

INTELLIGENT OPTIMIZATION OF HEAT EXCHANGER OPERATING PARAMETERS FOR IMPROVED ENERGY PERFORMANCE

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ABSTRACT

Heat exchangers are central to energy recovery in process industries, yet they are frequently operated at conservative, fixed set-points that ignore fouling and changing inlet conditions. This empirical study investigates whether a data-driven optimization framework can improve the energy performance of a counter-flow heat exchanger by tuning its operating parameters. A dataset of 1,500 operating records, generated from an effectiveness–NTU thermo-hydraulic model with 1% Gaussian measurement noise, covered hot- and cold-side flow rates, hot and cold inlet temperatures, and fouling resistance. Five surrogate learners were compared, and the best was coupled with a genetic algorithm and particle swarm optimization to maximize exergy efficiency subject to a minimum heat duty of 400 kW. Support vector regression gave the most accurate surrogate ($R^2 = 0.994$ for exergy efficiency on unseen data). Across clean, moderately fouled and severely fouled conditions, the optimized set-points raised exergy efficiency by 7.6%, 12.1% and 16.7%, cut pumping power by 73.1%, 67.3% and 51.4%, and reduced exergy destruction by up to 24%, while still delivering at least 405 kW. The two optimizers converged to practically identical solutions, within 1% of an exhaustive-search reference. The benefit grew with fouling severity, showing that adaptive set-points matter most when the unit is degraded. Pumping-energy savings of about 20 MWh per year were estimated for a single unit. Lower flow rates combined with a higher hot-inlet temperature, rather than customary high-flow practice, gave the best energy performance within the studied envelope. The findings should be confirmed on plant measurements before deployment.

Keywords: *Heat exchanger¹; energy performance²; exergy efficiency³; operating parameter optimization⁴; machine learning surrogate⁵; genetic algorithm⁶; particle swarm optimization⁷*

1. INTRODUCTION

1.1 Background and Motivation

Heat exchangers transfer thermal energy between process streams and underpin power generation, refining, chemical processing, HVAC and waste-heat recovery [1], [2]. Because they sit at the interface between energy supply and demand, small changes in their operating condition propagate into fuel use, electricity consumption and emissions across the whole plant. In practice, operators tend to run exchangers at conservative flow rates and fixed temperature set-points chosen at the design stage, so that duty is met even when the unit degrades [3]. This habit protects the process but wastes pumping energy and increases thermodynamic irreversibility. Rising energy costs and decarbonization targets therefore make operating-stage optimization attractive, since it needs no new hardware and can be applied to existing assets [4]. Even modest gains in effectiveness or pumping efficiency, multiplied across the many units installed in a facility, translate into significant annual energy savings.

1.2 Problem Statement and Research Gap

Most published optimization of heat exchangers addresses the design stage, where geometry, tube layout or fin parameters are selected to minimize cost or entropy generation [5], [6]. Operating parameters are studied less often, even though they must be adjusted throughout the life of the unit as fouling accumulates and inlet conditions drift [7]. First-principles models can optimize operation but are slow to embed in repeated search, whereas empirical rules of thumb ignore the interactions among flow rates, temperatures and fouling. Surrogate models learned from operating data offer a way to combine accuracy with speed [8], yet systematic comparisons of learners and metaheuristic optimizers, tested under different fouling states, remain scarce. As a result, set-points are rarely revisited, and the energy penalty of a degraded or over-pumped exchanger often goes unnoticed in routine operation.

1.3 Objectives and Contributions

This paper develops and evaluates an intelligent optimization framework for the operating parameters of a counter-flow heat exchanger. The objectives are to (i) construct a 1,500-record operating dataset covering flow rates, inlet temperatures and fouling; (ii) compare five machine-learning surrogates for predicting exergy efficiency and heat duty; (iii) couple the best surrogate with a genetic algorithm and particle swarm optimization to maximize exergy efficiency under a heat-duty constraint; and (iv) quantify the resulting gains in clean, moderately fouled and severely fouled states. The contribution is an empirical, data-centred demonstration, supported by five tables and five figures, that adaptive set-points improve energy performance most when the exchanger is degraded. The study also examines whether two widely used metaheuristics give different answers, and whether the choice of surrogate affects the quality of the optimum.

