



MULTI-VARIABLE THUNDERSTORM ALGORITHM FOR EFFICIENCY AND POWER STABILITY OPTIMIZATION IN BATTERY-INTEGRATED MICRO-HYDROPOWER SYSTEMS

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ABSTRACT

Small-scale hydropower can support sustainable electrification, yet field performance is often limited by sub-optimal operation that yields fluctuating power and modest conversion efficiency. This study applies the Thunderstorm Algorithm (TA) as a multi-variable optimizer to jointly tune net head (H), electro-mechanical efficiency (η), and gate opening in a battery-integrated micro-hydropower system. A composite objective maximizes daily stored energy while penalizing instability via the standard deviation of hourly power and the cumulative ramp. TA follows the Cloud–Streamer–Avalanche phases (40 clouds, 250 iterations) over the bounds $H \in [30, 100]$ m, $\eta \in [0.70, 0.95]$, and gate $\in [0.40, 1.00]$, using a 24-hour discharge series; battery capacity is fixed at 5 MWh, with $\text{weights}_{\text{std}} = \text{w}_{\text{ramp}} = 0.10$. The algorithm converges to an interior optimum $H = 64.95$ m, $\eta = 0.745$, gate = 0.904. Because the storage ceiling is binding, stored energy equals 5,000 kWh for both the baseline ($H = 60$ m, $\eta = 0.90$, gate = 0.90) and the TA solution; improvements arise from stability: the power standard deviation decreases 19.186→17.264 kW and the cumulative ramp 171.636→154.440 kW (=10% reductions). A linear surrogate fitted to TA samples attains RMSE 48.175 kWh, MAE 22.755 kWh, MAPE 0.49% (Accuracy $\approx 99.51\%$), $R^2 = 0.931$, and Pearson $r = 0.9701$. The results confirm that TA effectively navigates the bounded design space to preserve energy yield under a storage ceiling while materially smoothing the power profile—beneficial for power conditioning, battery thermal management, and grid interfacing.



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I. INTRODUCTION

The transition to clean energy systems places small-scale hydropower (microhydro) as one of the promising options for sustainable electrification [1], especially in regions with stable water flow availability [2]. The advantages of microhydro include mature technology [3], low operating costs, and minimal emissions [4]. However, its actual performance is often limited by fluctuating daily discharge dynamics and sub-optimal operating settings [5], resulting in fluctuating power output and suboptimal energy conversion efficiency [6]. In the context of microhydro systems integrated with energy storage, the challenge is twofold: the operating strategy must simultaneously maximize the energy actually stored in the battery and maintain the fineness of the power profile to make it reliable for supporting equipment and the power grid [7]. Various optimization approaches have been used in renewable power generation [8], ranging from deterministic methods to metaheuristics such as the Genetic Algorithm [9], Particle Swarm Optimization [10], and the Gray Wolf Optimizer [11]. While effective in certain scenarios, many studies still focus on tuning a single design variable or assessing performance solely in terms of energy efficiency, while temporal stability aspects (e.g., power variance and ramp rate) are less explicitly integrated into the objective function. Furthermore, storage capacity limitations are rarely modeled as operational constraints that affect the marginal benefit of increasing power at any given point in time [12].

This gap opens up opportunities for optimization approaches that simultaneously consider efficiency, stability, and storage limitations within a coherent framework. Recent studies have investigated a variety of metaheuristic techniques for optimizing micro-hydropower systems [13], with particular emphasis on Genetic Algorithms (GA), Particle Swarm Optimization (PSO) [14], and their derivatives. For instance, [15] applied a GA to optimize penstock configurations in small-scale hydropower plants, while [16] employed GA for optimal load distribution across multiple hydropower units [17]. A benchmarking study involving 14 evolutionary algorithms—including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE)—has demonstrated the robustness of metaheuristics in addressing nonlinear and constrained optimization problems [18]. The application of Messy GA has also been explored for optimizing microhydro layout configurations [15], [19], while the effectiveness of multi-objective PSO has been validated for energy dispatch optimization in residential microgrid scenarios [20]. These contributions affirm the versatility of evolutionary computation in renewable energy planning. However, only a few explicitly address the integration of battery storage systems while simultaneously managing trade-offs between energy yield, power stability, and capacity constraints. This gap highlights the need for an optimization framework capable of navigating such hybrid design spaces - where the TA, with its dynamic cloud-based search mechanism, presents a promising and underexplored solution.

