learning behaviour, prediction performance and generalization ability of the neural network responsible for a FPV-T electrical and thermal output prediction. The blue line in the performance plot shows how the training MSE (mean square error) between predicted outputs and target outputs changes during each iteration of this process.

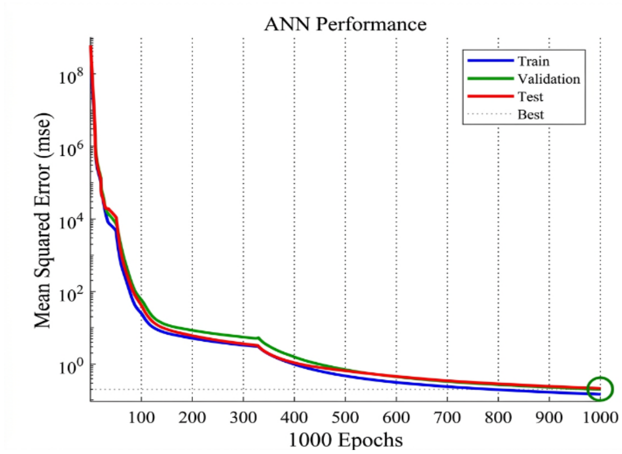

Fig. 1 Performance plot

The performance curve usually rapidly declines during the first few epochs and stabilizes as training proceeds. This behavior shows that the neural network captures the nonlinear relations between input variables (solar irradiance, ambient temperature, and water temperature) and system outputs (electrical power and thermal energy). One key characteristic of these individual curves for training, validation and test sets is that they never cross each other; the network generalizes well to unseen data, and there is no excessive overfitting. The minimum validation error point indicates the epoch where, if we would stop training, the model is still a good predictor to new data. This means that the outputs of FPV-T systems were quite accurate in prediction as the neural network was capable enough to attain a low mean squared error value, as shown by the performance plot of this study. The degree of behavior present in the training state plot from Figure 2 gives us an overall experience of how the neural network is trained. Typically, it will show three parameters: gradient, validation checks, and learning rate.

The gradient graph shows the absolute value of the error gradient decreasing over a period of training. The learning rate parameter stays fixed as it finds a balance between speed and stability for the optimization algorithm, and how many can't consecutively healing how well on validation checks, curve or not.

