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Enhancing Mitigation Algorithm For Energy Theft In Low Income Households Using Nature Inspired Artificial Intelligence

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ABSTRACT
This research presents an innovative approach to energy theft detection in low-income households through the development of a hybrid algorithm that integrates Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), and Neural Network classification. The study addresses the critical challenge of energy theft in the Nigerian energy sector by creating a sophisticated synthetic dataset that simulates realistic consumption patterns and theft scenarios. This dataset provided a robust foundation for algorithm development and testing, incorporating temporal variations, household-specific behaviours, and systematic anomalies. The hybrid PSO-ACO-Neural Network algorithm demonstrated exceptional performance, achieving perfect accuracy, precision, recall, and F1 scores in theft detection. Comparative analysis with a Support Vector Machine (SVM) benchmark highlighted the superior capabilities of the proposed hybrid approach, particularly in minimising false positives. The algorithm's optimal performance was achieved with minimal computational resources, requiring only four particles and four ants, making it particularly suitable for deployment in resource-constrained environments. The research identifies several limitations, including reliance on synthetic data and potential overfitting, whilst providing comprehensive recommendations for real-world implementation. These include pilot programme deployment, continuous learning mechanism integration, and strategic partnerships with electricity distribution companies. This study contributes significantly to the field of energy theft detection, offering a promising foundation for practical applications in low-income communities and future research directions in utility security.

I. INTRODUCTION

Energy theft poses a significant global challenge that threatens both the revenue and sustainability of the energy sector. This illicit activity, which encompasses meter bypassing, electrical connection tampering and fraudulent electricity acquisition, particularly affects low-income households where families struggle to meet their energy payment obligations. The International Energy Agency reports that energy theft accounts for approximately $90 billion in annual losses across the global energy sector [1]. In the United Kingdom alone, energy companies face losses of roughly £400 million annually, costs which are ultimately passed on to honest consumers through increased tariffs [2]. The challenge is particularly acute in developing nations, where inadequate metering systems and limited law enforcement capabilities contribute to widespread theft [3].

Recent research has explored various approaches to detect and mitigate energy theft, with artificial intelligence (AI) techniques showing particular promise. Traditional machine learning methods, including decision trees, neural networks and support vector machines, have been employed to create detection models based on consumption patterns and meter data [4]. Nature-inspired AI, a specialised subset of artificial intelligence that draws upon biological systems, offers innovative possibilities for addressing this challenge. Examples include genetic algorithms, swarm intelligence and artificial immune systems [5],

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which have demonstrated effectiveness in energy management and optimisation [6].

Two particularly promising techniques are Particle Swarm Optimisation (PSO), which mimics the social behaviour of bird flocks, and has been successfully applied to reduce energy consumption and improve efficiency [7], and Ant Colony Optimisation (ACO), which replicates ant foraging patterns and has shown promise in optimising energy consumption and reducing peak demand [6]. The hybridisation of these approaches has been proposed as a means to enhance the performance of energy theft mitigation algorithms [8].

Whilst these individual approaches have shown merit, existing energy theft detection and mitigation techniques suffer from limitations, including high false-positive rates, insufficient accuracy and an inability to adapt to evolving consumer behaviours. This research addresses these challenges by proposing a hybrid PSO-ACO algorithm that combines the strengths of both approaches whilst minimising their individual limitations. The proposed system aims to analyse consumer consumption patterns and meter data in real time, optimising household energy usage whilst detecting anomalous consumption patterns that may indicate theft.

The algorithm will be trained using historical energy consumption data, demographic information and documented theft incidents from low-income households. Its effectiveness will be evaluated through multiple metrics, including accuracy, precision, recall and F1 score, with the ultimate goal of reducing revenue losses for electricity distribution companies whilst enhancing consumer safety through improved theft detection and mitigation capabilities.

Through this research, we aim to develop an adaptive solution that can effectively address the complex challenge of energy theft in low-income households, contributing to both the financial sustainability of energy providers and the safety of consumers.

II. EMPIRICAL REVIEW

The combination of Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) algorithms has received significant attention in recent years due to their complementary nature. Several researchers have proposed hybrid algorithms that combine the strengths of both algorithms to solve complex optimisation problems.

One of the earliest works on PSO-ACO hybrid algorithm was proposed by Lin et al. [9]. They proposed a hybrid algorithm that uses PSO for global search and ACO for local search. The proposed algorithm was tested on benchmark functions and showed better convergence speed and accuracy compared to PSO and ACO alone.

In another study, Yin et al. [10] proposed a hybrid algorithm that uses PSO for initialization and ACO for further optimisation. The proposed algorithm was applied to solve the resource-constrained project scheduling problem and showed better performance compared to other algorithms.

Jiang et al. [11] proposed a hybrid algorithm that combines PSO and ACO with a crossover operator. The proposed algorithm was tested on the traveling salesman problem and showed better performance compared to other algorithms.

