Degradation-Aware Stochastic BPSO Optimization of Smart Home Energy Management under TOU Tariff

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ABSTRACT

Photovoltaic (PV), home energy storage (ESS), and electric vehicle (EV) deployments offer new Time-of-Use (TOU) tariff alternatives to lower household electricity expenses. When battery degradation is considered, ESS charging/discharging, V2H operation, and deferrable load scheduling are difficult to coordinate. A stochastic Binary Particle Swarm Optimization (BPSO) methodology is used to offer a degradation-aware Home Energy Management System (HEMS) for smart houses with PV–ESS–EV systems. For 24-hour household energy scheduling, the model uses a power balance formulation, ESS/EV operating restrictions, V2H availability, load-shifting options, and a throughput-based degradation cost. To assess ESS integration, V2H, load shifting, and degradation-aware control, five operational scenarios (S1–S5) are assessed. The results suggest that BPSO-based load shifting has the lowest daily operating cost and ESS and V2H reduce peak-period grid import. Adding degradation awareness reduces ESS throughput by 30.81%, extending battery life in a cost–health trade-off. The suggested framework improves residential PV–ESS–EV system economic performance and sustainability under TOU pricing.

Keywords: Home Energy Management System, Binary Particle Swarm Optimization, Vehicle-to-Home, ESS Degradation, Load Shifting

1. INTRODUCTION

The widespread adoption of rooftop photovoltaic (PV) systems, residential battery storage, and electric vehicles (EVs) presents new opportunities for households to reduce electricity costs and improve energy sustainability. However, the natural mismatch between PV generation and residential peak demand together with the high price variation imposed by Time-of-Use (TOU) tariffs necessitates intelligent coordination of these distributed energy resources. Energy Storage Systems (ESS) and Vehicle-to-Home (V2H) capabilities can mitigate peak-period grid reliance, but their benefits depend heavily on optimal scheduling decisions. Furthermore, inappropriate cycling behavior accelerates battery degradation, increasing long-term replacement costs. These challenges highlight the need for advanced Home Energy Management Systems (HEMS) capable of jointly optimizing ESS, EV, and load-shifting operations in a cost-effective and battery-aware manner.

Early research on Home Energy Management Systems (HEMS) primarily focused on demand-side management (DSM), dynamic pricing, and appliance scheduling to reduce residential electricity costs and peak demand. Interactive real-time pricing mechanisms and uncertainty-aware DSM frameworks demonstrated that adaptive load scheduling based on consumer behavior and tariff signals can effectively mitigate peak–valley fluctuations while maintaining user comfort [1] – [3]. In addition, IoT-enabled HEMS platforms with incentive-based demand response validated through real-world residential experiments confirmed the practical feasibility of automated peak-hour load control and cost reduction under TOU and dynamic pricing schemes [4]. These foundational studies established DSM and pricing-aware scheduling as essential components of intelligent residential energy management.

With the increasing penetration of photovoltaic (PV) systems, subsequent studies investigated PV-aware HEMS designs to enhance renewable utilization and system reliability. Optimal PV–battery sizing under uncertainties such as PV generation variability, market price fluctuations, EV energy levels, and grid outage risks was shown to significantly influence system cost and storage capacity decisions [5], [6]. Model-predictive and optimization-based EMS frameworks further improved PV self-consumption and lifecycle cost performance by coordinating PV generation with storage and household demand under realistic operating conditions [7], [8].

As Energy Storage Systems (ESS) became central to residential energy systems, extensive research ad-

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dressed ESS scheduling and load coordination using optimization and metaheuristic techniques. Approaches based on Mixed-Integer Linear Programming (MILP), Particle Swarm Optimization (PSO), Binary Particle Swarm Optimization (BPSO), and Multi-Objective Particle Swarm Optimization (MOPSO) demonstrated effective peak shaving, cost reduction, and improved grid independence through coordinated ESS operation and appliance scheduling under TOU or Real-Time Pricing (RTP) tariffs [9] – [14]. Advanced intelligent appliance scheduling methods, such as hybrid Grey Wolf–Crow Search Optimization, further showed that combining metaheuristics with user-comfort constraints can significantly reduce electricity cost, peak-to-average ratio, and waiting time in smart homes [15]. Community-level HEMS frameworks also highlighted the benefits of coordinated storage and load management at scale [16].

The integration of Electric Vehicles (EVs) introduced additional flexibility and complexity into HEMS architectures. Studies incorporating EV charging, V2H/V2G operation, and multi-energy coordination demonstrated that EVs can act as mobile storage resources, improving load smoothing, reducing peak-period grid import, and enhancing renewable energy utilization [17] – [25]. Intelligent multi-agent systems, hybrid optimization frameworks, and residential energy hub models consistently confirmed the value of EV participation in demand response and coordinated energy scheduling.

More recent work has emphasized the importance of battery degradation-aware energy management, recognizing that aggressive ESS and EV cycling can undermine long-term economic benefits. Studies incorporating throughput-based, cycle-based, and SoC/DoD-dependent degradation models revealed critical trade-offs between short-term cost savings and battery lifetime preservation [26] – [28]. Robust and stochastic optimization frameworks further demonstrated that accounting for degradation and uncertainty simultaneously leads to more sustainable and realistic HEMS operation [29].

Although substantial progress has been made in PV–ESS–EV coordination, appliance scheduling, and DR-driven optimization, current HEMS research still lacks: (1) fully integrated scheduling frameworks combining PV, ESS, EV/V2H, and load shifting; (2) explicit throughput-based degradation cost modeling; (3) metaheuristic optimization that accounts for stochastic load–PV uncertainty; and (4) evaluations tailored to real residential tariffs such as those in Thailand. These shortcomings motivate the degradation-aware, BPSO-based unified HEMS framework proposed in this study.

To address these gaps, this study proposes a degradation-aware stochastic Binary Particle Swarm Optimization (BPSO) framework for smart home energy management in a PV–ESS–EV system. The contributions are fourfold:

1. A unified HEMS formulation that simultaneously optimizes ESS scheduling, EV charging/V2H operation, and deferrable load shifting across a 24-hour horizon under realistic TOU pricing.
2. Integration of a throughput-based ESS degradation model that balances short-term cost savings against long-term battery health, enabling more sustainable operation.
3. A stochastic BPSO algorithm that encodes discrete operational decisions and efficiently identifies optimal charge/discharge and load-shifting patterns under system and availability constraints.
4. A comprehensive scenario-based evaluation (S1–S5) demonstrating the impacts of ESS integration, V2H, load shifting, and degradation awareness on cost reduction, grid import, PV self-consumption, ESS/EV SoC dynamics, and throughput reduction.