2. LITERATURE SURVEY

The thermal behaviour of heat exchangers is conventionally described by the effectiveness–number of transfer units (ϵ –NTU) method and the log-mean temperature difference approach, which relate duty to flow capacity rates and overall conductance [1]–[4]. Beyond the first law, exergy and entropy-generation analysis expose the

irreversibility caused by finite temperature differences and by friction, giving a more discriminating measure of quality than duty alone [5], [9], [10]. These tools make clear that thermal and hydraulic performance pull in opposite directions: higher flow raises the heat-transfer coefficient but also increases pumping power sharply. Fouling adds a time-varying penalty, raising thermal resistance and pressure drop together and eroding performance between cleaning events [7], [11]. A large body of work applies metaheuristics to exchanger design. Genetic algorithms have been used to minimize the total cost of shell-and-tube units, including capital and pumping expenses [6], [12], [13], and to account for maintenance [14]. Harmony search with sensitivity analysis [15], differential evolution [16], particle swarm optimization [17], artificial bee colony [18] and teaching–learning-based optimization [19] have each been reported to compare favourably with earlier methods, and genetic algorithms have also been applied to compact plate-fin exchangers [20]. These studies agree that metaheuristics handle the non-linear, constrained design space well, but nearly all of them treat geometry as the decision variable.

Data-driven models have become a practical companion to such searches. Artificial neural networks were shown early on to predict and control exchanger dynamics accurately [21], and neural networks cooperating with genetic algorithms have been used to design plate-fin exchangers [22]. The wider surrogate-modelling literature stresses that an inexpensive approximation can replace repeated calls to a costly model, provided its accuracy is verified [8]. Support vector regression [23], [24], random forests [25] and gradient boosting [26] offer alternatives to neural networks [27], with different behaviour on small, noisy datasets, and are readily available in open-source toolkits [28]. Their use in operation, as opposed to design, is far less documented. Three gaps emerge from this survey. First, operating parameters, which can be changed at no capital cost, receive far less attention than geometry. Second, studies rarely compare several learners before choosing a surrogate. Third, optimization is seldom tested across different fouling states, although degradation is the main reason that fixed set-points become inefficient. Closing them would allow exchanger operation to be adjusted in response to measured conditions rather than fixed at design values. The present work addresses these three gaps.

3. METHODOLOGY

A water-to-water counter-flow exchanger with 14 m² of area was simulated using ϵ -NTU relations [2]. Film coefficients scale with flow to the power 0.8; pressure drop scales with flow to the power 1.8 and rises with fouling; pump efficiency is 0.60. Hot flow m_h and cold flow m_c (0.8–3.5 kg/s), hot inlet (90–115 °C) and cold inlet (15–35 °C) temperatures, and fouling resistance ($0\text{--}4\times 10^{-4}$ m²·K/W) were sampled uniformly to give 1,500 records, and 1% Gaussian noise was added to every output. Outputs were heat duty Q , effectiveness, pumping power, pressure drop, exergy destruction and exergy efficiency η_{ex} , defined as exergy gained by the cold stream divided by exergy lost by the hot stream plus pumping work. Surrogates for η_{ex} and Q were trained on 80% of the data and tested on 20%. Linear regression, support vector regression (RBF kernel), random forest, gradient boosting and a two-layer neural network were compared by R^2 , RMSE, MAE and five-fold cross-validated R^2 , with standardized inputs, using scikit-learn [28]. Hyper-parameters were fixed a priori, and the same split was used for every model to keep the comparison fair. Pearson correlation and permutation importance quantified how each input drives the outputs.