Consequently, there is an urgent need for an optimization method that can jointly tune interdependent design variables under explicit storage constraints while trading off energy yield against temporal stability—capabilities for which the Thunderstorm Algorithm [21], with its Cloud–Streamer–Avalanche dynamics and strong exploration–exploitation balance, is particularly well suited [22]. This study proposes the application of the TA a metaheuristic algorithm that mimics the dynamics of thunderstorm clouds through the Cloud–Streamer–Avalanche phase—for multi-variable optimization of microhydro systems. The three design variables optimized simultaneously are net head (H), electromechanical efficiency (η), and valve/gate opening. The optimization objective is formulated as a composite function that maximizes the daily energy stored in the battery while penalizing power instability (measured by the raw power storage and the accumulated power rate of change). This formulation enables the search for a working point that not only produces high energy output but also suppresses temporal fluctuations that impact power conditioning confidentiality, battery thermal management, and the network interface. Methodologically, the main contributions of this research are: (i) the formulation of a comprehensive objective function that combines efficiency and stability with the calculation of storage capacity limits; (ii) the adaptation and implementation of TA in the form of multi-variable bounded search optimization for microhydro design spaces.

II. METHODS

This section describes the framework used to optimize the battery-integrated micro-hydropower system. We first specify the plant model and data (24-hour discharge series Q_t , constants ρ and g , design bounds for H , η , and gate, and a fixed 5-MWh battery capacity). We then formalize the performance metrics and the composite objective f that maximizes daily stored energy while penalizing instability via the power standard deviation σP and the cumulative ramp $\sum |\Delta P|$ relative to a baseline. Next, we detail the Thunderstorm Algorithm (TA)—Cloud → Streamer → Avalanche—including initialization, striking-path updates, bound reflection/clipping, elitism, and convergence settings (40 clouds, 250 iterations, fixed random seed). Finally, we outline the evaluation protocol contrasting the TA optimum with the baseline and the linear surrogate used for sensitivity and accuracy analysis. The overall workflow is summarized in the flowchart below.

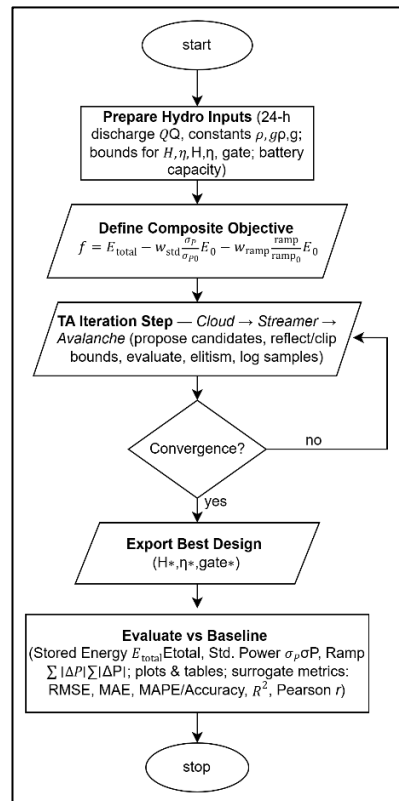


Figure 1: Research flowchart.
Source: Authors, (2026).

II.1 SYSTEM MODEL

Hourly discharge Q_t (24 h) is converted to electric power by Power model

$$P_t = \frac{\rho g (Q_t \cdot gate) H \eta}{1000} [kW] \quad (1)$$

Battery-constrained stored energy.

$$C_0 = 0, e_t = \min(P_t, C_{max} - C_{t-1}) \quad (2)$$

$$C_t = C_{t-1} + e_t, E_{total} = \sum_{t=1}^{24} e_t \quad (3)$$

Stability metrics.

$$\sigma_P = std(P_t), ramp = \sum_{t=2}^{24} |P_t - P_{t-1}| \quad (4)$$

Daily stored energy is the sum $E_{total} = \sum_t P_t$ subject to the battery capacity limit. Stability is quantified by the standard deviation σ_P and the cumulative ramp $|\sum_t |P_t - P_{t-1}|$.

II.2 DESIGN VARIABLES AND BOUNDS

Three interdependent design parameters are optimized: the net head H , the electromechanical efficiency η , and the gate opening ratio. These are bounded respectively as follows:

- $H \in [30, 100]$ meters
- $\eta \in [0.70, 0.95]$
- $gate \in [0.40, 1.00]$.