The remainder of this paper is organized as follows. Section 2 describes the system model, including the power balance formulation, TOU tariff, household load characteristics, and ESS/EV operational constraints. Section 3 presents the proposed degradation-aware BPSO optimization framework, including the objective function, constraint formulation, decision encoding, and algorithmic workflow. Section 4 provides detailed simulation results for five operating scenarios and discusses cost performance, power flow behavior, SoC dynamics, load shifting, grid import reduction, and ESS degradation impact. Section 5 concludes the study and highlights future research directions.

2. SYSTEM MODELING AND PROBLEM DESCRIPTION

2.1 Smart Home Architecture

The smart home considered in this work consists of four major components: a rooftop photovoltaic (PV) generation system, an energy storage system (ESS), an electric vehicle (EV) with Vehicle-to-Home (V2H) capability, and residential loads classified as deferrable and non-deferrable appliances. All components are connected to a unified AC bus interfacing with the utility grid under the Time-of-Use (TOU) tariff.

The Home Energy Management System (HEMS) oversees real-time power flow, allocates energy among Distributed Energy Resources (DERs), and determines the optimal scheduling of ESS/EV actions and load shifting. In addition, the HEMS must ensure compliance with operational constraints, including charge/discharge limits, inverter power limits, and battery SoC thresholds. The system boundaries assume no export to the grid, ensuring all PV surplus must be self-consumed or stored.

Compared with traditional HEMS models, the present work incorporates three additional real-world complexities:

1. stochastic variations in PV and load profiles,
2. EV availability restricted to 18:00–07:00, and
3. ESS degradation cost explicitly embedded into the scheduling process.

These features reflect realistic Thai residential behavior and enhance the applicability of the proposed framework.

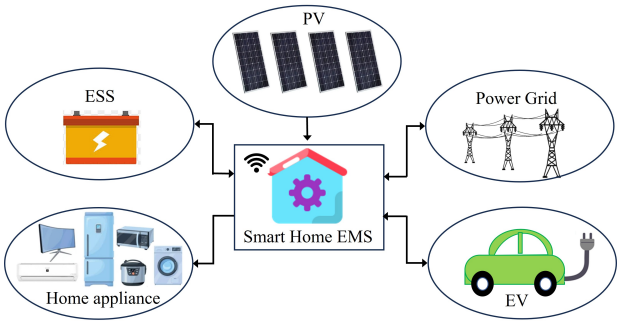

***Fig. 1**: The Proposed smart home EMS architecture.*

The HEMS determines hourly ESS/EV actions and deferrable load schedules over a 24-hour horizon. The system structure is shown in Fig. 1.

2.2 Power Balance Formulation

Equation (1) represents the hourly power balance of the smart home system, ensuring that total power supply equals total demand at every time step.

$$P_{PV}(t) + P_{ESS}(t) + P_{EV}(t) + P_{grid}(t) = P_{load}(t) \quad (1)$$

where:

$P_{\text{PV}}(t)$: PV power generation available at hour t(kW).

$P_{\text{ESS}}(t)$: ESS charging/discharging power at hour t(kW), where positive values denote discharging and negative values denote charging.

$P_{\text{EV}}(t)$: EV charging/V2H power at hour t(kW), where positive values represent V2H operation (discharging to supply the load) and negative values represent EV charging.

$P_{\text{grid}}(t)$: Power imported from the utility grid at hour t(kW).

$P_{\text{load}}(t)$: Total household electrical demand at hour t(kW).

This equation guarantees system feasibility for every hour and links power flow decisions directly with electricity consumption patterns.

The sign convention is:

$P_{\text{ESS}}(t) > 0$: ESS discharging

$P_{\text{ESS}}(t) < 0$: ESS charging

$P_{\text{EV}}(t) > 0$: V2H operation

$P_{\text{EV}}(t) < 0$: EV charging

$P_{\text{grid}}(t) > 0$: energy imported from grid

Export to the grid is disabled. The daily energy cost is computed as:

$$C_{grid} = \sum_{t=1}^{24} P_{grid}(t)\,\lambda(t) \quad (2)$$

where C_{grid} is Total daily cost of electricity imported from the grid (THB) and $\lambda(t)$ is the TOU tariff.

This summation captures the time-varying price structure and penalizes consumption during on-peak hours.

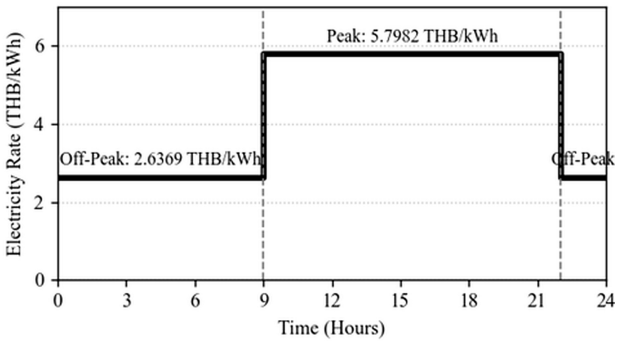

***Fig. 2**: Thai TOU Tariff Curve (On-peak vs Off-peak).*

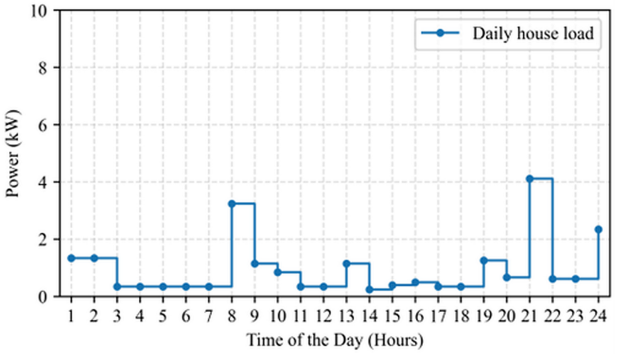

***Fig. 3**: Daily household load profile (kW).*

2.3 Time-of-Use Tariff Model

The TOU tariff $\lambda(t)$ [30] exhibits substantial price asymmetry between on-peak and off-peak periods. On-peak hours (09:00–22:00) incur significantly higher prices, incentivizing ESS discharge and deferrable load scheduling during these intervals.

$$\lambda(t) = \begin{cases} 5.7982 \text{ THB/kWh}, & 09.00 - 22.00 \\ 2.6369 \text{ THB/kWh}, & 22.00 - 09.00 \end{cases} \quad (3)$$

This structure allows the HEMS to exploit arbitrage by shifting consumption toward low-price hours and storing excess PV during midday.