The best surrogate was embedded in a genetic algorithm [29] and a particle swarm optimizer [30] that choose m_h , m_c and hot inlet temperature to maximize η_{ex} , penalizing predicted duty below 408 kW (400 kW plus 2% margin). Each used 40 individuals and 60 generations, with 20 independent runs for clean, moderate (1.5×10^{-4}) and severe ($3.5 \times 10^{-4} \text{ m}^2 \cdot \text{K/W}$) fouling at a 25 °C cold inlet. Solutions were re-evaluated on the thermo-hydraulic model, compared with a baseline of 2.6 kg/s, 2.2 kg/s and 100 °C, and checked against an exhaustive grid search. Feasibility was judged on the model, not the surrogate. The surrogate with the highest test R^2 is selected and passed to the GA and PSO search, which maximizes exergy efficiency subject to a minimum 400 kW duty. The best set-points are re-evaluated on the thermo-hydraulic model so that surrogate errors are not trusted blindly, and finally converted into energy-performance indicators: exergy efficiency, pumping power and exergy destruction. The loop can be repeated whenever fouling or inlet conditions change, retraining the surrogate on fresh data.

4. DATA COLLECTION AND ANALYSIS

This section reports the empirical analysis in five tables and four further figures. It begins with a description of the dataset, moves to surrogate accuracy and sensitivity, and then presents the optimization outcomes and their robustness to fouling. Unless stated otherwise, the cold inlet temperature is 25 °C and the heat-duty requirement is 400 kW.

4.1 Dataset Description

Table 1. Descriptive statistics of the 1,500-record operating dataset.

Variable	Unit	Min	Max	Mean	SD
Hot-side flow rate $\dot{m}_h$	kg/s	0.80	3.50	2.19	0.78
Cold-side flow rate $\dot{m}_c$	kg/s	0.80	3.50	2.12	0.77
Hot inlet temperature $T_{h,in}$	°C	90.0	115.0	102.7	7.1
Cold inlet temperature $T_{c,in}$	°C	15.0	35.0	25.4	5.8
Fouling resistance R_f	$10^{-4} \text{ m}^2 \cdot \text{K/W}$	0.00	3.99	1.97	1.16
Heat duty Q	kW	179.2	878.8	428.4	129.3
Effectiveness ϵ	–	0.568	0.997	0.811	0.095
Exergy efficiency η_{ex}	–	0.056	0.709	0.496	0.107
Pumping power W_p	kW	0.16	12.42	3.86	2.30
Exergy destruction	kW	7.2	98.3	33.8	13.3
Total pressure drop ΔP	kPa	119	2184	876	382

Table 1 summarizes the 1,500-record dataset. The inputs span wide operating windows, with flow rates covering a 4.4-fold range and fouling resistance approaching $4.0 \times 10^{-4} \text{ m}^2 \cdot \text{K/W}$. The outputs vary strongly: heat duty ranges from 179 to 879 kW and exergy efficiency from 0.056 to 0.709, with a mean of 0.496. Pumping power varies by almost two orders of magnitude (0.16–12.4 kW) because pressure drop scales steeply with flow. This spread confirms that operating choices materially affect energy performance, which justifies optimization, and it implies that any model must capture strongly non-linear behaviour rather than simple linear trends.

4.2 Surrogate Model Performance

Table 2: Surrogate model performance on the 300-record test set (cross-validation uses all 1,500 records).