A fixed baseline configuration is used as a reference: $H = 60$ m, $\eta = 0.90$, and $gate = 0.90$. These bounds reflect real-world operational ranges and define the feasible search space for optimization.

II.3 OBJECTIVE FUNCTION

The optimization objective combines energy maximization and stability improvement into a single composite score:

$$f = E_{total} - w_{std} \left(\frac{\sigma_P}{\sigma_{P0}} \right) E_0 - w_{ramp} \left(\frac{ramp}{ramp_0} \right) E_0 \quad (5)$$

With penalty weights $w_\sigma = w_r = 0.10$. Here, E_0 , σ_{P0} , and $ramp_0$ are baseline values for energy, standard deviation, and ramp rate, respectively. This formulation enables the optimizer to balance between maximizing stored energy and minimizing hourly power fluctuations, yielding a profile more compatible with downstream energy applications.

II.4 THUNDERSTORM ALGORITHM (CLOUD-STREAMER-AVALANCHE)

The optimization uses the Thunderstorm Algorithm, a metaheuristic that simulates storm behavior via three phases:

- **Cloud Phase:** A population of 40 candidate solutions ("clouds") is initialized, each with random variations in H , η , and $gate$ settings.
- **Streamer Phase:** These clouds move toward a pilot solution based on probabilistic paths—mimicking electrical streamers—with boundary reflection and clipping.
- **Avalanche Phase:** Improving solutions are retained, a subset reinforced toward the leader, and elitism ensures retention of the best-so-far candidate.

The algorithm iterates through 250 cycles with a fixed random seed to ensure reproducibility and convergence stability.

II.5 EVALUATION

The performance of the TA-optimized solution is benchmarked against the baseline across multiple criteria: daily stored energy E_{total} , standard deviation σ_P , and total ramp $\sum |\Delta P|$. Additionally, a linear regression surrogate is trained on TA samples to evaluate sensitivity and approximation accuracy. Performance metrics—RMSE, MAE, MAPE, Pearson r , and R^2 —are reported to validate the surrogate's reliability and explainability. The proposed methodological framework synthesizes hydrodynamic modeling, energy storage dynamics, and power fluctuation penalties into a multi-variable optimization landscape. By integrating both efficiency- and stability-oriented components into the objective function, the formulation enables an informed trade-off between instantaneous power gain and temporal regularity. Furthermore, the bounded search space and operational constraints, such as the battery storage ceiling, reflect real-world limitations faced in rural or off-grid microhydro deployments. The Thunderstorm Algorithm (TA), with its exploratory-exploitative phases and bound-aware update mechanisms, is well-suited for navigating such constrained, multi-objective domains.

Unlike prior works that often isolate efficiency or neglect intraday fluctuations, the proposed TA-based framework jointly calibrates the system design parameters to satisfy multiple competing criteria. This ensures that the optimized solution not only preserves maximum daily energy yield but also enhances the smoothness of power output—benefiting downstream equipment and storage systems. The evaluation using a linear surrogate model further corroborates the reliability and robustness of the TA, reinforcing its applicability to real-world battery-integrated hydropower systems.

III. RESULTS AND DISCUSSIONS

III.1 CONVERGENCE OF TA

Figure 2 illustrates the evolution of the optimal composite objective $f(H, \eta, \text{gate})$, which maximises daily stored energy while penalising power variability and ramping relative to the baseline. Using 40 clouds and 250 iterations, the curve shows the characteristic pattern of the Cloud–Streamer–Avalanche dynamics: a rapid rise in the early stage as streamers intensify toward the pilot leader and avalanche acceptance locks in improvements, followed by a smooth plateau as exploration noise contributes only marginal gains. Because elitism is enforced and bound handling uses reflection with clipping, the best-so-far value is non-decreasing. It remains feasible over the entire trajectory, evidencing a stable balance between exploration and exploitation

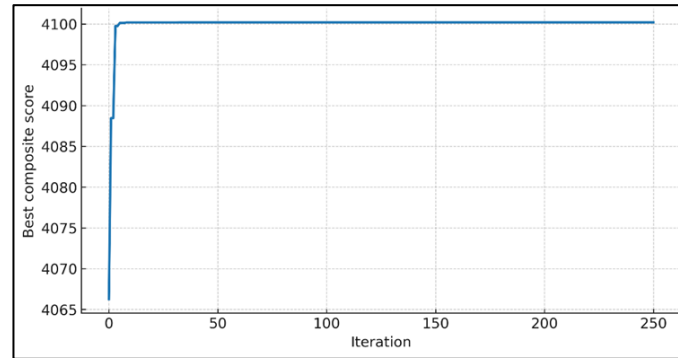


Figure 2: Thunderstorm Algorithm Convergence.