2.4 Household Load Profile

The residential load profile captures typical Thai household behavior with pronounced morning and evening peaks. Deferrable loads have flexible operating windows but fixed energy requirements. Their scheduling is optimized only in Scenarios S4 and S5.

To capture uncertainty, stochastic variations of ±10% may be applied to load and PV inputs during the optimization stage, enhancing robustness of the resulting schedule. Daily household load profile is shown in Fig.3.

Table 1 summarizes all appliances. Deferrable loads are scheduled optimally only in Scenarios S4–S5.

***Table 1**: Residential loads appliance [27].*

No	Category of appliance		Power rating (kW)	Duration of operation (h)
	Non-deferrable Loads	Deferrable Loads		
1	Light bulbs		0.2	6
2	CCTV		0.06	24
3	Refrigerator		0.15	24
4	Fan		0.1	7
5	Television		0.15	4
6	Air Conditioner		2	4
7	Hair dryer		1	0.1
8	Laptop		0.05	4
9	Water Heater		2	0.2
10	Microwave		0.8	0.2
11	Water pump		0.2	0.8
12	Rice cooker		0.6	0.4
13		Washing machine	1	1
14		Iron	1.4	1
15		Vacuum cleaner	1.5	1
16		EV Charger	7.2	5

***Table 2**: Specification of PV, ESS and EV Battery [27].*

Component	Capacity	Charging, Discharging efficiency	Min. SoC	Max. SoC
PV	5 kW	-	-	-
ESS	10 kWh	95%	0.3	0.9
EV	50 kWh	90%	0.3	0.9

2.5 ESS and EV Operating Limits

The technical parameters of PV, ESS, and EV are summarized in Table 2.

The following constraints apply:

1. ESS SoC

$$SoC_{\text{ESS}}^{\min} \leq SoC_{\text{ESS}}(t) \leq SoC_{\text{ESS}}^{\max} \tag{4}$$

2. EV Availability

The EV is physically connected between 18:00–07:00, matching the SoC behavior in Fig. 13:

$$SoC_{\text{EV}}^{\min} \leq SoC_{\text{EV}}(t) \leq SoC_{\text{EV}}^{\max} \tag{5}$$

$$SoC_{\text{EV}}(07:00) \geq 0.9 \tag{6}$$

SoC_{EV} (07:00) represents the EV state-of-charge at the user-defined departure time (07:00), the minimum required departure SoC is set to 90%.

3. Charge/Discharge Power Limits

$$0 \leq P_{\text{ESS}}^{\text{ch}}(t), \quad P_{\text{ESS}}^{\text{dis}}(t) \leq P_{\text{ESS}}^{\max} \tag{7}$$

where $P_{\text{ESS}}^{\text{ch}}(t)$ and $P_{\text{ESS}}^{\text{dis}}(t)$ denote the ESS charging and discharging power at time interval t, respectively. The parameters $P_{\text{ESS}}^{\text{ch,max}}$ and $P_{\text{ESS}}^{\text{dis,max}}$ represent the maximum allowable charging and discharging power of the ESS.

In the implemented simulation model, both limits are defined by the same parameter, i.e., $P_{\text{ESS}}^{\text{ch,max}} = P_{\text{ESS}}^{\text{dis,max}} = P_{\text{ESS}}^{\max}$. In this study, the maximum ESS charging and discharging power is set to $P_{\text{ESS}}^{\max} = 4.4$ kW. A similar limit applies to EV charging/V2H operations.

4. V2H Constraint

$$P_{\text{EV}}(t) > 0 \text{ allowed only for } t \in [18:00,\ 22:00] \tag{8}$$

2.6 ESS Degradation Model

In this study, ESS degradation is modeled using a throughput-based approach, in which the degradation effect is quantified by the total ESS charging and discharging energy over the scheduling horizon. This term is incorporated into the objective function through a weighting factor α_{deg}, which penalizes excessive battery cycling.

$$J = \sum_{t=1}^{T} C_{\text{grid}}(t) + w \sum_{t=1}^{T} \left(P_{\text{ESS}}^{\text{ch}}(t) + P_{\text{ESS}}^{\text{dis}}(t) \right) \tag{9}$$

where w is the weighting factor associated with the ESS throughput penalty. A higher ESS throughput indicates more intensive battery cycling, which may accelerate battery degradation. In this study, the degradation weighting factor is set to $w = 0.3$.

It should be noted that the adopted throughput-based degradation model provides a simplified representation of battery aging. While this approach effectively captures the impact of charge/discharge cycling intensity and is computationally efficient for optimization, it does not explicitly account for several important degradation mechanisms, such as depth-of-discharge (DoD) effects, temperature dependence, C-rate influence, and calendar aging.

Therefore, the proposed model is intended to approximate the relative degradation impact of different scheduling strategies rather than to predict the exact battery lifetime. Despite this limitation, the throughput-based formulation remains widely used in energy management studies due to its simplicity and suitability for real-time optimization. Future work may incorporate more detailed electrochemical or semi-empirical degradation models to further improve accuracy.

2.7 Optimization Problem Description

The decision variables include:

1. ESS charge/discharge action $a_{\text{ESS}}(t) \in -1, 0, +1$
2. EV charge/V2H/idle action $a_{\text{EV}}(t) \in -1, 0, +1$
3. Deferrable load activation $b_i(t) \in 0, 1$

The problem is:

$$\min_{x} \quad \mathbb{E}\left[C_{\text{grid}}(x) + wC_{\text{deg}}(x)\right] \tag{10}$$

where $\mathbb{E}$ denotes the expected value over all stochastic scenarios, capturing uncertainties in PV generation and load variations. x represents the 24-hour action vector consisting of ESS charge/discharge decisions, EV charge/V2H actions, and the scheduling of deferrable loads. C_{grid} is the TOU-based electricity cost. C_{deg} is the ESS degradation cost derived from throughput.

The weighting factor is set to $w = 0.3$. This value is selected to balance the trade-off between electricity cost minimization and battery degradation. Specifically, a relatively small weight is assigned to the degradation term to ensure that cost reduction remains the primary objective, while still penalizing excessive battery cycling. This choice enables the proposed model to achieve meaningful degradation reduction without significantly compromising economic performance. This model forms the foundation for the BPSO-based scheduler in Section 3.