Model	$R^2 (\eta_{ex})$	RMSE	MAE (η_{ex})	$R^2 (Q)$	RMSE (Q),	CV $R^2 (\eta_{ex})$
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		(η_{ex})			kW	
Linear regression	0.798	0.0489	0.0370	0.853	52.9	0.801
SVR (RBF)	0.994	0.0084	0.0061	0.997	6.9	0.995
Random forest	0.899	0.0346	0.0255	0.969	24.2	0.884
Gradient boosting	0.979	0.0156	0.0119	0.987	15.7	0.979
ANN (MLP)	0.977	0.0166	0.0129	0.994	10.5	0.972

Table 2 compares the five surrogates on the held-out test set. Linear regression is clearly inadequate ($R^2 = 0.798$ for η_{ex}), confirming non-linearity. Random forest improves this to 0.899, while gradient boosting and the neural network reach 0.979 and 0.977. Support vector regression is best, with $R^2 = 0.994$, an RMSE of 0.0084 and an MAE of 0.0061 for η_{ex} , and $R^2 = 0.997$ for heat duty with an RMSE of 6.9 kW. A cross-validated R^2 of 0.995 shows that this result is not an artefact of one split. SVR was therefore selected for optimization; its error is comparable with the 1% noise injected into the data, which sets a practical accuracy floor.

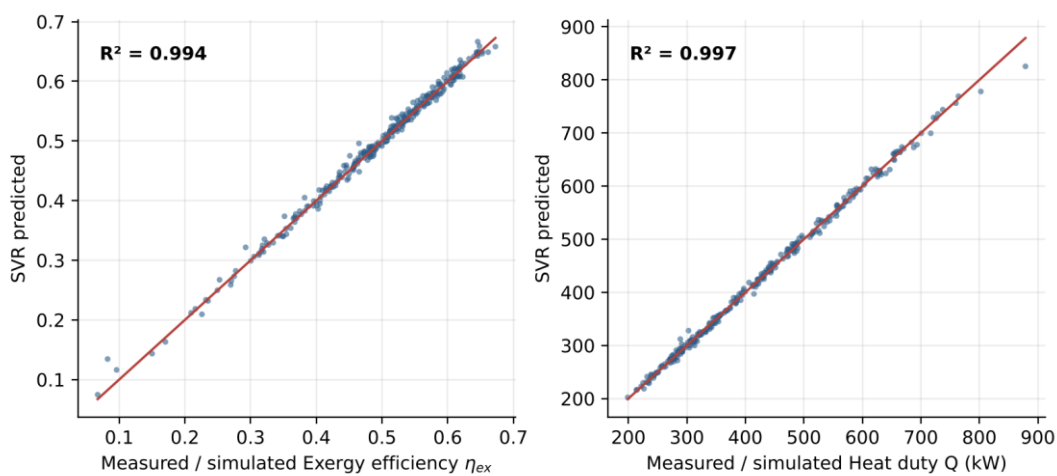


Figure 1: Predicted versus simulated exergy efficiency (left) and heat duty (right) for the SVR surrogate on the test set.

Figure 1 plots surrogate predictions against simulated values for the 300 test records. Points cluster tightly around the 45-degree line for both exergy efficiency (left) and heat duty (right), with R^2 values of 0.994 and 0.997. Scatter is slightly larger at low exergy efficiency, where the response is steep (RMSE 0.0099 against 0.0076 elsewhere). The mean bias is small, about +0.0015 in exergy efficiency, so the surrogate is essentially unbiased in the region the optimizer will search. This agreement justifies replacing the thermo-hydraulic model with SVR during search, which allowed 2,440 evaluations per run in about 0.2 seconds per optimizer run.

4.3 Sensitivity of Energy Performance to Operating Parameters

Table 3: Pearson correlation of inputs with outputs and permutation importance for exergy efficiency (SVR surrogate).