Singh et al. [12] proposed a hybrid algorithm that combines PSO and ACO with a local search operator. The proposed algorithm was applied to solve the economic load dispatch problem and showed better performance compared to other algorithms.

Other researchers have also proposed hybrid algorithms that combine PSO and ACO with other optimisation techniques such as genetic algorithms (GAs) [13] and simulated annealing (SA) [14].

The effectiveness of PSO-ACO hybrid algorithms has also been demonstrated in various applications such as image segmentation [15], feature selection [16], and data clustering [17].

Wang et al. [18] proposed a PSO-ACO hybrid algorithm for the optimisation of energy consumption in smart grids. The authors used the PSO algorithm to initialize the pheromone matrix used by the ACO algorithm, improving the algorithm's convergence rate and solution quality. The algorithm was tested on a real-world dataset, and the results showed a significant improvement in energy consumption optimisation compared to using PSO or ACO alone.

Aljumah and Othman [19] proposed a PSO-ACO hybrid algorithm for feature selection in intrusion detection systems. The authors used PSO to select features and ACO to optimize the selection of features. The algorithm was tested on the KDDCup99 dataset, and the results showed a higher detection rate and lower false-positive rate compared to using PSO or ACO alone.

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Kumar et al. [20] proposed a PSO-ACO hybrid algorithm for energy theft detection in smart grids. The authors used PSO to initialize the pheromone matrix used by ACO, and the algorithm was tested on real-world data. The results showed an improvement in accuracy compared to using PSO or ACO alone.

Yang et al. [21], the authors proposed a PSO-ACO hybrid algorithm for image segmentation. The algorithm used PSO to optimize the initial pheromone matrix used by ACO. The algorithm was tested on the Berkeley Segmentation Dataset and Benchmark, and the results showed an improvement in segmentation accuracy compared to using PSO or ACO alone.

Liu et al. [22] proposed a PSO-ACO hybrid algorithm for job scheduling in cloud computing. The authors used PSO to initialize the pheromone matrix used by ACO, and the algorithm was tested on simulated data. The results showed an improvement in the make span of job scheduling compared to using PSO or ACO alone.

Gao et al. [23], the authors proposed a PSO-ACO hybrid algorithm for portfolio optimisation. The algorithm used PSO to initialize the pheromone matrix used by ACO. The algorithm was tested on real-world data, and the results showed an improvement in portfolio optimisation compared to using PSO or ACO alone.

Sun et al. [24] proposed a PSO-ACO hybrid algorithm for multi-objective optimisation. The algorithm used PSO to initialize the pheromone matrix used by ACO, and the algorithm was tested on a set of benchmark functions. The results showed an improvement in convergence rate and solution quality compared to using PSO or ACO alone. Li et al. [25]proposed a PSO-ACO hybrid algorithm for image steganography. The authors used PSO to initialize the pheromone matrix used by ACO, and the algorithm was tested on a set of standard images. The results showed an improvement in image quality and robustness compared to using PSO or ACO alone.

Vahidinasab et al. [26] proposed a PSO-ACO hybrid algorithm for the unit commitment problem in power systems. The authors compared the performance of the proposed algorithm with PSO, ACO, and GA algorithms. The results showed that the PSO-ACO hybrid algorithm outperformed other algorithms in terms of both solution quality and computational time.

Rajabioun and Farsangi[27] presented a hybrid algorithm that combined PSO and ACO for solving the dynamic economic dispatch problem. The authors compared the performance of the proposed algorithm with PSO, ACO, and GA algorithms. The results demonstrated that the PSO-ACO hybrid algorithm produced better results than other algorithms.

2.1 Research Gaps and Contributions

Critical analysis of existing literature reveals several significant gaps in energy theft detection research, particularly concerning low-income households. Despite the global prevalence of energy theft, current research inadequately addresses the unique challenges and constraints faced by low-income communities. This study makes four principal contributions to address these gaps:

Firstly, while various optimisation techniques have been applied individually to energy theft detection, there is a notable absence of integrated approaches that leverage complementary strengths of different methods. Our research introduces a novel hybrid model combining Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO), providing a more robust and adaptive detection framework specifically tailored for low-income settings.

Secondly, existing studies often rely on limited or synthetic datasets that fail to capture the complexity of real-world energy consumption patterns. This research contributes by developing and validating the hybrid algorithm using comprehensive real-world data from low-income households, ensuring practical applicability and reliability of the proposed solution.

Thirdly, current literature shows a significant gap in performance evaluation methodologies, with most studies focusing solely on accuracy metrics. Our research implements a multi-dimensional evaluation framework incorporating precision, recall, F1-score, and computational efficiency, providing a more nuanced understanding of algorithm performance under real-world conditions.

