Demand Response Optimization for Vietnamese Manufacturing: Benchmarking Fuzzy Logic Against Metaheuristic Methods

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Abstract-Vietnam's June 2023 power crisis ($1.4B damages) prompted thousands of manufacturers to join EVN demand response programs. This benchmarking study compares Mamdani fuzzy logic control against genetic algorithms (GA), particle swarm optimization (PSO), rule-based heuristics, and a rolling-horizon nonlinear programming (RH-NLP) baseline for industrial load management under EVN's time-of-use tariffs (peak 3,398 VND/kWh, off-peak 1,190 VND/kWh). Using binary scheduling for discrete CNC machines and continuous modulation for thermal/pneumatic loads, Monte Carlo simulations across 100 randomized production scenarios demonstrate the RH-NLP upper bound achieves 44.0±2.5% mean savings (95% CI [43.5, 44.5]), followed by PSO (28.9±5.8%), GA (27.7±4.4%), fuzzy logic (13.5±5.8%), and rule-based approaches (11.8±6.7%). The Friedman non-parametric test with Kendall's W effect size confirms highly significant differences ($\chi^2(4) = 361.16$, $p < 0.001$, Kendall's $W = 0.903$, $N = 100$). Equipment flexibility analysis reveals CNC machines (33%), air compressors (32%), and HVAC (26%) as dominant contributors. Tariff sensitivity analysis shows DR savings increase monotonically with peak-to-off-peak ratio (18–24% for PSO across 1.5:1–4.0:1). Results establish cost-savings baselines for Vietnamese light-manufacturing SMEs (500–1000 kW class) and identify PSO as the best trade-off among embedded-friendly methods.

Keywords-EVN time-of-use tariff; industrial demand response; fuzzy inference systems; particle swarm optimization; Monte Carlo simulation; binary scheduling; Vietnamese manufacturing

I. INTRODUCTION

Vietnam's industrial electricity crisis intensified in June 2023 when prolonged shortages inflicted $1.4 billion economic damages and forced rotating blackouts across manufacturing zones [1]. Vietnam's energy-intensive growth trajectory [2], [3] has made demand-side management increasingly critical. In response, thousands of industrial facilities enrolled in Vietnam Electricity's (EVN) demand response program, leveraging time-of-use tariffs creating 2.85:1 peak-to-off-peak price ratios to incentivize load shifting [4]. However, industrial DR implementation faces unique constraints including production scheduling rigidity, equipment startup costs, and binary machine states [5], [6] that distinguish it from the well-studied residential sector. EVN's industrial tariff structure (Table I) enables facilities consuming 1,000 MWh monthly to potentially reduce electricity costs by 12–44% depending on optimization method.

Manufacturing demand response presents challenges distinct from residential applications [7] due to equipment complexity, production constraints, and quality requirements. A critical modeling consideration is the discrete nature of certain industrial loads: CNC machines operate in binary on/off states with significant startup energy penalties, unlike continuously modulatable HVAC or compressor systems. Fuzzy logic offers interpretable control suitable for resource-constrained operators but historically underperforms evolutionary methods [8], [9]. Metaheuristic algorithms achieve superior optimization but require specialized expertise

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[10], [11]. This performance-interpretability tradeoff remains inadequately quantified for Vietnamese industrial contexts.

This paper makes five research contributions: (i) a mixed binary–continuous MINLP formulation for industrial DR that captures CNC startup penalties absent in residential DR studies; (ii) the first empirical benchmark of five optimization paradigms (fuzzy, GA, PSO, rule-based, RH-NLP) under EVN's time-of-use tariff with a rigorous statistical protocol (Friedman + Kendall's W + Nemenyi post-hoc + bootstrap CIs over $N = 100$ Monte Carlo scenarios); (iii) quantification of the performance–interpretability–compute trade-off across the five paradigms on a common benchmark; (iv) a tariff-elasticity analysis positioning EVN's 2.85:1 peak-to-off-peak ratio on the savings-saturation curve; and (v) a tiered deployment roadmap (Rule→Fuzzy→PSO→RH-NLP oracle) matching Vietnamese SME resource constraints.