3. DEGRADATION-AWARE BPSO OPTIMIZATION FRAMEWORK

The proposed framework coordinates the operation of the photovoltaic system, energy storage system (ESS), electric vehicle (EV), and deferrable household loads using a stochastic Binary Particle Swarm Optimization (BPSO) algorithm. The optimizer generates a 24-hour schedule of discrete charge, discharge, and load-shifting actions to minimize operating cost under the Time-of-Use (TOU) tariff while preserving battery health.

3.1 Objective Function

The objective function jointly considers energy cost and degradation:

$$J(x) = \mathbb{E}\left[\sum_{t=1}^{24} P_{\text{grid}}(t)\,\lambda(t) + w \cdot E_{\text{throughput}}\right] \tag{11}$$

The objective function in Eq. (10) minimizes the expected total daily operating cost, which consists of the electricity cost from grid import under the time-of-use (TOU) tariff and the battery degradation cost associated with ESS usage. The first term represents the accumulated cost of grid energy over a 24-hour horizon, while the second term models degradation as a function of total ESS energy throughput. In this formulation, w is the weighting factor that controls the trade-off between cost minimization and battery lifetime preservation. $E_{throughput}$ (kWh) is the total daily energy processed by the ESS. The expectation operator accounts for stochastic variations in load and PV generation, ensuring robust scheduling performance under uncertainty.

A higher value of w imposes stronger penalties on battery cycling, leading to reduced ESS throughput and improved long-term battery health at the expense of slightly higher operational cost.

3.2 Operational Constraints

This study explicitly models:

1. Nonlinear charge/discharge efficiencies,
2. Availability of EV,
3. Exclusive operation windows for deferrable appliances,
4. SoC continuity constraints,
5. Prohibition of simultaneous ESS charge and discharge,
6. V2H limited by inverter capacity.

$$0 \le P_{\text{EV}}(t) \le P_{\text{EV}}^{\text{V2H,max}}, \qquad \text{(V2H operation)} \tag{12}$$

The V2H operation is constrained by the inverter capacity, which limits the maximum discharging power from the EV to the household. This ensures that the EV cannot supply power beyond the inverter's rated capacity during V2H operation.

These constraints ensure realistic schedules acceptable for on-site implementation. This constraint reflects practical hardware limitations in residential systems, where the inverter capacity determines the maximum allowable power exchange between the EV and the household.

3.3 BPSO Decision Encoding

In the proposed framework, the scheduling problem is formulated as a discrete optimization problem, where the operational decisions of the ESS, EV, and deferrable loads are determined on an hourly basis over a 24-hour horizon. To enable the application of Binary Particle Swarm Optimization (BPSO), the decision variables are encoded into a binary vector representation.

A candidate solution (particle) is represented as a concatenated binary vector:

$$X = \left[X_{\text{ESS}},\ X_{\text{EV}},\ X_{\text{load}}\right] \tag{13}$$

where X_{ESS}, X_{EV}, and X_{load} denote the binary sub-vectors corresponding to ESS operation, EV operation, and deferrable load scheduling, respectively.

Since the operational state of ESS and EV consists of three discrete actions (charging, idle, and discharging), a two-bit encoding scheme is adopted. Specifically, each action at time step t is represented using a pair of binary variables, allowing the BPSO algorithm to handle multi-state decisions within a binary search space. The encoding is defined as follows: (00) idle, (01) charging and (10) discharging

The binary vector is then mapped to the action variable a(t), which is defined as:

$$a(t) \in \{-1,\ 0,\ 1\}, \qquad \forall t = 1, 2, \ldots, 24 \qquad (14)$$

where $a(t) = -1$ represents charging, $a(t) = 0$ represents idle, and $a(t) = 1$ represents discharging.

For consistency with the power balance formulation in Eq. (1), the sign convention is defined such that positive power values indicate energy supplied to the household load, while negative values represent energy consumption. Accordingly, for EV operation, $a(t) = 1$ corresponds to Vehicle-to-Home (V2H) discharging, whereas $a(t) = -1$ corresponds to EV charging.

3.4 Stochastic Handling

The stochastic behavior in this study is introduced through randomized processes within the optimization and system operation. First, the BPSO algorithm starts from randomly initialized particles for load shifting and ESS/EV operating actions. Second, the EV arrival state-of-charge (SoC) is randomly generated within a predefined range to represent uncertainty in the EV energy state upon returning home. This can be expressed as

$$SOC_{EV,arr} = C_{EV}\left(SOC_{min} + \left(SOC_{max} - SOC_{min}\right)u\right) \qquad (15)$$

where $SOC_{EV,arr}$ denotes the state-of-charge of the EV at the arrival time, C_{EV} is the battery capacity of the EV (kWh), SOC_{min} and SOC_{max} represent the minimum and maximum bounds of the arrival SoC (set to 0.50 and 0.60, respectively), and $u \sim U(0, 1)$is a uniformly distributed random variable used to generate stochastic variations within the specified range. This formulation allows the proposed method to capture practical uncertainty in EV availability conditions while maintaining consistency with the implemented simulation model.

3.5 BPSO Optimization Procedure

The position update is performed directly in a discrete action space, where particle states are updated using velocity-based adjustments followed by integer rounding and bounding operations. This approach enables the BPSO algorithm to handle multi-state decision variables efficiently without relying on any transfer function. The optimization process terminates when the maximum number of iterations is reached. In this study, the maximum number of iterations is set to $N_{\mathrm{iter}} = 30$, which provides a balance between solution quality and computational efficiency. No additional error-based stopping criterion is used in this implementation.

The parameters used in this study are summarized in Table 3 and are selected to provide a suitable balance between exploration and exploitation.

All simulations were performed on a standard desktop computer (Intel Core i5, 16 GB RAM), where the average computational time was approximately 0.53 seconds per run., indicating that the proposed method is computationally efficient and suitable for practical home energy management applications.