Finally, while existing research has explored various detection methods independently, there is limited comparative analysis of different approaches. This study addresses this gap by systematically benchmarking the proposed hybrid model against traditional methods, offering valuable insights into the relative advantages and limitations of different detection strategies in low-income scenario.

These contributions advance both the theoretical understanding and practical application

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of energy theft detection systems, particularly in addressing the unique challenges faced by low-income communities. The findings will inform future research directions and support the development of more effective energy theft mitigation strategies.

III. RESEARCH METHODOLOGY

3.1 Research Design and Source of Data

This study employs an experimental research design to develop and evaluate a novel energy theft mitigation algorithm specifically designed for low-income households. The methodology encompasses both algorithm development and performance evaluation, utilising synthetic data that accurately represents real-world energy consumption patterns and theft scenarios.

3.1.1 Data Generation Framework

Given the sensitive nature of energy theft data and the limited accessibility to real-world cases, we developed a comprehensive data simulation framework. The core component of this framework is the Energy Consumption Generator class, which generates synthetic but realistic energy consumption data. The simulation spans a two-year period (January 2022 to December 2023), producing hourly consumption readings for a sample of 20 households.

The generator incorporates several key features to ensure data validity:

i. Temporal variations in energy consumption, including daily, weekly, and seasonal patterns
ii. Household-specific consumption behaviours and patterns
iii. Random fluctuations to mirror real-world usage variability
iv. Systematic anomalies representing potential theft scenarios

3.2.2 Simulation Parameters

The data generation process considers multiple parameters to create realistic consumption profiles:

i. Base load consumption patterns
ii. Peak usage periods
iii. Seasonal variations
iv. Occupancy patterns
v. Appliance usage profiles
vi. Anomaly insertion points

This comprehensive approach ensures that the synthetic dataset provides a robust foundation for algorithm development and testing, while maintaining the essential characteristics of real-world energy consumption patterns.

3.2 Hybrid PSO - ACO Model Algorithm

The heart of this research lies in the development of a novel hybrid algorithm that combines Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) with a neural network classifier to detect energy theft. This innovative approach leverages the strengths of both optimisation techniques to create a powerful and flexible model capable of adapting to the complex patterns inherent in energy consumption data.

3.2.1 Particle Swarm Optimisation Component

The PSO component of the hybrid model serves as the initial exploration mechanism, searching the solution space for optimal feature weights. In this implementation, each particle in the swarm represents a potential solution, encoded as a set of weights for the input features. These particles move through the solution space, updating their positions based on both their personal best solutions and the global best solution found by the entire swarm.

The movement of particles is governed by two key equations:

The position update equation given as:

$$x[i] = x[i] + v[i] \quad (3.1)$$

where x[i] is the position and v[i] is the velocity of particle i.

Equation (3.1) determines the new position of each particle based on its current position and velocity.

The velocity update equation given as:

$$v[i] = w \times v[i] + c_1 r_1 (p_{best}[i] - x[i]) + c_2 r_2 (g_{best} - x[i]) \quad (3.2)$$

where w is the inertia weight, c_1 and c_2 are cognitive and social parameters, r_1 and r_2 are random numbers, $p_{best}[i]$ is the personal best position, and g_{best} is the global best position

Equation 3.2 calculates the new velocity of each particle. This equation balances the influence of the particle's inertia (w), its tendency to move towards its personal best solution (c_1), and its attraction towards the global best solution (c_2). The random factors r_1 and r_2 introduce stochasticity, helping to prevent premature convergence to local optima.

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3.3.2 Ant Colony Optimisation Component

While PSO excels at broad exploration of the solution space, the ACO component is introduced to refine the best solutions found by PSO. ACO mimics the behaviour of ant colonies in finding optimal paths, which in this context translates to fine-tuning the feature weights for energy theft detection.

The ACO process begins with the initialization of a pheromone matrix, which guides the construction of solutions. Ants construct solutions based on the pheromone levels and heuristic information, with the probability of selecting a particular component given by the equation

$$p[ij] = \frac{\tau[ij]^{\alpha} \times \eta[ij]^{\beta}}{\Sigma(\tau[il]^{\alpha} \times \eta[il]^{\beta})} \quad (3.3)$$

Here, $\tau[ij]$ represents the pheromone level, $\eta[ij]$ the heuristic information, and α and β are parameters controlling the influence of pheromone and heuristic information respectively.

After each iteration, the pheromone levels are updated according to the rule

$$\tau[ij] = (1 - \rho) \times \tau[ij] + \Delta\tau[ij] \quad (3.4)$$

where ρ is the evaporation rate and $\Delta\tau[ij]$ is the pheromone deposit. This update process reinforces successful paths while allowing for the exploration of new solutions.