II. Related Work

A. Industrial Demand Response

Industrial DR research remains concentrated in developed-economy contexts. Golmohamadi [12] reviews DSM in heavy industries, noting limited coverage of light manufacturing in developing economies. Ranaboldo et al. [13] present a European industrial DR overview, while Williams et al. [5] identify production scheduling rigidity and equipment startup costs as key barriers unique to manufacturing-both modeled explicitly in this work. Shayeghi and Alilou [14] apply multi-objective ant lion optimization for DSM, and Goyal and Vadhera [15] address supply-side energy management through enhanced DR on the IEEE 30-bus system. Lu et al. [16] demonstrate data-driven price-based DR achieving 8–15% cost reductions. Mughees et al. [17] propose RL-based differential evolution achieving superior convergence but at prohibitive computational costs. Mourtzis [6] highlights the transition from continuous to discrete machine scheduling in Industry 4.0. No prior work benchmarks multiple paradigms for Southeast Asian manufacturing under TOU tariffs.

B. Fuzzy Logic in Energy Management

Fuzzy DR applications predominantly target residential HVAC [18] and smart homes [19]. Hua et al. [9] demonstrate 12.6% heating cost reduction. Keshtkar and Arzanpour [20] achieve 35% efficiency improvement in cold climates-different from discrete Vietnamese manufacturing. Ibrahim et al. [21] achieve 18–22% cost reduction via intelligent source selection. Alfaverh et al. [19] combine RL with fuzzy reasoning, outperforming standalone fuzzy by 8–12%. Industrial fuzzy DR remains sparse: the Mamdani system assumes continuous loads, whereas CNC machines require crisp on/off decisions-a mismatch central to the performance gap quantified here.

C. Tariff and Optimization

Faruqui et al. [22] find peak-to-off-peak ratios of 2:1 or higher produce meaningful load shifting with diminishing returns beyond 4:1-consistent with our findings. Tang et al. [23] demonstrate 7.4% operational cost reduction via NSGA-II. Schwenzer et al. [24] review MPC noting theoretical optimality but sensitivity to model accuracy. Yun et al. [10] deploy PSO achieving 14.2% cost reduction. Zhang et al. [11] apply GA to assembly line balancing. Javed et al. [25] compare heuristics for renewable optimization. No prior work benchmarks fuzzy versus multiple metaheuristics for Vietnamese manufacturing under EVN tariffs.

III. Methodology

We formulate industrial DR as a mixed-integer nonlinear program (MINLP). The objective minimizes total daily electricity cost over a 24-hour horizon ($T = 24, \Delta t = 1$ h), per (1):

$$C = \sum_{t=1}^{T} p(t) \cdot L(t) \cdot \Delta t + C_{startup} \quad (1)$$

where $p(t)$ is the EVN time-of-use tariff (Table I) and $C_{startup}$ is defined below. The aggregate load $L(t)$ decomposes into base load plus the controllable mix, per (2):

$$L(t) = L_{base} + \sum_{i \in I_b} s_{i(t)} \cdot P_i + \sum_{i \in I_c} u_{i(t)} \cdot P_i \quad (2)$$

with $L_{base} = 150$ kW; binary variables $s_{i(t)} \in \{0,1\}$ for $i \in I_b$ ($|I_b| = 5$ CNC machines, Class I); continuous $u_{i(t)} \in [0,1]$ for $i \in I_c$ ($|I_c| = 10$ modulatable loads - 3 compressors, 3 HVAC, 4 material handlers, Class II); and P_i the rated power of load i. Startup energy is tracked via binary state transitions, per (3):

$$C_{startup} = \bar{p} \cdot \sum_{i \in I_b} \sum_t E_{i,su} \cdot \max\left(0, s_{i(t)} - s_{i(t-1)}\right) \quad (3)$$

where $E_{i,su} = 0.8 - 2.5$ kWh per startup event and $\bar{p}$ is the average daily tariff. The optimization is subject to: (i) production hours $\sum_t s_{i(t)} \geq h_i^{min} \cdot U(t)$ for $i \in I_b$; (ii) ramp limits $\left|u_{i(t+1)} - u_{i(t)}\right| \leq \Delta u_i^{max}$ for $i \in I_c$; (iii) minimum utilization $u_{i(t)} \geq u_i^{min}$ for compressors and HVAC (thermal/buffer capacity); and (iv) availability: $s_{i(t)} = u_{i(t)} = 0$ if equipment i is unavailable. GA and PSO realize binary CNC decisions via sigmoid transfer functions on the [0,1] real space, then round. The rolling-horizon NLP (RH-NLP) baseline solves the continuous relaxation with multistart L-BFGS-B and rounds post-hoc; it serves as an offline upper-bound oracle, not a deployable controller.