Input	r with Q	r with η_{ex}	r with W_p	Permutation importance (η_{ex})
Hot flow $\dot{m}_h$	0.56	0.29	0.72	0.207
Cold flow $\dot{m}_c$	0.56	-0.59	0.53	0.403
Hot inlet $T_{h,in}$	0.31	0.09	0.00	0.005
Cold inlet $T_{c,in}$	-0.24	0.55	0.01	0.299
Fouling R_f	-0.14	-0.29	0.22	0.087

Table 3 relates each input to the outputs through Pearson correlation and to exergy efficiency through permutation importance. Heat duty rises with both flow rates ($r \approx 0.56$) and, more weakly, with hot inlet temperature (0.31). Pumping power is dominated by hot-side flow ($r = 0.72$) and cold-side flow (0.53). Exergy efficiency, however, falls as cold-side flow increases ($r = -0.59$) and rises with cold inlet temperature (0.55), because a smaller temperature gap reduces irreversibility. Permutation importance ranks cold flow (0.40) and cold inlet temperature (0.30) first and hot flow (0.21) next, while hot inlet temperature (0.005) hardly affects exergy efficiency directly, although it strongly controls duty.

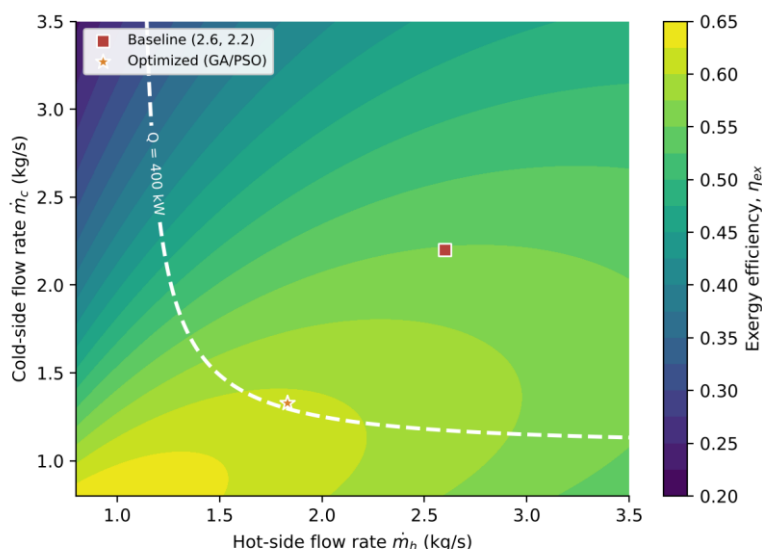


Figure 2: Exergy-efficiency response surface over hot- and cold-side flow rates for moderate fouling (hot inlet 113.8 °C, cold inlet 25 °C). The baseline marker is shown at its flow rates only; its own hot inlet temperature is 100 °C.

Figure 2 maps exergy efficiency over the hot- and cold-side flow plane for moderate fouling, a hot inlet of 113.8 °C and a cold inlet of 25 °C. Efficiency is highest at low flows, where effectiveness is large and pumping is small, but such flows cannot deliver the required duty. The dashed white contour marks the 400 kW boundary, and feasible points lie above and to the right of it. The optimum therefore sits on this boundary, at roughly 1.8 and 1.3 kg/s, whereas the baseline of 2.6 and 2.2 kg/s lies well inside the feasible region on a lower-efficiency plateau.

4.4 Optimization Results

Table 4: Optimization results for moderate fouling ($R_f = 1.5 \times 10^{-4} \text{ m}^2 \cdot \text{K/W}$, $T_{c,in} = 25 \text{ °C}$). GA and PSO columns show the median run, re-evaluated on the thermo-hydraulic model.

Parameter	Baseline	GA	PSO	Grid search (reference)
Hot flow $\dot{m}_h$ (kg/s)	2.60	1.83	1.82	1.90
Cold flow $\dot{m}_c$ (kg/s)	2.20	1.33	1.33	1.25
Hot inlet $T_{h,in}$ (°C)	100.0	113.6	113.8	115.0
Heat duty Q (kW)	510.8	406.1	405.9	400.0
Effectiveness ε	0.740	0.822	0.820	0.849