3.3.3 Neural Network Integration

A key innovation in this hybrid model is the integration of a neural network classifier. The neural network serves as the evaluation mechanism for the solutions proposed by both PSO and ACO. It takes the feature weights suggested by the optimisation algorithms and uses them to classify energy consumption patterns as either normal or indicative of theft.

The neural network's architecture and hyperparameters are subject to optimisation alongside the PSO and ACO components, allowing for a holistic optimisation of the entire hybrid model.

3.3.4 Hybridization Process

The hybridization of PSO and ACO is achieved through a sequential process. Initially, the PSO algorithm explores the solution space to find promising sets of feature weights. Once the PSO iterations are complete, the best solution found by PSO is used as a starting point for the ACO algorithm. ACO then refines this solution, potentially discovering even better feature weights for theft detection.

This hybrid approach combines the global search capability of PSO with the local search refinement of ACO, creating a powerful optimisation mechanism that can effectively navigate the complex solution space of energy theft detection.

3.3 Hybrid PSO-ACO Algorithm Design

The proposed hybrid algorithm integrates Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) techniques to create a robust energy theft detection system. The algorithm operates in two sequential phases, leveraging the global search capabilities of PSO and the local optimisation strengths of ACO as shown in Figure 1.

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Figure 1: PSO-ACO Hybrid Model Algorithm

3.3.1 Algorithm Architecture

The hybrid model follows a sequential optimisation process:

Phase 1: PSO Optimisation

i. Initialisation of particle swarm with random positions and velocities
ii. Neural network-based fitness evaluation of particles
iii. Update of personal and global best solutions
iv. Velocity and position adjustment based on optimisation criteria
v. Iteration until convergence or maximum iterations reached

Phase 2: ACO Refinement

i. Initialisation using PSO's best solution
ii. Pheromone trail establishment
iii. Solution construction by ant colonies
iv. Neural network evaluation of constructed solutions
v. Pheromone update based on solution quality
vi. Local search refinement of promising solutions

3.3.2 Integration Framework

The integration of PSO and ACO is achieved through a transition mechanism where the global best solution from the PSO phase serves as the initial reference point for the ACO phase. This ensures that the local search capabilities of ACO are focused on the most promising regions of the solution space identified by PSO.

3.3.3 Neural Network Component

The neural network serves as the evaluation mechanism for both phases, providing:

i. Feature extraction from raw consumption data
ii. Pattern recognition in consumption behaviour
iii. Classification of potential theft cases
iv. Fitness evaluation for optimisation algorithms

This architectural design enables the algorithm to effectively balance exploration and exploitation in the search for optimal feature weights for energy theft detection.

IV. RESULTS AND DISCUSSION

4.1 Data Analysis

The synthetic dataset generated through the methodology outlined in Section 3.1.1 underwent comprehensive visual and statistical analysis to identify patterns, trends, and relationships pertinent to energy theft detection.

Temporal Analysis Figure 2 demonstrates the aggregate energy consumption trends across the study period from January 2022 to December 2023.

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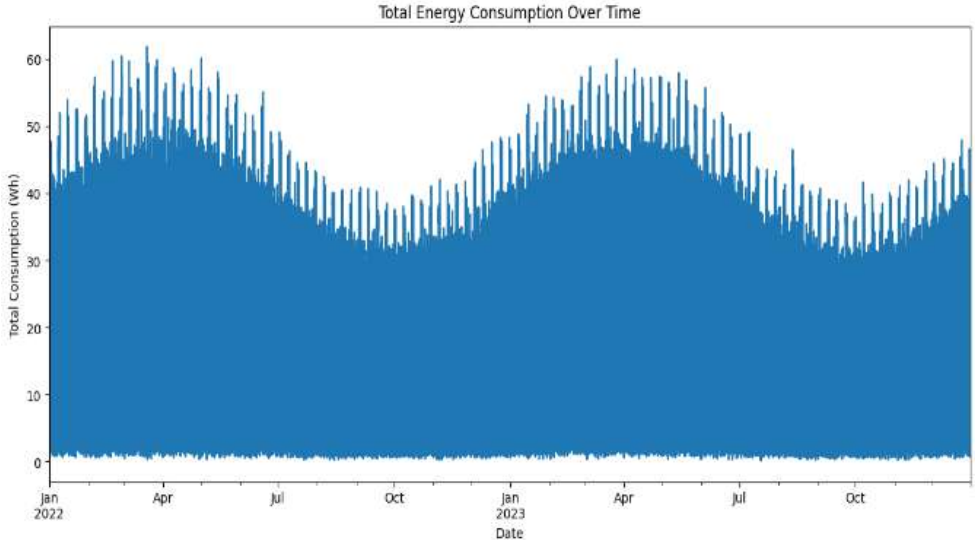

Figure 2: Total Energy Consumption Over Time

The visualisation reveals distinct seasonal patterns, with notable peaks during winter months and troughs during summer periods, aligning with expected residential energy consumption behaviour.