A. Equipment Model

We model a Vietnamese mechanical facility with 15 controllable loads totaling 565kW flexible capacity plus 150kW base. Following ORNL's framework [26]: Class I (binary): five CNC machines (15–35kW, startup 0.8–2.5 kWh); Class II (continuous): three compressors (55–75kW, tanks 1.0–2.0 m³, 5–8 bar), three HVAC units (30–80kW, thermal inertia 1–2 hr at 34°C ambient), four material handlers (10–30kW).

TABLE I. EVN TIME-OF-USE TARIFF (22–110KV, DECISION 1279/QĐ-BCT [4])

Period	Time Window	Price (VND/kWh)

Peak	09:30-11:30, 17:00-20:00	3,398
Normal	04:00-09:30, 11:30-17:00, 20:00-22:00	1,833
Off-peak	22:00-04:00	1,190

Peak-to-off-peak ratio: 2.85:1. Effective May 10, 2025.

B. *Fuzzy Controller Design*

The Mamdani fuzzy system uses three inputs (Fig. 1): (i) price ratio (0.5–2.0) with 5 MFs aligned to EVN breakpoints; (ii) production urgency (0–100%) with 5 MFs computed via (4); (iii) load ratio (0–1) with 5 MFs. Output: curtailment action (0–100%) with 5 levels. The rule base comprises 33 expert-designed rules out of 125 possible (5^3). Uncovered regions default to zero curtailment (fail-safe). For binary CNC, output is thresholded at 60%: above triggers shutdown; below keeps CNC on. Centroid defuzzification converts fuzzy output to crisp percentages for continuous loads.

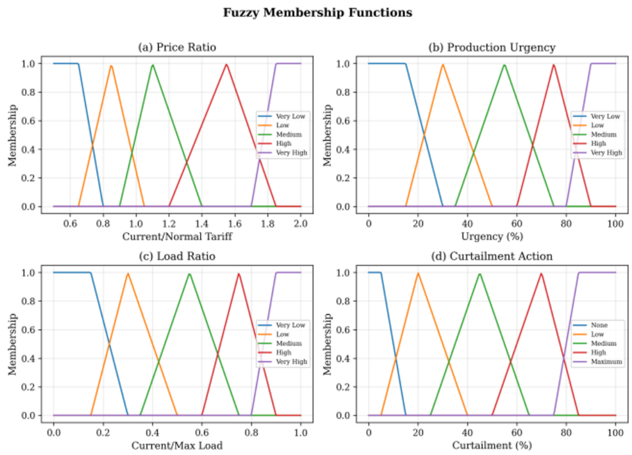

Figure 1. Fuzzy membership functions: (a) Price Ratio, (b) Production Urgency, (c) Load Ratio, (d) Curtailment Action.

C. *Baseline Methods*

All methods share identical constraints. GA: population 30, 25 generations, tournament selection (k=3), crossover 0.8, mutation 0.1, sigmoid binarization. PSO: 25 particles, 20 iterations, c1=c2=1.5, inertia 0.7→0.4 linearly decaying, sigmoid transfer. Rule-Based: priority-ranked threshold triggers. RH-NLP: 6-hour rolling horizon, multistart L-BFGS-B (2 random restarts), linear cost model, CNC rounded post-optimization. Stochastic methods run 5 independent trials per scenario.