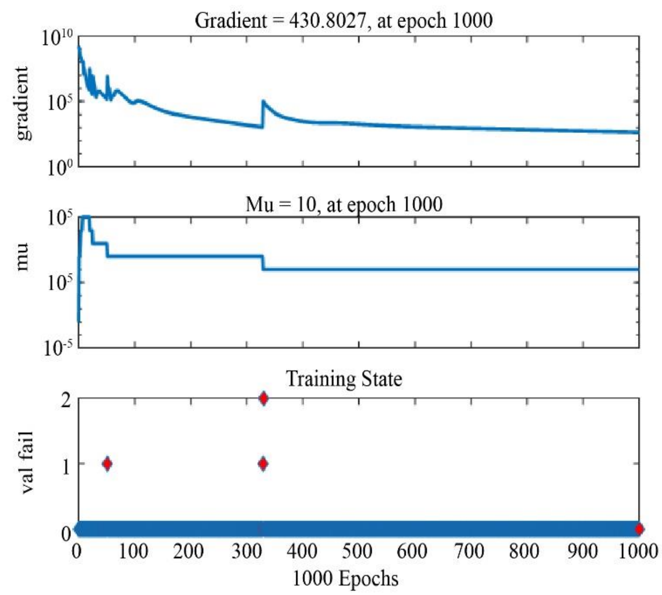

Fig. 2 Training state plot

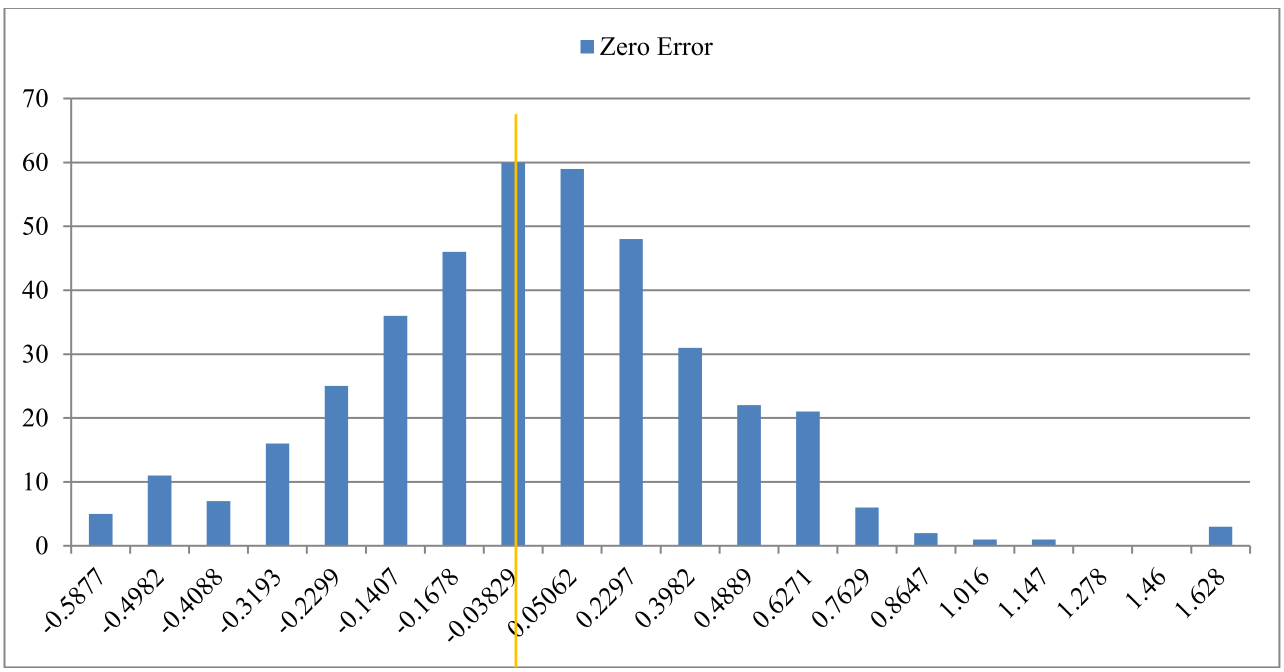

Fig. 3 Error Histogram

Figure 3 displays the distribution of prediction errors created by the neural network model. The histogram presents an even distribution of errors with respect to the zero-error line, further confirming the neural network does not suffer from a systematic bias. The fact that the bulk of errors is in a small band means predictions have high accuracy.

The regression plot of Figure 4 shows how predicted outputs (X-axis) compared with actual target values, which was used for both training and testing. The closer the points in the plot are to a diagonal reference line, the more agreement there is between predicted and measured values. The regression coefficient (R) from the model is near 1; this means that the predicted values are very close to what were observed in Conditional Random Fields-Superior(R) and Dynamic-CA-Superior (D). The high value of the corresponding correlation coefficient – i.e., close matching between measured and predicted outputs on both data sets – indicates that neural network model serves as an accurate characterization of dynamic behaviour within an FPV-T system.