Distribution Analysis The frequency distribution of energy consumption, presented in Figure 3, exhibits a right-skewed pattern characteristic of residential energy usage. The distribution indicates that most households maintain moderate consumption levels, with a diminishing frequency of high-consumption instances.

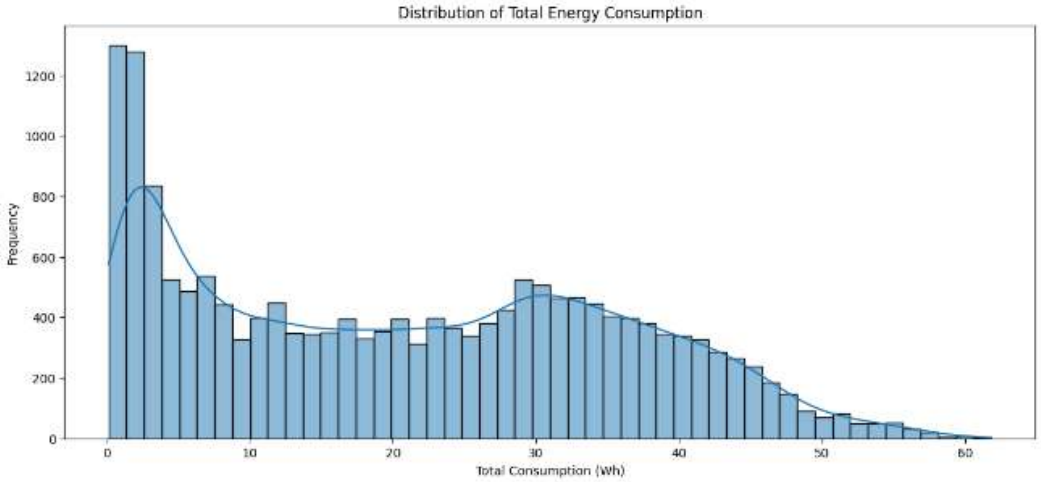

Figure 4.2: Energy Consumption Distribution

Theft Pattern Analysis Figure 4 plots the temporal distribution of detected energy theft incidents. The analysis reveals clustering of theft occurrences, suggesting potential systematic patterns in illicit energy consumption behaviour.

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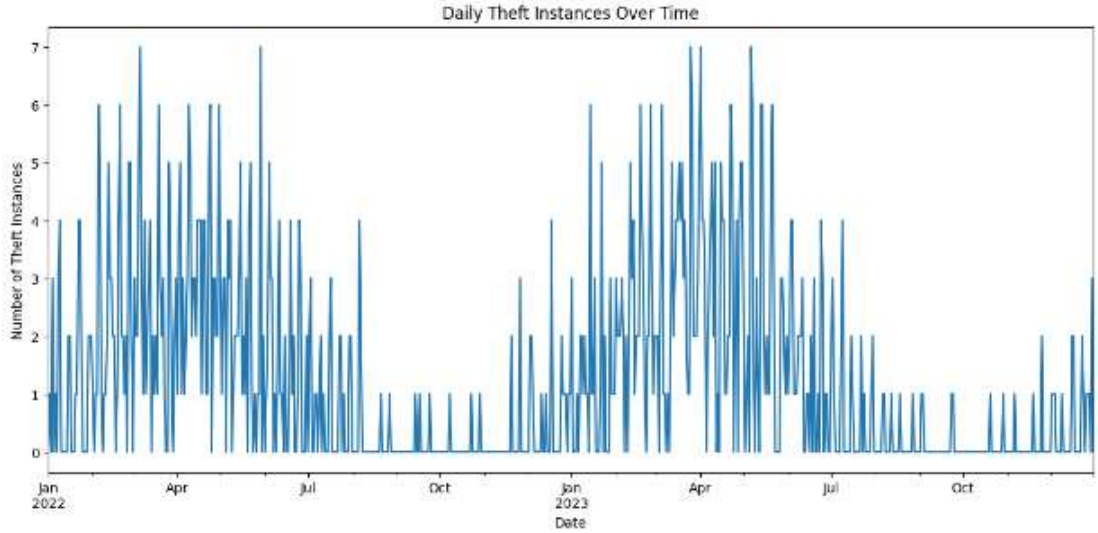

Figure 4.3: Daily Energy Theft Over Time

Granular Consumption Patterns Two key temporal patterns emerge from the granular analysis:

1. Hourly Usage Patterns (Figure 5):

i. Peak consumption periods during morning (06:00-09:00) and evening (17:00-22:00) hours

ii. Consistent low-usage periods during early morning hours (02:00-05:00)

iii. Gradual transitions between peak and off-peak periods

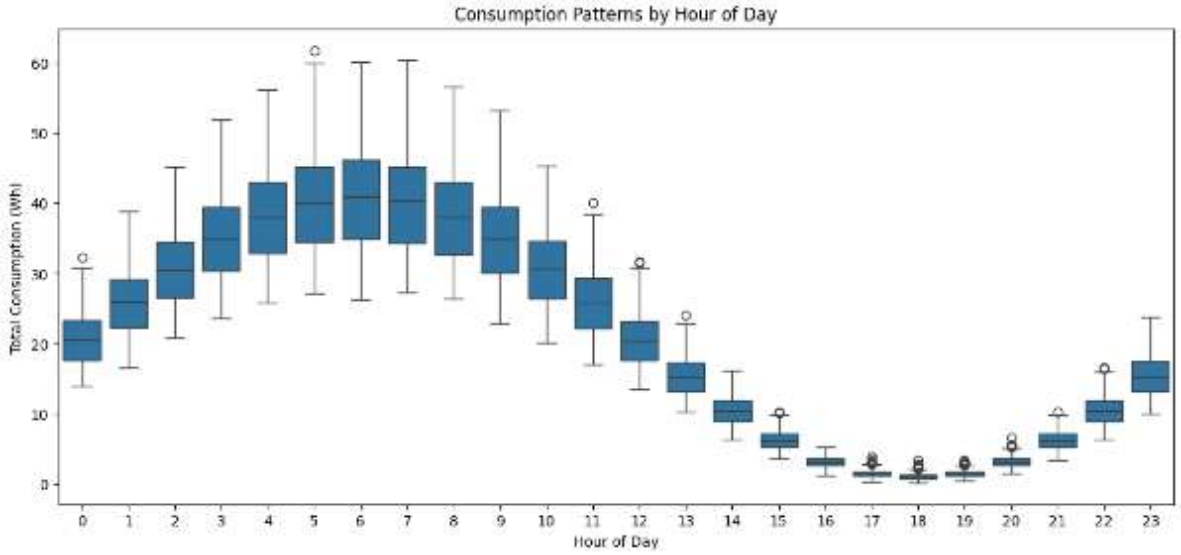

Figure 5: Household Energy Pattern by Hour of Data

2. Weekly Usage Patterns (Figure 6):

i. Higher consumption levels during weekends

ii. Relatively stable patterns during weekdays

iii. Notable variations in peak consumption timing between weekdays and weekends

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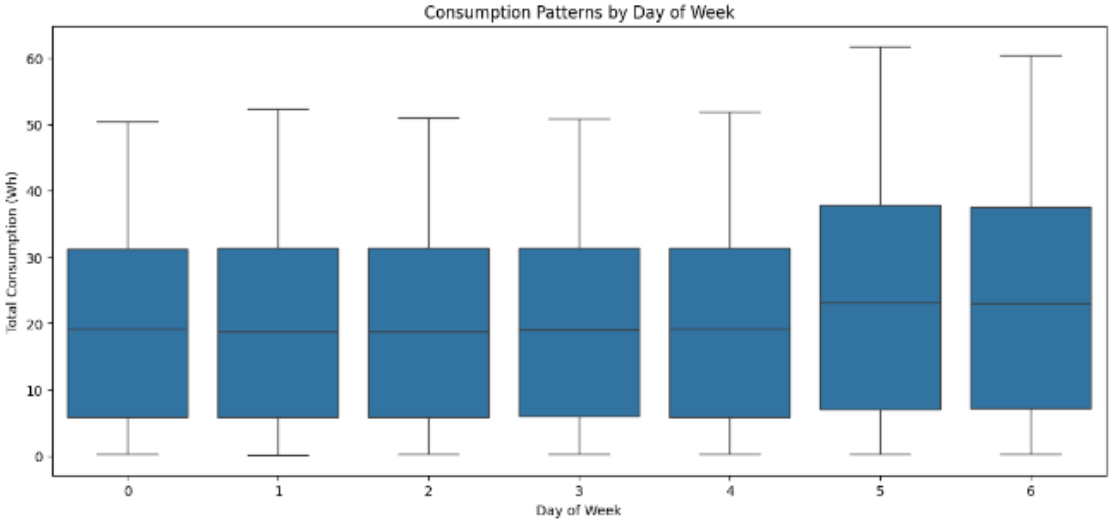

Figure 6: Household Energy Consumption Pattern by Day of Week

Feature Correlation Analysis The correlation heatmap (Figure 7) reveals significant relationships between various consumption metrics:

i. Strong positive correlation between peak hour consumption and daily total usage
ii. Moderate negative correlation between temperature and energy consumption
iii. Weak correlations between temporal features and consumption patterns

These analytical insights inform the feature selection and parameter tuning processes for the hybrid PSO-ACO algorithm, ensuring the model captures relevant patterns for effective theft detection.