Source: Authors, (2026).

At convergence, the algorithm yields an interior optimum $H = 64.95$ m, $\eta = 0.745$ and $\text{gate} = 0.904$. The stored energy term reaches the battery capacity limit of 5,000 kWh—identical to the baseline—so subsequent objective gains arise from the stability components. This is reflected in the final operating profile: the standard deviation of hourly power decreases from 19.186 kW (baseline) to 17.264 kW and the cumulative ramp $\sum |\Delta P|$ declines from 171.636 kW to 154.440 kW, representing =10.0% reductions for both metrics. The location of the optimum—interior for H and gate and nearer the lower side for η —indicates a deliberate trade-off implicitly learned by the optimizer: slightly tempering instantaneous power to produce a smoother hourly trajectory without sacrificing the day-end energy outcome once the storage ceiling is reached. Overall, the convergence behaviour confirms that the proposed TA configuration efficiently navigates the bounded, multi-variable design space and consistently settles into a high-quality region where energy saturation is preserved and stability is materially improved.

III.2 OPTIMAL DESIGN PARAMETERS

Table 1 summarizes the optimal parameter set returned by the Thunderstorm Algorithm (TA) and contrasts it with the fixed baseline. TA converges to an interior solution with $H=64.95$ m, $\eta=0.745$, and $\text{gate}=0.904$. Relative to the baseline configuration ($H = 60.0$ m, $\eta = 0.90$, $\text{gate} = 0.90$), the optimized head increases modestly by about 8.25%, while the gate opening remains close to the original setting and the effective electro-mechanical efficiency moves toward a lower operating point. This shift reflects the composite objective: once daily stored energy reaches the battery capacity limit (5,000 kWh for both baseline and TA), the optimizer prioritizes stability to further improve the score. Consistent with that logic, the optimized design reduces the standard deviation of hourly power from 19.186 kW to 17.264 kW and lowers the cumulative ramp $\sum |\Delta P|$ from 171.636 kW to 154.440 kW—improvements of −1.922 kW and −17.196 kW, respectively, which correspond to =10.0% reductions for both metrics. In practical terms, a slightly higher head combined with nearly unchanged gate opening and a more conservative effective efficiency yields a smoother intra-day power trajectory without compromising the end-of-day energy outcome, which is constrained by storage saturation. The result illustrates how TA navigates the head–efficiency–gate trade space to preserve energy yield under a capacity ceiling while materially enhancing operational stability—an attribute that is beneficial for downstream power conditioning, battery thermal management, and grid interfacing.

Table 1: Baseline vs TA Optimal Design.

Parameter	Baseline Design	TA Optimal Design
Head, H (m)	60.0	64.95
Efficiency, η (–)	0.90	0.745
Gate Opening (–)	0.90	0.90
Stored Energy (kWh)	5	5
Std. of Power (kW)	19.186	17.264
Ramp Rate $\sum \Delta P $ (kW)	171.64	154.44

Source: Authors, (2026).

III.3 HOURLY POWER PROFILES

Figure 3 contrasts the 24-hour power trajectories of the baseline configuration with the Thunderstorm Algorithm (TA) design obtained in Section 3.2 under the same inflow series. While both settings deliver the same end-of-day stored energy due to the battery capacity ceiling (5,000 kWh), the TA solution reshapes the intraday profile to be measurably smoother. By jointly selecting $H = 64.95$ m, $\eta = 0.745$ and $\text{gate} = 0.904$, TA tempers hour-to-hour fluctuations relative to the baseline ($H = 60$ m, $\eta = 0.90$, $\text{gate} = 0.90$), reducing the standard deviation of hourly power from 19.186 kW to 17.264 kW and the cumulative ramp $\sum |\Delta P|$ from 171.636 kW to 154.440 kW (both $\approx 10\%$ decreases). Visually, the TA curve exhibits less pronounced rises and falls across the day—particularly around transitions between lower- and higher-flow periods—indicating that the optimizer traded small increments in instantaneous output for improved temporal regularity once energy saturation made further gains in daily yield unattainable. This smoothing is operationally relevant: it mitigates inverter/loading stress, eases battery thermal management, and simplifies power-conditioning and grid-interface control without sacrificing total energy delivered.