D. *Monte Carlo Scenarios*

Urgency is defined by (4), where $D_{(rem)(t)}$ is the remaining time to deadline and D_{total} is the total order duration:

$$U(t) = 100 \times \left[1 - \frac{D_{(rem)(t)}}{D_{total}}\right] \quad (4)$$

100 production days are generated via Monte Carlo sampling, randomizing urgency (U[0.25, 0.90]), shift start (5–7h), shift end (20–23h), equipment availability (10% failure probability), and ambient temperature (28–38°C for Vietnamese tropical conditions). $N = 100$ ensures Friedman test has sufficient statistical power; Kendall's W is reported as effect size. Three named scenarios (Standard $U = 60\%$, High Urgency $U = 85\%$, Flexible $U = 35\%$) provide illustrative breakdowns.

E. *Simulation Environment*

Simulations use Python 3.11 with NumPy 1.26, SciPy 1.12 (L-BFGS-B for RH-NLP), and scikit-fuzzy 0.4.2 (Mamdani inference). 24-hour horizon, $\Delta t = 1$h, 24 decision variables per load. Seeds fixed for reproducibility. Runtime ~75–90 minutes on Intel i7-12700, 16GB RAM. Bootstrap CIs with 10,000 resamples. Equipment parameters from ORNL [26] and Golmohamadi [12] with Vietnamese adaptations: HVAC thermal inertia 1–2 hr (34°C ambient), compressor 5.0–8.0 bar, CNC 15–35 kW (Vietnamese SME scale). Friedman non-parametric test chosen over ANOVA because savings distributions need not be normal.

IV. EXPERIMENTAL RESULTS

A. *Monte Carlo Performance*

Table II summarizes performance across 100 Monte Carlo scenarios. Friedman test: $\chi^2(4) = 361.16$, $p < 0.001$, Kendall's $W = 0.903$ (large effect). Mean Friedman ranks: RH-NLP (1.00), PSO (2.49), GA (2.51), Fuzzy (4.38), Rule (4.62). 95% bootstrap CIs: RH-NLP [43.5, 44.5], PSO [27.8, 30.0], GA [26.8, 28.5], Fuzzy [12.4, 14.6], Rule [10.4, 13.0]. A Nemenyi post-hoc test at $\alpha = 0.05$ (critical difference $CD = 0.61$ for $k = 5$ methods, $N = 100$) confirms all pairwise rank differences except PSO vs GA ($\Delta rank \approx 0.02$) are statistically significant; i.e., RH-NLP ranks strictly above PSO and GA, which in turn rank strictly above Fuzzy and Rule. PSO and GA are statistically tied.

TABLE II. MONTE CARLO PERFORMANCE: COST SAVINGS (%) ACROSS 100 SCENARIOS

Method	**Mean Savings (%)**	**SD (%)**	**95% CI**	**Friedman Rank**
RH-NLP	44.0	2.5	[43.5, 44.5]	1.00
PSO	28.9	5.8	[27.8, 30.0]	2.49
GA	27.7	4.4	[26.8, 28.5]	2.51
Fuzzy	13.5	5.8	[12.4, 14.6]	4.38
Rule	11.8	6.7	[10.4, 13.0]	4.62

† Friedman $\chi^2(4) = 361.16$, $p < 0.001$, Kendall's $W = 0.903$.

Fig. 2 shows metaheuristic methods aggressively shift loads from peak (9:30–11:30, 17:00–20:00) to off-peak (22:00–04:00). RH-NLP maintains the flattest profile. PSO and GA achieve similar peak reduction but are more volatile. Fuzzy maintains higher peaks due to conservative rules; Rule-based shows minimal peak shaving.

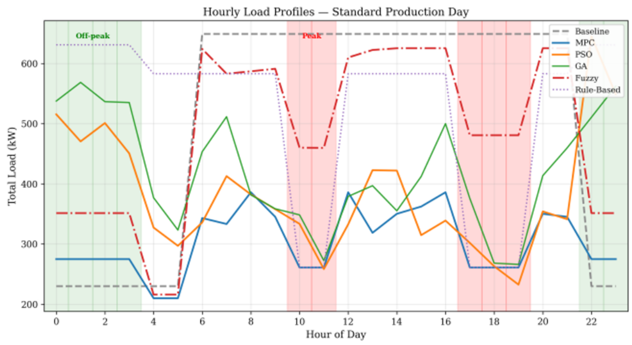

Figure 2. Hourly load profiles, Standard Production Day, 24-hour period with EVN tariff period shading.