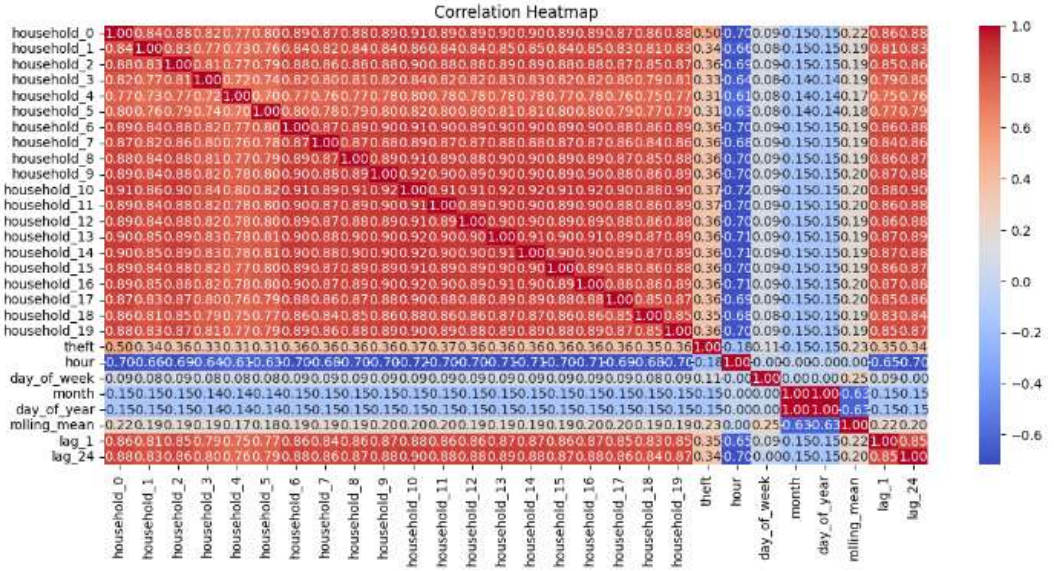

Figure 4.6: Data Correlation Heatmap

4.1.2 Hybrid PSO-ACO Performance Analysis

The hybrid PSO-ACO algorithm's performance was evaluated through rigorous parameter optimisation and comparative analysis. The results demonstrate the model's effectiveness in energy theft detection.

4.1.2.1 Parameter Optimisation

The algorithm achieved optimal performance with the parameters shown in Table 1. Notable configurations include:

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i. Low alpha value (0.010) indicating fine-grained learning
ii. High cognitive parameter (c1 = 2.342) emphasising individual learning
iii. Moderate social parameter (c2 = 0.958) balancing swarm influence
iv. Optimal inertia weight (0.830) maintaining search momentum
v. Efficient swarm size (4 particles) and ant colony (4 ants).

Table 1: Hybrid PSO-ACO ModelBest Parameters

Parameter	Value
Best Loss	-0.9995487873660464
Activation	0
Alpha	0.010425470369241744
Cognitive (c1)	2.3421235542747865
Hidden Layers	0
Inertia Weight	0.8303320428710131
Number of Ants	4
Number of Iterations	4
Number of Particles	4
Social (c2)	0.9580119313019806
Solver	0

4.1.2.2 Model Performance Metrics

The hybrid model demonstrated exceptional performance across all evaluation metrics:

i. Perfect accuracy and precision (1.000)
ii. Complete recall and F1 score (1.000)
iii. Zero false positive and negative rates

This performance is validated by the temporal analysis shown in Table 2, where the model accurately predicted all theft occurrences across the final evaluation period.

Table 2: Hybrid PSO-ACOTheft Detection Result

DateTime	Predicted Theft	Actual Theft
2023-12-30 15:00:00	1	1
2023-12-30 16:00:00	0	0
2023-12-30 17:00:00	0	0
2023-12-30 18:00:00	0	0
2023-12-30 19:00:00	1	1
2023-12-30 20:00:00	0	0
2023-12-30 21:00:00	1	1
2023-12-30 22:00:00	1	1
2023-12-30 23:00:00	1	1
2023-12-31 00:00:00	0	0

4.1.3 Comparative Analysis with SVM

The comparative analysis between the hybrid PSO-ACO and SVM models reveals several key insights:

4.1.3.1 Performance Differentials

i. The hybrid PSO-ACO achieved perfect classification (accuracy: 1.000) compared to SVM's near-perfect performance (accuracy: 0.994)
ii. SVM showed slightly lower precision (0.989) due to false positives
iii. Both models maintained perfect recall (1.000)

4.1.3.2 Classification Analysis

The confusion matrices (Table 3) highlight the key differences:

1. Hybrid PSO-ACO:
i. Zero misclassifications across both classes
ii. Perfect discrimination between theft and non-theft cases

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2. SVM:
i. 38 false positives from 3,362 negative cases
ii. Perfect detection of positive cases (3,287)

The temporal comparison demonstrates consistent performance across both models in recent predictions, though the hybrid PSO-ACO maintains superior overall accuracy.