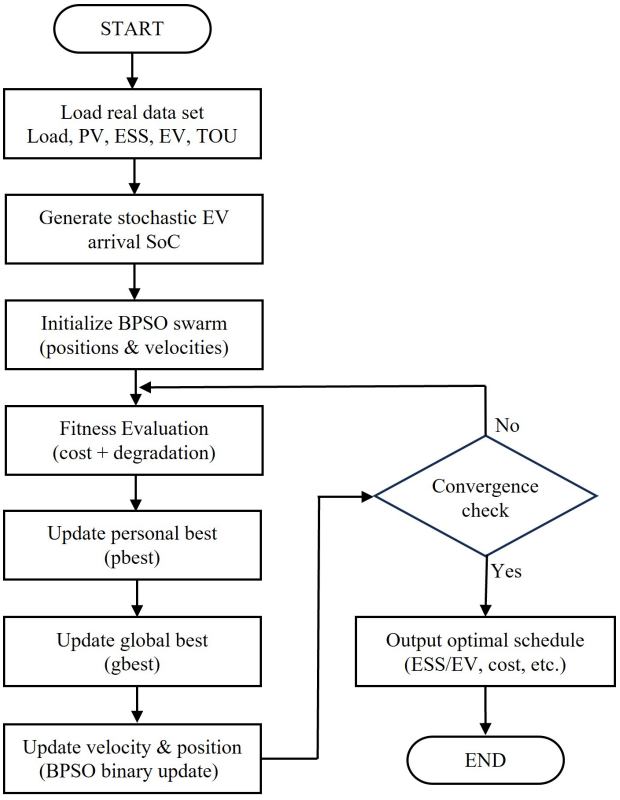

***Fig. 4**: Flowchart of the Degradation-Aware Stochastic BPSO Optimization Procedure.*

***Table 3**: Parameters Used in the Simulation.*

Parameter	Symbol	Value
Swarm size	N_{pop}	20
Maximum iterations	N_{iter}	30
Inertia weight	φ_{in}	0.7
Cognitive coefficient	c_1	1.4
Social coefficient	c_2	1.4
Degradation weighting factor	w	0.3

4. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed Home Energy Management System (HEMS). It should be noted that the results presented for each scenario are obtained from a single simulation run rather than averaged across multiple stochastic realizations. Although stochastic components are included, the reported results represent a typical optimized outcome under the given conditions. Performing multiple stochastic runs and reporting averaged results will be considered

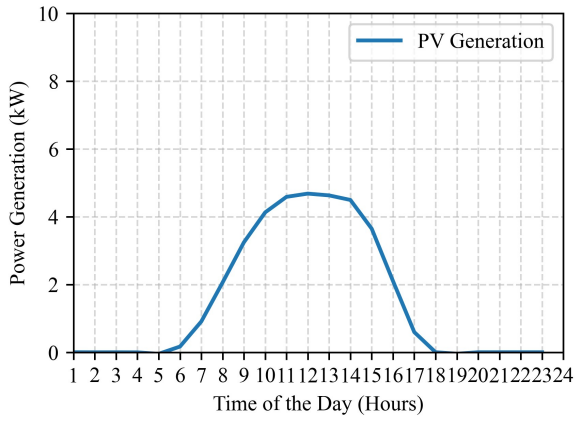

***Fig. 5**: PV generation profile (kW).*

***Table 4**: Description of scenarios S1–S5.*

Scenario	Description
S1	Baseline Scenario (Grid+PV, No ESS, No V2H, No Load Shifting)
S2	Grid+PV+ESS (PV-based ESS Charging, No V2H, No Load Shifting)
S3	Grid + PV + ESS + V2H (No Load Shifting)
S4	Grid + PV + ESS + V2H + Load Shifting (BPSO Optimization)
S5	Full model. Grid + PV + ESS + V2H + Load Shifting (BPSO Optimization) + ESS Degradation Control

in future work.

4.1 Baseline Energy and PV Generation Profiles

Fig.5 illustrates the PV generation curve, which peaks between 11:00–14:00 [24]. This midday peak results in substantial surplus energy that can be used for ESS charging or direct load supply. The mismatch between load peaks and PV generation underscores the importance of ESS and smart scheduling mechanisms to shift energy availability toward high-demand periods.

4.2 Scenario Definitions

Table 4 outlines the functional differences among the five scenarios (S1–S5).

It should be noted that Scenarios S2 and S3 employ rule-based control strategies rather than optimization techniques. In these scenarios, the ESS operation follows predefined heuristics, where the ESS is charged when PV generation exceeds the load demand and discharged during on-peak periods to reduce electricity costs. In Scenario S3, the EV additionally supports the load through V2H operation during the evening peak period (18:00–22:00).

***Table 5**: Daily energy cost (THB) under S1–S5.*

Scenario	Daily cost (THB)	Grid import (kWh)	PV self-consumption (%)	% Saving vs S1
S1	105.00	30.62	18.73	0.00
S2	63.22	23.97	36.70	39.79
S3	54.78	20.77	26.12	47.83
S4	49.67	17.07	19.55	52.70
S5	53.85	17.84	18.75	48.71

Specifically, the ESS control strategy in S2 and S3 can be summarized as follows: (i) charge the ESS when PV surplus is available, (ii) discharge the ESS during on-peak hours, and (iii) remain idle during off-peak periods.

In contrast, Scenarios S4 and S5 utilize the BPSO algorithm to optimally determine load shifting and ESS/EV scheduling.

4.3 Daily Energy Cost Comparison

Table 5 and Fig.6 compare daily operational costs, grid import, and PV self-consumption across all scenarios.

- S1 → S2: Adding ESS increases PV self-consumption from 18.73% → 36.70%, lowering cost by 39.79%, as surplus PV is stored rather than curtailed.
- S2 → S3: Allowing V2H further reduces grid import from 23.97 kWh → 20.77 kWh, increasing savings to 47.83%.
- S3 → S4: BPSO-driven load shifting minimizes energy use during on-peak hours, resulting in the lowest cost (49.67 THB) and 52.70% savings, the best among all scenarios.
- S5: When degradation cost is considered, daily cost rises slightly relative to S4 because the optimizer protects the battery from unnecessary cycling. However, the overall cost remains lower than S2 and S3.

It can be observed that the PV self-consumption decreases in Scenarios S4 and S5 compared to S2 and S3. This is because the BPSO optimization prioritizes minimizing the total electricity cost rather than maximizing PV utilization. As a result, the scheduling strategy may favor off-peak grid charging for EV, while reserving stored energy for use during high tariff periods. Consequently, PV generation is not always fully utilized for local consumption or storage, leading to a reduction in the PV self-consumption ratio.

In particular, the optimized strategy tends to shift energy usage to economically favorable periods, which may not always coincide with peak PV generation. This trade-off between cost minimization and PV utilization explains the observed reduction in PV self-consumption in S4 and S5.

This result highlights the inherent trade-off between economic optimization and renewable energy utilization in smart home energy management systems.