Exergy efficiency η_{ex}	0.539	0.604	0.605	0.608
Pumping power W_p (kW)	3.86	1.29	1.26	1.34
Exergy destruction (kW)	36.1	28.0	28.0	28.4
Mean η_{ex} over 20 runs ($\pm$ SD)	–	0.6041 ± 0.0003	0.6046 ± 0.0004	–
Time per run (s) / evaluations	–	0.20 / 2,440	0.19 / 2,440	–
Feasible runs ($Q \geq 400$ kW)	–	100%	100%	–

Table 4 compares the baseline with GA, PSO and an exhaustive-search reference for moderate fouling. Both metaheuristics reduce hot flow from 2.6 to about 1.8 kg/s and cold flow from 2.2 to 1.33 kg/s while raising the hot inlet temperature to about 113.7 °C. Heat duty falls from 511 to 406 kW, which still meets the 400 kW requirement. Exergy efficiency improves from 0.539 to 0.604 (GA) and 0.605 (PSO), pumping power falls from 3.86 to about 1.27–1.29 kW, and exergy destruction drops by roughly 22%. The 20-run means differ by only 0.0005 and every run was feasible, so the two optimizers are practically indistinguishable. The grid reference reaches 0.608, confirming near-optimality.

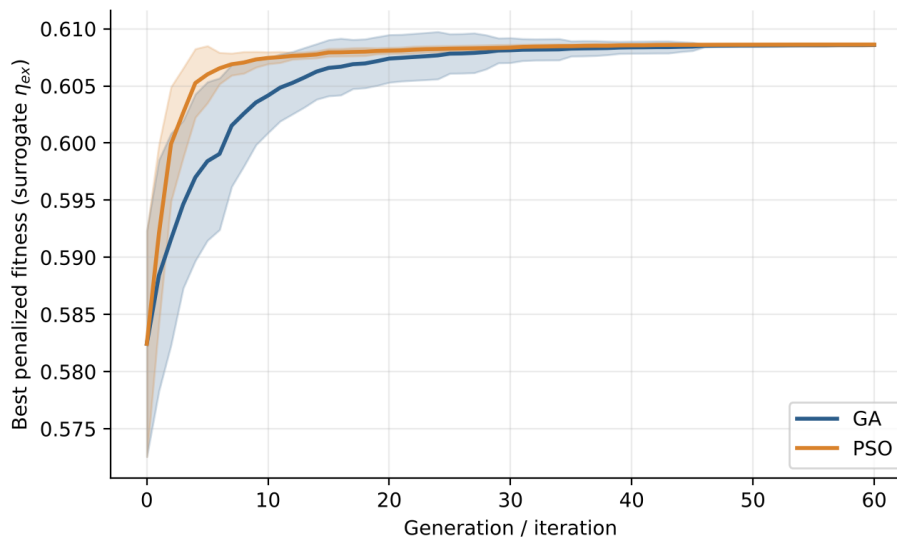


Figure 3: Convergence of GA and PSO (mean $\pm$ SD of 20 runs) for moderate fouling.

Figure 3 shows the best penalized fitness against generation or iteration, averaged over 20 runs (population best, 40 individuals), with shaded bands of one standard deviation. Both algorithms start from random populations near 0.58 and climb quickly. PSO is faster, coming within 0.001 of its final value after about 12 iterations, whereas GA needs about 23 generations. Both then settle at about 0.609, the surrogate-predicted value, which is slightly above the 0.604–0.605 obtained when the solutions are re-evaluated on the thermo-hydraulic model. The narrow bands show that results do not depend on the random seed. Either algorithm is adequate here.

4.5 Performance under Different Fouling States

Table 5: Optimized (PSO) versus baseline performance in three fouling states (R_f in $m^2 \cdot K/W$; savings at 8,000 h per year).