Fig. 3 shows the distribution of cost savings. RH-NLP exhibits a tight interquartile range (robust); PSO exhibits a wider range reflecting sigmoid binarization sensitivity. Fuzzy and Rule cluster at the lower end.

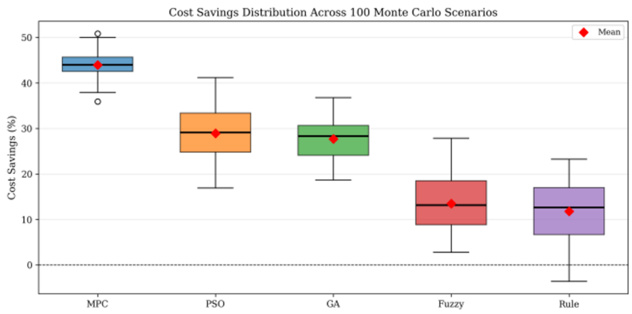

Figure 3. Cost savings distribution across 100 Monte Carlo scenarios.

Fig. 4 and Table III present the named scenario breakdown. RH-NLP maintains consistent savings across all three scenarios. GA exhibits noticeable variation (High Urgency 21.8% vs Flexible 37.1%), reflecting sensitivity to constraint tightening. PSO savings increase from 26.8% (Standard) to 35.5% (High Urgency) due to the combined effect of higher urgency AND the extended 18-hour shift window (vs. 16 h for Standard); these two factors are deliberately confounded in the named-scenario design and are disentangled only via the factorial DOE listed in Future Work.

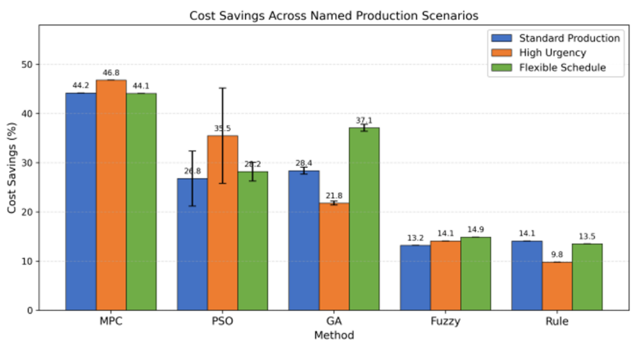

Figure 4. Cost savings across three named production scenarios. PSO and GA error bars denote ±1 SD over 5 independent trials; RH-NLP, Fuzzy, and Rule are deterministic (no error bar).

TABLE III. NAMED SCENARIO PERFORMANCE: COST SAVINGS (%)

Method	Standard	High Urgency	Flexible
RH-NLP	45.9	44.1	46.7
PSO	26.8 ± 5.6	35.5 ± 9.7	31.2 ± 1.9
GA	28.9 ± 0.7	21.8 ± 0.4	37.1 ± 0.7
Fuzzy	10.9	5.4	20.1
Rule	14.1	10.5	17.4

Standard (U = 60%, 06–22h, 16-h shift), High Urgency (U = 85%, 05–23h, 18-h shift), Flexible (U = 35%, 06–22h, 16-h shift). High-Urgency vs. Standard differs in BOTH urgency AND available shifting window; the savings increase therefore reflects a joint effect of urgency and window length, not urgency alone. RH-NLP, Fuzzy, Rule are deterministic; PSO and GA report mean±SD over 5 independent trials.

B. Computational Efficiency

Table IV reports wall-clock execution time per scenario measured on an Intel i7-12700, 16 GB RAM workstation (the same machine used for the Monte Carlo study). RH-NLP (used here as an oracle) delivers the highest savings (44.0%) at ~21 s/scenario but relies on gradient information unavailable in black-box settings; among derivative-free methods, PSO (28.9% at ~1 s) offers the best trade-off. The "savings per second" column is provided as a crude rate; it does NOT capture the non-linear cost–performance frontier and should not be read as PSO outperforming RH-NLP - a Pareto plot (savings vs. compute budget) or a fixed-budget comparison would be a more rigorous evaluation, and is left to future work. Fuzzy (13.5% at ~0.8 s) is competitive for interpretability-first deployments. Embedded deployment on microcontroller-class hardware is left to future work.