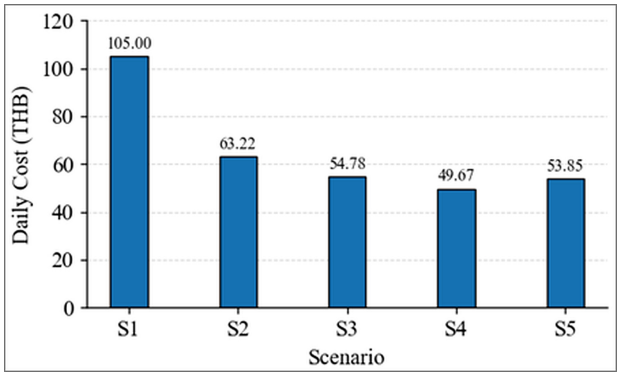

***Fig. 6**: Comparison of daily energy cost for S1–S5.*

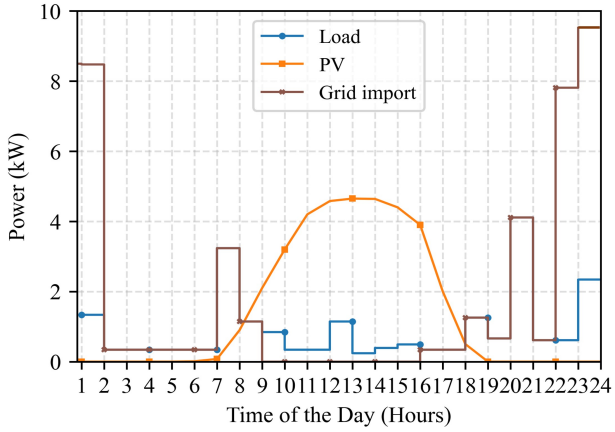

***Fig. 7**: Power flow profile for Scenario S1: Grid + PV (Baseline).*

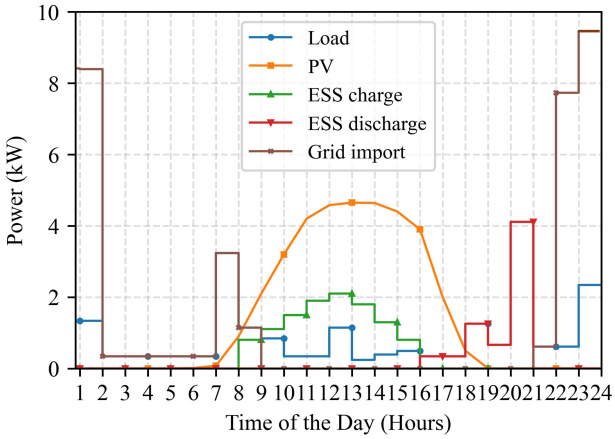

***Fig. 8**: Power flow profile for Scenario S2: Grid + PV + ESS.*

4.4 Power Flow Analysis

Fig. 7–11 provide detailed hourly power flow profiles for each scenario:

Fig. 7 illustrates the baseline power flow without ESS and EV support. It can be observed that PV generation is directly used to supply household loads during midday; however, excess PV energy cannot be stored and is therefore curtailed. During peak demand periods, particularly in the evening, the household relies entirely on grid import. The peak observed around 22:00–24:00 is attributed to EV charging. This behavior highlights the fundamental limitation of the baseline system, where the mismatch between PV generation and load demand results in inefficient energy utilization. Compared to other scenarios, S1 exhibits the highest grid dependency and peak demand intensity, demonstrating the necessity of energy storage integration for effective peak shaving and self-consumption improvement.

Fig. 8 shows the impact of integrating ESS into the system. The ESS is charged during midday using surplus PV generation and subsequently discharged during peak hours to support the load. This significantly reduces grid import during high-tariff periods. Compared to S1, the inclusion of ESS enables temporal energy shifting, improving PV self-consumption and reducing peak demand. The charging and discharging pattern also demonstrate effective utilization of TOU pricing, where energy is stored during low-cost periods and used during expensive intervals.

Fig. 9 demonstrates the effect of incorporating EV with V2H capability. In addition to ESS support, the EV contributes energy during peak periods through V2H operation. This results in a further reduction in grid import compared to S2. The combined operation of ESS and EV provides enhanced flexibility in energy management. The EV acts as an additional distributed storage resource, enabling deeper peak shaving and improved load balancing. This coordinated behavior leads to a more stable and flattened power flow profile during high-demand periods.

Fig.10 illustrates the optimized power flow under BPSO-based load shifting. Deferrable loads are strategically shifted to off-peak periods, resulting in a significant reduction in peak load demand. Compared to S3, the load profile becomes more evenly distributed across the day, indicating effective peak shaving and valley filling. The coordination between ESS, EV, and optimized load scheduling enables the system to minimize grid import during high-tariff hours while maximizing the use of PV energy. This result highlights the effectiveness of BPSO in identifying optimal scheduling strategies that balance cost reduction and operational constraints.

Fig. 11 presents the power flow behavior under degradation-aware optimization. Compared to S4, the charging and discharging patterns of the ESS and EV become smoother and less aggressive. This is due to the inclusion of degradation cost in the objective function, which penalizes excessive battery cycling. Although the system still performs peak shaving and load shifting, the depth and frequency of charge/discharge cycles are reduced. This results in slightly higher grid import compared to S4 but significantly improves battery longevity. The observed behavior demonstrates a clear trade-off between short-term economic benefits and long-term battery health, confirming the effectiveness of the degradation-aware strategy in achieving sustainable