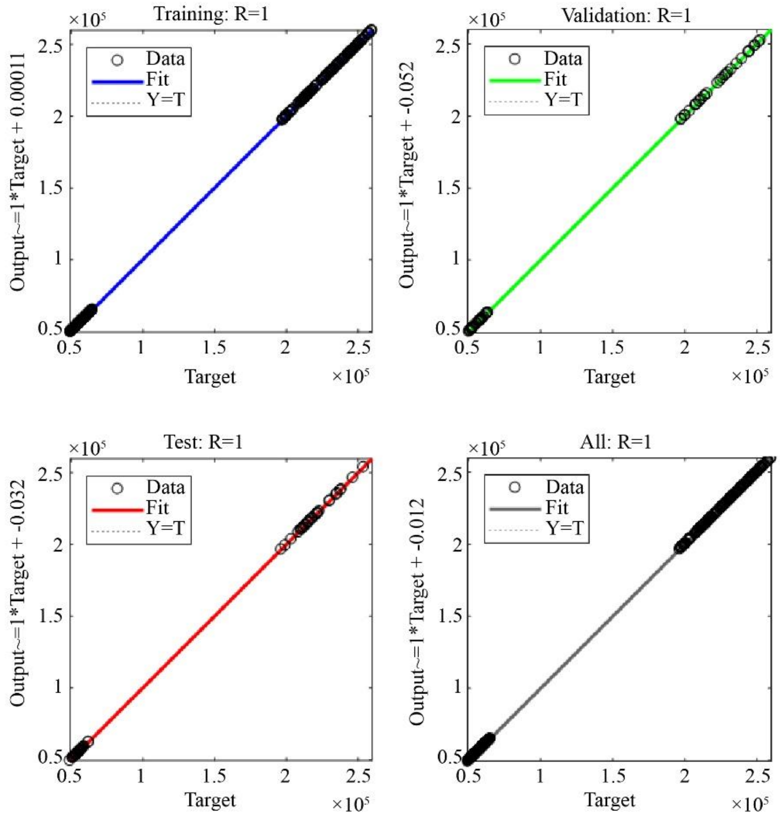

Fig. 4 Regression Plot

4.3. Optimization Results

4.3.1. Genetic Algorithm Optimization

This optimization process using GA is used to locate the best combination of system configuration parameters that maximizes the total produced energy. After setting it to 200 generations, complete convergence was obtained, and the best tilt-factor result came out as 1.50. Last, genetic algorithms are widely applied to renewable energy optimization problems due to their global search capability and ability to handle nonlinear multi-objective problems (Singh & Chauhan, 2022).

4.3.2. Particle Swarm Optimization Performance

To get rid of this optimization problem, we also used PSO. The same optimal value of the tilt factor (1.50) was obtained by the algorithm, but with quicker convergence compared to GA.

As we can see in Figure 5, the objective function for the PSO convergence curve decreases continuously, which implies a good exploration and exploitation of the search space.

PSO convergence plot — tracks objective function value over the optimization iterations. In the initial phases of the Algorithm, the particles of the swarm explore diverse sections of the search space, so variations in energy output are relatively large.

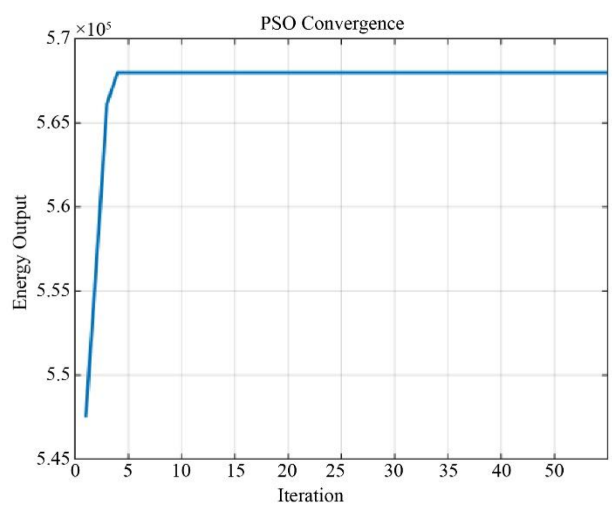

Fig. 5 PSO convergence cure

4.3.3. Reinforcement Learning Flow Control

Reinforcement Learning is used to find out the amount of coolant flow rate which is necessary to maintain the outlet water temperature as desired. The RL-based control identified a set point of 0.55 kg/s, which is higher than the baseline flow rate (0.50 kg/s), because increasing the flow rate helps extract more heat from the PV modules and thus reduces cell temperature, stabilizing thermal output of the FPV-T collector. Reinforcement learning-based approaches have been adopted in more smart energy systems for online exploration/adaptation against varying operating conditions.