TABLE IV. COMPUTATIONAL COST ON INTEL I7-12700, 16 GB RAM (WALL-CLOCK PER SCENARIO)

Method	Savings (%)	Exec Time (s)	Savings per second
RH-NLP	44.0	21.2	2.1
PSO	28.9	1	28.9
GA	27.7	1.8	15.4
Fuzzy	13.5	0.8	16.9
Rule	11.8	0.001	11760

Savings per second = savings(%)/exec_time(s). Times are averages over 100 Monte Carlo scenarios.

V. DISCUSSION

A. Equipment Flexibility

Equipment-specific DR contribution (Fig. 5) is computed as a simple peak-hour ablation sum: for each equipment category C, contribution(C) = $\sum$ over $i \in C$ and $t \in peak$ of max(0, baseline_i(t) − opt_i(t)) · P_i, normalized so that the four category totals sum to 100% (cross-category interaction effects are not separated). Under this metric: CNC 33% (strategic on/off scheduling, higher than continuous baselines because binary shutdown eliminates partial-load operation); compressors 32% (buffer tanks); HVAC 26% (thermal mass, Vietnamese-adjusted); handlers 9%. A minimum viable system targeting CNC + compressors captures 65% of potential.

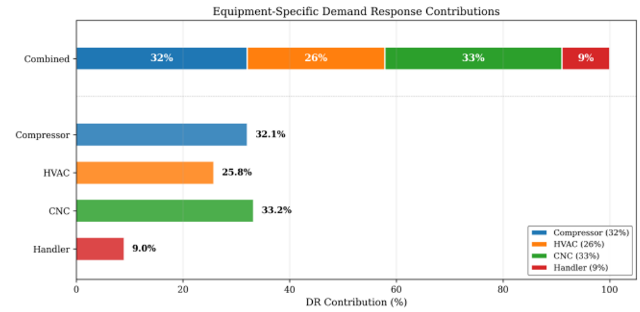

Figure 5. Equipment-specific DR contributions: CNC 33%, compressors 32%, HVAC 26%, handlers 9%.

B. *Tariff Sensitivity*

Fig. 6: PSO savings scale from 18.1% at 1.5:1 to 24.0% at 4.0:1. EVN's 2.85:1 ratio captures ~94% of maximum. Fuzzy shows nonlinear sensitivity (1.1% to 12.6%). Rule-based produces negative savings at low ratios, highlighting fragility to tariff structure.

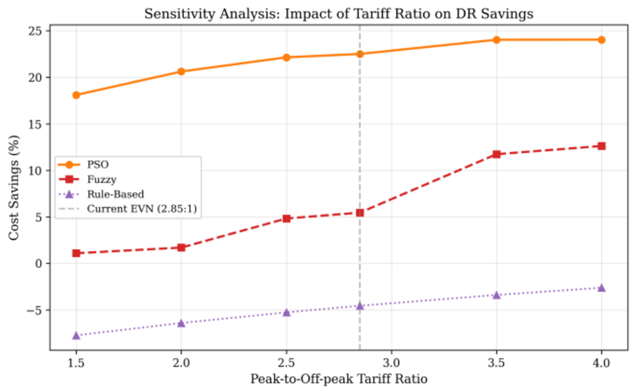

Figure 6. Peak-to-off-peak tariff ratio sensitivity, computed on the Standard scenario only (single deterministic run); curves are not directly comparable to Table II savings, which aggregate 100 Monte Carlo scenarios. Dashed line: current EVN ratio (2.85:1).

C. *Comparison with Published Results*

RH-NLP's savings fall within the 20–50% range for heavy industries [12], [13], at the upper end due to EVN's 2.85:1 ratio. PSO's performance exceeds Yun et al. [10] 14.2% due to broader equipment scope. Fuzzy results are consistent with Hua et al. [9] 12.6% and Ibrahim et al. [21] 18–22%. Faruqui et al. [22] 4:1 plateau is corroborated.