R_f state	η_{ex} base	η_{ex} opt.	$\Delta\eta_{ex}$ (%)	W_p base (kW)	W_p opt. (kW)	ΔW_p (%)	Δ Exergy destr. (%)	Pump saving (MWh/yr)
Clean (0)	0.602	0.648	+7.6	3.15	0.85	−73.1	−24.0	18.5

Moderate (1.5×10^{-4})	0.539	0.605	+12.1	3.86	1.26	-67.3	-22.7	20.8
Severe (3.5×10^{-4})	0.472	0.551	+16.7	4.81	2.34	-51.4	-11.8	19.8
Mean	—	—	+12.1	—	—	-63.9	-19.5	19.7

Table 5 tests the PSO solution against the baseline in three fouling states. The relative gain in exergy efficiency grows with degradation, from 7.6% when clean to 12.1% when moderately fouled and 16.7% when severely fouled. Pumping power falls by 73.1%, 67.3% and 51.4%, and exergy destruction by 24.0%, 22.7% and 11.8%. Every case still delivers more than 405 kW. Averaged over the three states, efficiency rises 12.1%, pumping power falls 63.9% and exergy destruction falls 19.5%. The pumping saving of 18.5–20.8 MWh per year, at 8,000 operating hours, is broadly stable across fouling states, so the thermal benefit is what grows with degradation.

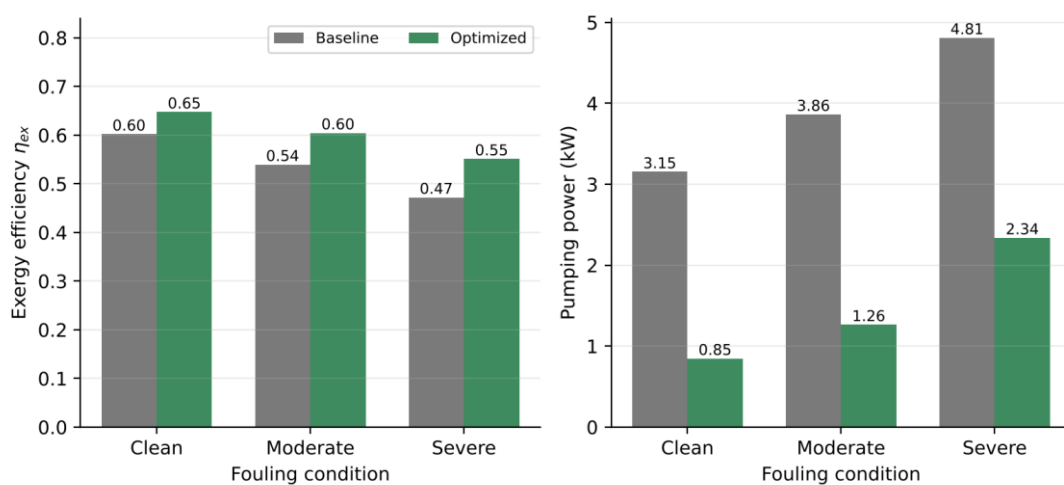


Figure 4: Baseline versus optimized exergy efficiency (left) and pumping power (right) under three fouling states.

Figure 4 contrasts baseline and optimized operation under clean, moderate and severe fouling. The left panel shows exergy efficiency, which declines with fouling for both strategies but is always higher after optimization, widening the gap from 0.05 to 0.08. The right panel shows pumping power, which grows with fouling in the baseline from 3.15 to 4.81 kW, while optimized values stay between 0.85 and 2.34 kW. The figure therefore visualizes the central result: adaptive set-points mitigate fouling penalties and cut hydraulic energy at the same time. Duty remains above 405 kW throughout, so these savings do not sacrifice process requirements.