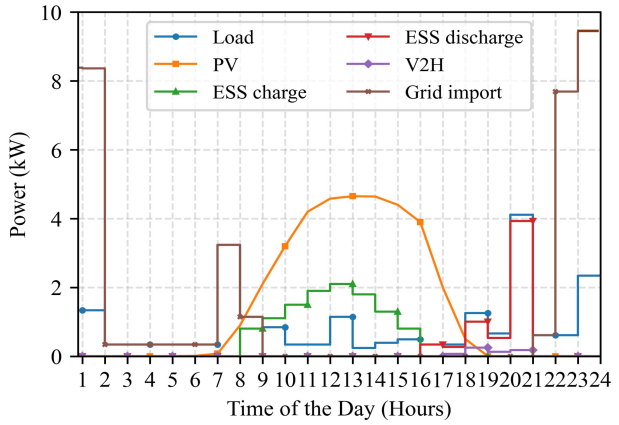

***Fig. 9**: Power flow profile for Scenario S3: S2 + Vehicle-to-Home (V2H).*

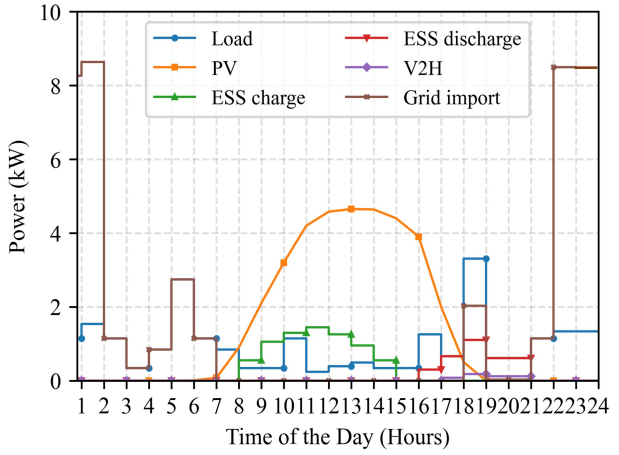

***Fig. 10**: Power flow profile for Scenario S4: S3 + Load Shifting using BPSO.*

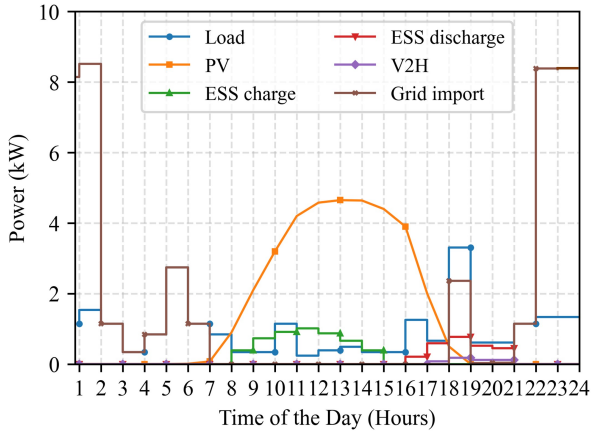

***Fig. 11**: Power flow profile for Scenario S5: S4 + ESS degradation control.*

energy management.

Overall, the comparative analysis of power flow across Scenarios S1–S5 clearly demonstrates the progressive enhancement in energy management performance achieved by integrating ESS, EV, and intelligent scheduling strategies. The transition from S1 to S3 highlights the fundamental role of distributed storage in reducing grid dependency and mitigating peak demand through energy shifting and V2H support. The introduction of BPSO-based load shifting in S4 further improves system efficiency by smoothing the load profile and minimizing peak-period consumption. Finally, the degradation-aware strategy in S5 provides a more sustainable operational pattern by reducing excessive battery cycling while maintaining acceptable economic performance. These results confirm that coordinated control of PV, ESS, EV, and flexible loads not only enhances cost efficiency but also improves load smoothing, peak shaving, and long-term battery health, making the proposed HEMS framework both economically effective and practically viable for real-world residential applications.

4.5 ESS State-of-Charge (SoC) Dynamics

Fig. 12 illustrates the ESS state-of-charge (SoC) trajectories for Scenarios S2–S5. In Scenario S2, the ESS exhibits the lowest SoC levels, as it is the sole storage resource supporting load demand, resulting in more frequent charging and discharging cycles. In Scenario S3, the inclusion of EV with V2H capability reduces the reliance on the ESS during peak periods, leading to a higher SoC compared to S2.

In Scenario S4, the optimized scheduling further improves energy management by strategically coordinating ESS and EV operations, resulting in an overall increase in ESS SoC. Finally, Scenario S5 shows the highest SoC levels, as the degradation-aware optimization discourages excessive ESS cycling, preserving battery energy and maintaining a higher SoC throughout the day.

4.6 EV State-of-Charge (SoC) Behavior

Fig. 13 illustrates the EV state-of-charge (SoC) trajectories under different scenarios, considering that the EV is available between 18:00 and 07:00. In Scenario S2, the EV is only charged without participating in V2H operation, resulting in the highest SoC levels. In Scenario S3, V2H operation during peak hours causes a reduction in SoC compared to S2. In Scenario S4, although V2H is still present, load shifting reduces peak demand, leading to less EV discharge and a higher SoC than in S3. In Scenario S5, the SoC is slightly lower than in S4. This is because the degradation-aware strategy limits ESS discharge, causing the EV to supply more load during certain periods and resulting in slightly deeper discharge.

4.7 Load Shifting Performance (S4)

Fig.14 compares load shifting schedules for S4. In S4, high-power appliances are shifted aggressively into off-peak hours, resulting in a distinctly restructured load profile.