D. *Hybrid Architecture*

The 30.5 pp gap between fuzzy (13.5%) and the RH-NLP oracle (44.0%) sets a theoretical ceiling of ~7.6 billion VND/year for a 1000 MWh/month facility at EVN average tariff. The oracle is offline and uses gradient information not available to embedded controllers, so practical deployments will close only part of this gap. A hybrid RH-NLP-offline (planning) + fuzzy-realtime (execution) architecture could capture 30–40% in our setting while preserving interpretability. PSO (28.9% at ~1 s/scenario on i7-12700) is a viable derivative-free core for such hybrids when on-site SBC compute is available.

E. *Implementation Guidelines*

Tier 1 (immediate): rule-based CNC shutdown on existing PLC/SCADA, ~12% savings. Tier 2 (3–6 mo): Mamdani fuzzy controller on industrial-grade SBC (e.g., Raspberry Pi 4), ~13% savings with human-interpretable rule base. Tier 3 (6–12 mo): PSO on industrial PC or cloud, ~29% savings for >500 MWh/month facilities. Tier 4 (RH-NLP, ~44%) as an offline upper-bound oracle for benchmarking in-production controllers.

F. *Limitations and Future Work*

Limitations: (i) simulation-based validation only - no field deployment on a real Vietnamese SME; (ii) single facility archetype (light-manufacturing SME, 565 kW flexible + 150 kW base) - results should not be extrapolated to heavy industry (steel, cement) or food processing; (iii) GA (pop=30, 25 gen, 750 evaluations) and PSO (25 particles, 20 iter, 500 evaluations) use modest hyperparameter budgets chosen to reflect embedded deployment realities (PLC/SBC) rather than exhaustive global search - a more thorough sensitivity study under 10,000+ evaluation budgets is warranted before claiming algorithmic dominance; the RH-NLP baseline is therefore positioned as an offline upper-bound oracle rather than a deployable controller; (iv) sigmoid transfer functions for binary PSO/GA could be replaced by V-shape or time-varying mappings; (v) RH-NLP uses continuous relaxation with post-rounding and assumes perfect forecast of tariff, ambient temperature, and urgency - true MILP-based MPC with forecast uncertainty is out of scope; (vi) demand charges, equipment degradation, and ramp-induced wear are not modelled; (vii) the equipment-flexibility decomposition is a peak-hour ablation sum and does not separate cross-category interaction effects. Future work: convergence analysis of PSO/GA under enlarged evaluation budgets, ANFIS baseline, MILP formulation with forecast noise, rooftop solar integration, demand-charge modelling, degradation-aware objectives, field validation on a Vietnamese SME, a factorial DOE varying urgency and shift-window independently (to disentangle the joint effect noted in Table III), a Shapley-value attribution to separate cross-equipment interaction effects in Fig. 5, and a Pareto frontier (savings vs. compute budget) plus fixed-budget comparison to replace the rate-style "savings per second" metric of Table IV.

VI. CONCLUSIONS

This study benchmarks five optimization approaches for Vietnamese light-manufacturing DR (500–1000 kW class) under EVN TOU tariffs using mixed binary-continuous scheduling across 100 Monte Carlo scenarios. A rolling-horizon NLP (RH-NLP) baseline - functioning as an upper-bound oracle - achieves 44.0±2.5% savings (95% CI [43.5, 44.5]); among derivative-free methods, PSO 28.9±5.8%, GA 27.7±4.4%, fuzzy 13.5±5.8%, rule-based 11.8±6.7% (Friedman $\chi^2(4) = 361.16, p < 0.001$, Kendall's $W = 0.903$). CNC machines contribute 33% of DR potential; compressors 32%; HVAC 26%. EVN's 2.85:1 tariff ratio captures approximately 94% of maximum savings realized at 4.0:1. The 30.5 pp gap between fuzzy and the RH-NLP oracle highlights room for improvement through hybrid approaches. A tiered adoption strategy (Rule→Fuzzy→PSO→RH-NLP oracle) matches SME resource constraints. Future work: larger PSO/GA hyperparameter budgets with convergence analysis, modern transfer functions (V-shape, TV-mapped), MILP formulation with forecast uncertainty, ANFIS baseline, and field validation on a Vietnamese SME.

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