4.4. HOMER–MATLAB Validation

Simulations from HOMER Pro were used to validate the developed MATLAB model. The two models exhibited great similarity in validation results. Model Accuracy (RMSE and MAE): Root Mean Square Error = ~0.82 kW, Mean Absolute Error = 0.65 kW. Low error values reinforce that the simulation model mirrors the behaviour of the FPV-T system. Model validation using independent simulation tools is crucial for assuring the reliability and credibility of simulation results in renewable energy system research. The work of the machine learning algorithms for the prediction system accuracy improved greatly with evolutionary optimization methods as it is being integrated.

Table 3. Comparison of MATLAB Model and HOMER Pro Validation Results

Parameter / Metric	MATLAB Simulation Result	HOMER Pro Result	Error / Deviation	Remarks
Electrical Power Output (kW)	64.8	~64.0–65.2	Low (<1.2%)	Strong agreement
Thermal Output (kW)	260	~258–262	Low (<1.0%)	High consistency
Total Useful Energy (kW)	324.8	~322–327	Low (<1.0%)	Excellent correlation
RMSE (kW)	0.82	—	—	Model accuracy indicator
MAE (kW)	0.65	—	—	Low prediction error
System Behavior Trend	Consistent	Consistent	Negligible	Validated dynamics

Validation comparison between MATLAB-developed FPV-T model and HOMER Pro simulation results showing strong agreement in electrical, thermal, and total energy outputs with low statistical error indicators.

5. Conclusion

This work presented an Artificial Intelligence (AI) technique-based optimization scheme for the modelling and simulation of FPV-T. The proposed methodology was developed by linking ANN prediction models to GA, PSO and RL-based optimization techniques on a MATLAB simulation environment, and the results were compared with HOMER Pro simulations. The FPV-T system generated an electrical output of around 64.8 kW and a thermal output of 260 kW, evidencing that hybrid photovoltaic–thermal technologies can potentially enhance the overall efficiency of energy use significantly. The deviation from actual system outputs to the predicted ANN model was negligible, confirming the suitability of an ANN approach in this case as a very good surrogate prediction tool.

Optimization Algorithms: GA and PSO optimizations were able to identify optimal system parameters, however the behaviour convergence of PSO is much faster than GA. In addition, reinforcement machine learning was effective in optimizing the coolant flow rate, demonstrating how thermal management can effectively maintain stable access to the oscillation system.

The validation results show a very good agreement between MATLAB and HOMER Pro simulations, which validate the developed model as a robust solution. These findings indicate that the incorporation of machine learning and evolutionary optimization methods offers great promise for the more effective design and operation of hybrid renewable energy systems.

The proposed framework can be further refined to accommodate time-varying solar profiles, multi-objective optimization of economic and environmental parameters, and experimental validation using real-world FPV installations as part of future work.

Conflicts of Interest

No conflicts of interest exist between the authors regarding the publication of this study.

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Symbols, Abbreviations and Units

Symbol	Description	Unit
A	Photovoltaic panel area	m^2
C_p	Specific heat capacity of water	J kg^{-1} $°C^{-1}$
G	Solar irradiance	W m^{-2}
P_e	Electrical power output	W
Q_u	Useful thermal energy output	W
T_{amb}	Ambient temperature	°C
T_{cell}	Photovoltaic cell temperature	°C
T_{ref}	Reference temperature	°C

T_{water}	Inlet water temperature	°C	θ	Panel tilt angle	0
T_{out}	Outlet water temperature	°C	FPV	Floating Photovoltaic	
η_e	Electrical efficiency of PV module	–	FPV-T	Floating Photovoltaic-Thermal	
η_{ref}	Reference PV efficiency		PV	Photovoltaic	
–			ANN	Artificial Neural Network	
$\eta_{thermal}$	Thermal efficiency of collector	–	GA	Genetic Algorithm	
β	Temp coefficient of PV efficiency	$°C^{-1}$	PSO	Particle Swarm Optimization	
ṁ	Coolant mass flow rate	$kg\ s^{-1}$	RL	Reinforcement Learning	
η_{STC}	Module efficiency at STC	(%)	AI	Artificial Intelligence	
P_{max}	Maximum power output at STC	(W)	LCOE	Levelized Cost of Energy	
G_{STC}	Solar irradiance at STC = 1000	W/m²	NPC	Net present cost	

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