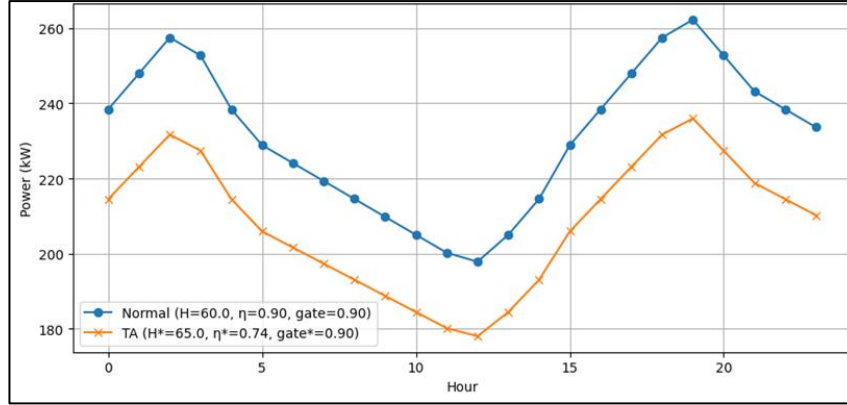


Figure 3: Hourly Power Profile: Baseline vs TA.
Source: Authors, (2026).

Although both configurations deliver identical daily stored energy due to the battery capacity ceiling, the temporal structure of the power trajectories reveals a fundamentally different dynamic behavior. In the baseline configuration, power output more directly follows discharge variability, resulting in a more reactive system response. In contrast, the TA-optimized design exhibits a damped dynamic profile, where inter-hour transitions occur more gradually. This behavior can be interpreted through the coupled interaction of head, efficiency, and gate opening in the power model (Equation 1). A moderate increase in head combined with an adjusted effective efficiency redistributes instantaneous power production over the 24-hour horizon. Rather than maximizing peak output, the optimizer reduces the system's sensitivity to inflow fluctuations, effectively reshaping the energy release pattern without altering the daily total constrained by storage capacity. From a power systems perspective, this smoother trajectory carries important operational benefits. Reduced variability lowers switching stress on power electronics, mitigates DC-side current oscillations in the storage interface, and decreases rapid gradient changes that may accelerate battery thermal cycling. Therefore, the observed stability improvement is not merely statistical but functionally relevant for hardware reliability and long-term system durability. Furthermore, the results demonstrate that under storage saturation conditions, a more conservative yet controlled power profile can enhance operational robustness without sacrificing yield. This confirms that the Thunderstorm Algorithm inherently internalizes system constraints and adaptively shifts from instantaneous maximization toward dynamic stability enhancement. The temporal differences between the baseline and TA-optimized power profiles shown in Figure 3 can be theoretically interpreted through the composite objective function defined in Equation (5). This formulation simultaneously maximizes daily stored energy E_{total} while penalizing power variability via the standard deviation σ_P and cumulative ramp $\sum |\Delta P|$, weighted by w_σ and w_r , respectively. When daily stored energy reaches the battery capacity ceiling, the marginal contribution of additional power to E_{total} effectively vanishes. Consequently, the partial derivative of the objective function with respect to the energy term approaches zero. Under this condition, the objective gradient becomes dominated by the stability penalties:

$$\frac{\partial f}{\partial x} \approx -w_\sigma \frac{\partial \sigma_P}{\partial x} - w_r \frac{\partial (\sum |\Delta P|)}{\partial x} \quad (6)$$

Where $x \in \{H, \eta, \text{gate}\}$.

This theoretical shift implies that the optimization search direction transitions from energy maximization toward fluctuation minimization once the storage constraint becomes binding. Hence, although both configurations achieve identical daily energy, the TA solution improves the composite objective by reshaping the temporal power distribution. Moreover, due to the nonlinear coupling between design variables and instantaneous power (Equation 1), small variations in head, efficiency, and gate opening alter the time-domain structure of power output differently. Because the stability penalties operate globally across the 24-hour horizon, the optimizer implicitly reduces system sensitivity to inflow variability rather than merely suppressing peak power.

III.4 CORRELATION ANALYSIS

Table 2 reports the predictive performance of a simple linear surrogate that maps the design variables (H, η, gate) to daily stored energy E_{total} using a 75/25 train–test split. The surrogate achieves strong association with the ground truth (Pearson $r = 0.9701$; $R^2 = 0.9310$), indicating that it explains about 93% of the variance in E_{total} while preserving a near-linear ranking of outcomes across the design space.