5. DISCUSSION

5.1 Critical Analysis of the Data

The results show consistent gains, but several features of the data deserve scrutiny. First, part of the improvement comes from removing duty over-delivery: the baseline supplies 466–550 kW against a 400 kW requirement, so some pumping and exergy loss is avoided simply by meeting, not exceeding, the target. Second, the optimizer drives the hot inlet temperature to or near its 115 °C upper bound in every state, so the solution is constraint-active and its benefit depends on the process permitting that temperature. Third, the surrogate RMSE

of 0.0084 is close to the injected noise, so the GA–PSO difference of 0.0005 is below model resolution and should not be read as superiority. Fourth, the baseline is a single assumed operating point; a better-tuned manual set-point would narrow the margin, although the exhaustive search shows that the true optimum lies close to the GA and PSO solutions. Fifth, the annual savings estimate assumes continuous operation at constant fouling, which real plants rarely achieve in practice. Finally, the data are generated from a model rather than measured on a plant, so effects such as flow maldistribution, property variation and dynamic fouling are absent, and the percentages are indicative rather than guaranteed.

5.2 Comparison with Past Work

The findings are consistent with, and extend, earlier work. Metaheuristic design studies of shell-and-tube exchangers using genetic algorithms [6], [12]–[14], particle swarm optimization [17] and other algorithms [15], [16], [18], [19] report lower cost or better thermal–hydraulic trade-offs than reference designs. The present results echo that conclusion for operation rather than design, since both GA and PSO reduced pumping energy while preserving duty. Some earlier comparisons found one algorithm superior to another on design problems [16], [17], [19]; here GA and PSO are practically equivalent, which is plausible because only three decision variables are involved.

Earlier surrogate-assisted work paired neural networks with genetic algorithms for plate-fin design [22] and used neural networks for dynamic exchanger prediction [21]. The present comparison adds that, on a moderately sized, noisy tabular dataset, support vector regression slightly outperformed a neural network, whereas linear regression and random forest were inferior. This does not contradict the neural-network literature, because network performance depends on data volume and tuning [27], but it cautions against defaulting to neural networks. Surrogate error, rather than algorithm choice, therefore limits the accuracy of the final solution, as the 0.004 gap between predicted and re-evaluated efficiency shows.

Previous studies mostly treated geometry as the decision variable and evaluated a single fouling state. By contrast, the present study optimizes set-points of an existing unit, and its benefit increases with fouling severity, which links to the degradation described in the fouling literature [7], [11]. Using exergy efficiency as the objective follows the thermodynamic view of [5], [9], [10] and penalizes both temperature gaps and pumping. Because the records here are simulated, direct numerical comparison of percentage gains with published case studies would be misleading. Finally, because the optimizer is cheap to run, it can be repeated each time fouling is re-estimated, something design-stage studies cannot offer.

6. CONCLUSION

This study set out to determine whether intelligent, data-driven optimization of operating parameters can improve the energy performance of a counter-flow heat exchanger. Using a 1,500-record dataset, five surrogate learners and two metaheuristic optimizers, the answer within the studied envelope is yes. Support vector regression proved the most reliable surrogate, with R^2 of 0.994 for exergy efficiency, and made repeated search practical at about 0.2 seconds per run. The genetic algorithm and particle swarm optimization converged to nearly identical set-points, lowering hot flow to about 1.7–2.2 kg/s and cold flow to about 1.3–1.4 kg/s, and

raising the hot inlet temperature towards its upper limit. These set-points lifted exergy efficiency by 7.6%, 12.1% and 16.7% in clean, moderately fouled and severely fouled conditions, reduced pumping power by 51–73% and exergy destruction by 12–24%, and still delivered more than 405 kW. The gain increased with fouling, confirming the relationship stated in the abstract: adaptive operating set-points matter most when the exchanger is degraded. The estimated saving of roughly 20 MWh of pumping electricity per year, although modest for one unit, becomes substantial across a plant. The results rest on simulated records, and part of the improvement comes from removing duty over-delivery, so field validation with plant data and dynamic fouling models is the necessary next step. Future work should extend the framework to multi-objective trade-offs, online learning and cleaning-schedule decisions. Taken together, the evidence supports a practical recommendation: operate with lower flows and a higher hot-inlet temperature, and re-optimize as fouling develops.

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