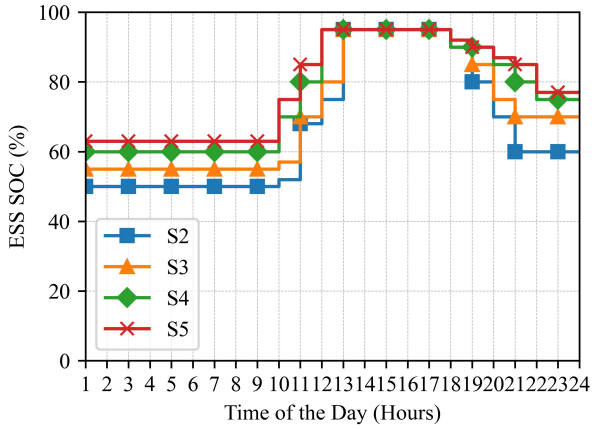

***Fig. 12**: ESS SoC summary for S2–S5.*

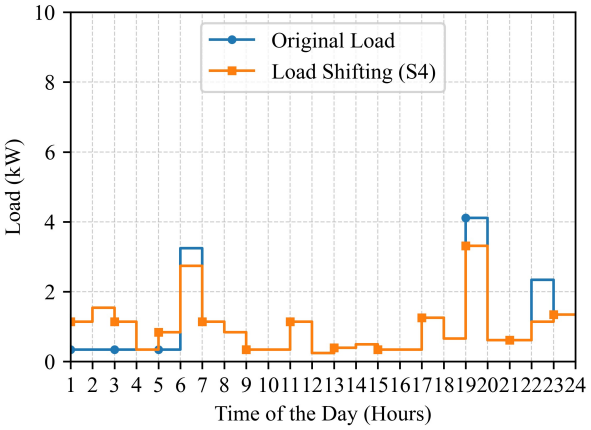

***Fig. 14**: Load shifting profile for Scenario S4.*

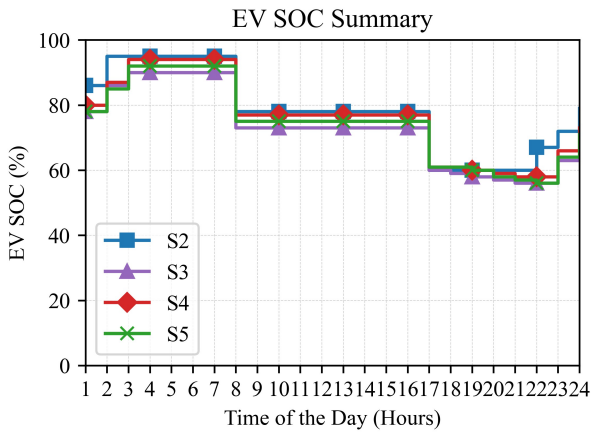

***Fig. 13**: EV SoC summary.*

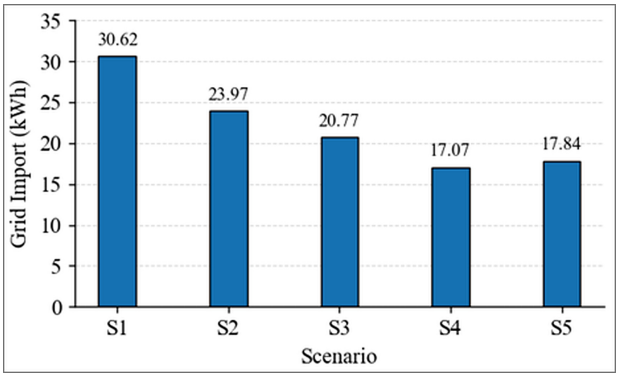

***Fig. 15**: Grid import comparison for all scenarios.*

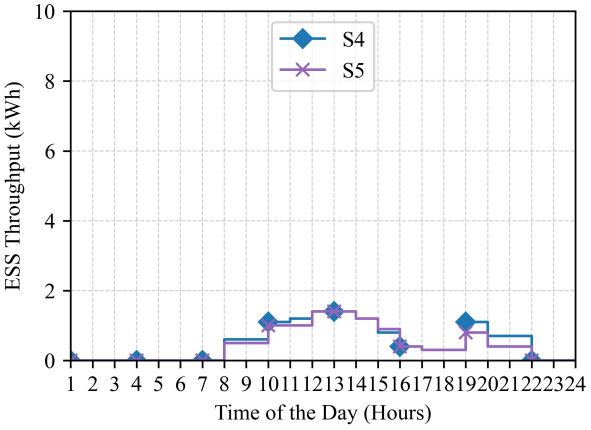

***Fig. 16**: ESS throughput S4 and S5.*

4.8 Grid Import Reduction Analysis

Fig. 15 summarizes grid import reduction across scenarios. S1 has the highest grid import due to absence of storage. ESS addition in S2 markedly lowers grid reliance. S3 achieves further reduction via V2H. S4 attains the lowest grid import, demonstrating the effectiveness of combined storage and load shifting. S5 slightly increases import compared with S4 due to degradation control but still remains significantly below S1–S3.

4.9 ESS Degradation Cost Analysis (S5)

Fig.16 and Table 6 present ESS throughput and degradation impact. ESS throughput drops from 17.37 kWh (S4) to 12.02 kWh (S5), a reduction of 30.81%, reflecting substantially less cycling. Despite a slightly higher daily energy cost, S5 offers longer ESS lifespan and reduced long-term replacement cost. The degradation-aware model produces more sustainable scheduling by selectively avoiding unnecessary charging/discharging cycles.

In addition to reducing daily ESS throughput, the degradation-aware strategy in S5 can also be interpreted in terms of battery lifetime extension. Assuming that ESS lifetime is approximately inversely proportional to the daily energy throughput, the reduction in throughput from 17.37 kWh/day in S4 to 12.02 kWh/day in S5 suggests a relative lifetime increase of approximately 30.81%. This estimate is obtained from the ratio 17.37 / 12.02 = 1.445. Therefore, the degradation-aware scheduling strategy may extend the effective ESS service life by about 1.45 times compared to the cost-only optimization case.

***Table 6**: ESS Degradation Reduction.*

Scenario	Daily cost (THB)	ESS throughput (kWh)	ESS Degradation Reduction vs S4 (%)
S4	49.67	17.37	0.00
S5	53.85	12.02	30.81

It should be noted that this is an approximate engineering estimate based on throughput reduction only. The actual battery lifetime also depends on other factors such as temperature, depth of discharge, charging rate, and calendar aging.

5. CONCLUSION

This study proposed a degradation-aware stochastic Binary Particle Swarm Optimization (BPSO) framework for smart home energy management integrating photovoltaic (PV) generation, an energy storage system (ESS), and an electric vehicle (EV) under a Thai Time-of-Use (TOU) tariff environment. Five operating scenarios (S1–S5) were evaluated to assess the contribution of ESS scheduling, Vehicle-to-Home (V2H), load shifting, and degradation-aware optimization.

The results demonstrate that incorporating ESS and EV flexibility significantly reduces daily household energy costs compared to the baseline. Scenario S2 (Grid + PV + ESS) reduced daily cost by 39.79%, while S3 (with V2H) achieved 47.83% savings. The optimal BPSO-based load shifting strategy in S4 further lowered the cost to its minimum, yielding 52.70% savings relative to S1. When ESS degradation was integrated in S5, the total cost slightly increased due to more conservative battery usage; however, ESS throughput dropped markedly by 30.81%, indicating effective reduction of battery cycling stress and improved long-term battery health.

Power flow analyses revealed that optimization not only decreased grid import but also enhanced PV self-consumption and reshaped the load profile during peak tariff periods. ESS and EV SoC trajectories confirmed that BPSO successfully coordinated charging and discharging actions within operational constraints, especially during the EV availability window (18:00–07:00). Load shifting in S4 and S5 redistributed high-power appliances to off-peak periods, reducing dependence on the grid during expensive hours.

The findings confirm that a degradation-aware BPSO-based HEMS can effectively balance operational cost savings and battery longevity. The framework provides practical value for Thai residential consumers by mitigating TOU tariff impacts while preserving ESS lifespan. Future work may extend this approach to multi-day horizons, multi-home energy communities, and integration with Sodium-ion battery technologies.

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