In absolute terms, the MAE is modest at = 22.76 kWh, whereas the RMSE is = 481.75 kWh; the latter is inflated by a small number of high-error points near the storage-saturation boundary, where the ceiling effect makes errors more sensitive to local deviations. Crucially, the relative error remains very low (MAPE = 0.49%, Accuracy = 99.51%), reflecting that, on the daily-energy scale of several MWh, the surrogate's predictions are practically indistinguishable from the simulated values for most samples. These results justify using the surrogate for rapid sensitivity screening and design-space visualization alongside the full TA-based simulator, while recognizing that ceiling-induced heteroscedasticity can inflate RMSE without undermining the high correlation and low percentage error observed in Table 2.

Table 2: Surrogate Regression Metrics (Etotal).

Metric	Value
RMSE (kWh)	48.175
MAE (kWh)	22.7551
MAPE (%)	0.49
Accuracy (%)	99.51
R ²	0.9310
Pearson r	0.9701

Source: Authors, (2026).

The results in Table 2 demonstrate that the linear surrogate explains 93.10% of the variance in daily stored energy ($R^2 = 0.9310$) with a very strong correlation ($r = 0.9701$). The extremely low MAPE (0.49%) and high predictive accuracy (99.51%) indicate that, at the multi-MWh daily energy scale, the relative prediction error is practically negligible. This suggests that within the bounded design space, the relationship between the design variables (H , η , gate) and stored energy behaves approximately linearly. Nevertheless, the higher RMSE compared to MAE reveals localized heteroscedasticity, particularly near the battery storage ceiling. Under saturation conditions, additional power increases do not translate into higher stored energy due to the 5 MWh capacity constraint. Consequently, small deviations in the design variables can yield squared errors that inflate RMSE, even though the relative percentage error remains minimal. From an optimization perspective, this confirms that once the energy ceiling is reached, further improvements in the composite objective arise primarily from stability terms (σP and cumulative ramp) rather than energy maximization. This behavior substantiates the adaptive nature of the Thunderstorm Algorithm (TA), which implicitly shifts focus from yield maximization toward power smoothing when storage saturation occurs. Future Refinement Directions, Several improvements may further strengthen the framework: Employ nonlinear surrogate models (e.g., polynomial regression or Gaussian Process regression) to better capture the saturation boundary behavior. Conduct variance-based sensitivity analysis (e.g., Sobol indices) to quantify the relative influence of H , η , and gate on both energy and stability. Perform robustness testing against variations in battery capacity and penalty weights. Extend the formulation toward an explicit multi-objective TA to generate a Pareto front illustrating the trade-off between energy yield and temporal stability. These refinements would enhance methodological robustness and reinforce the contribution of the proposed TA framework to battery-integrated micro-hydropower optimization.

IV. CONCLUSIONS

The Thunderstorm Algorithm (TA) effectively explores the bounded micro-hydropower design space, consistently delivering a configuration that preserves daily energy while reducing power variability. With $H = 64.95$ m, $\eta = 0.745$, and gate = 0.904, stored energy remains at the battery ceiling (5,000 kWh), whereas the power standard deviation drops from 19.186 kW to 17.264 kW and $\sum|\Delta P|$ from 171.636 kW to 154.440 kW ($\approx 10\%$ reductions). Pearson correlation and the surrogate regression (RMSE 48.175 kWh; $R^2 = 0.93$; MAPE 0.49%) confirm that η is the most influential driver, followed by gate and head. Joint tuning via TA therefore produces smoother intraday power without sacrificing yield, making it practical for power conditioning, battery thermal management, and grid interfacing. Future work will validate the approach experimentally, extend to multi-objective TA with explicit constraints, and investigate capacity and weight sensitivities.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Samsurizal, Yulisya Zuriatni and Andi Makkulau.

Methodology: Samsurizal.

Investigation: Samsurizal, Yulisya Zuriatni and Andi Makkulau.

Discussion of results: Samsurizal and Andi Makkulau.

Writing – Original Draft: Samsurizal.

Writing – Review and Editing: Samsurizal, Yulisya Zuriatni.

Resources: Samsurizal, Yulisya Zuriatni and Andi Makkulau.

Supervision: Samsurizal.

Approval of the final text: Samsurizal.

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