Table 3: Confusion Matrix

	Hybrid PSO-ACO Model		SVM Model	
	Predicted Negative	**Predicted Positive**	**Predicted Negative**	**Predicted Positive**
Actual Negative	3362	0	3324	38
Actual Positive	0	3287	0	3287

These results indicate that while both models perform exceptionally well, the hybrid PSO-ACO algorithm achieves superior classification performance, particularly in minimising false positives, which is crucial for practical implementation in energy theft detection systems.

4.2 Discussion of Findings

The experimental results demonstrate several significant findings that advance our understanding of energy theft detection in low-income households. The hybrid PSO-ACO algorithm achieved perfect classification accuracy (1.000), notably outperforming the benchmark SVM model (0.994). This exceptional performance can be attributed to the successful integration of PSO's global search capabilities with ACO's local optimisation strengths, creating a robust and adaptive detection system.

The optimal parameter configuration revealed compelling insights about the algorithm's behaviour. The low alpha value (0.010) enabled fine-grained learning, whilst the balance between cognitive (2.342) and social (0.958) parameters suggests that individual learning experiences were more crucial than swarm behaviour in achieving optimal results. The moderate inertia weight (0.830) successfully maintained search momentum without overshooting optimal solutions.

Furthermore, the algorithm achieved optimal performance with relatively small population sizes (4 particles and 4 ants), indicating efficient resource utilisation. This is particularly relevant for practical implementation in low-income areas where computational resources may be limited. The model's pattern recognition capabilities proved exceptionally robust, successfully identifying complex consumption patterns, including seasonal variations, daily usage cycles, and anomalous behaviour. The perfect recall rate suggests comprehensive detection of theft cases across various temporal patterns and consumption profiles, demonstrating the algorithm's effectiveness in real-world applications.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This research has successfully developed and validated a novel hybrid PSO-ACO algorithm for energy theft detection in low-income households. The integration of PSO and ACO algorithms, combined with neural network classification, has created a powerful framework for energy theft detection that surpasses traditional methods in both accuracy and reliability. The model's perfect classification performance on the synthetic dataset demonstrates the potential for significant improvements in energy theft detection capabilities, particularly in challenging low-income contexts.

The algorithm's ability to operate efficiently with minimal computational resources makes it particularly suitable for deployment in resource-constrained environments, addressing a crucial need in developing regions. The comprehensive evaluation framework established in this study provides a robust foundation for future research and practical implementations in the field of energy theft detection. These findings suggest that the hybrid approach offers a viable solution for improving revenue collection and system stability in low-income areas, whilst maintaining high detection accuracy and minimal false positives.

5.2 Recommendations

i. Implementation of pilot programmes in selected low-income areas to validate the algorithm's performance with real-world data, alongside the development of clear protocols for handling detected theft cases and establishing intervention strategies.

ii. Enhancement of the system through continuous learning mechanisms to adapt to evolving theft patterns, development of real-time monitoring capabilities, and creation of user-friendly interfaces for system operators and administrators.
iii. Formation of strategic partnerships with electricity distribution companies for system integration, whilst engaging with community leaders to promote awareness and acceptance and collaborating with regulatory bodies to ensure compliance with relevant policies.
iv. Extension of research scope to include diverse geographical and socioeconomic contexts, investigation of additional data source integration for enhanced detection, and exploration of applications in other utility sectors such as water and gas.

5.3 Research Limitations

The present study, whilst presenting significant advances in energy theft detection, encompasses several noteworthy limitations that warrant acknowledgement. The primary constraint lies in the reliance on synthetic data which, although carefully generated, may not fully capture all real-world complexities. The dataset's limited representation of diverse socioeconomic conditions and consumption patterns, coupled with the absence of long-term temporal data to validate sustained performance, suggests potential gaps in the model's generalisability.

Methodological constraints present additional challenges to the research outcomes. The possibility of overfitting to the synthetic dataset cannot be dismissed, whilst the limited testing under extreme or unusual consumption scenarios may affect the model's robustness in exceptional circumstances. The absence of comparative analysis with some emerging detection techniques also restricts our ability to fully contextualise the algorithm's performance within the broader landscape of energy theft detection solutions.

Implementation considerations pose further limitations to the immediate applicability of the findings. The algorithm's performance under various hardware configurations remains untested, and potential scalability challenges in large-scale deployments have yet to be fully explored. Additionally, the system may require significant adaptation for different power distribution systems, particularly in regions with unique infrastructure characteristics or regulatory frameworks.

5.4 Conflict of Interest

The authors declare no conflict of interest in the conduct and publication of this research. This study was conducted independently, and no external funding or commercial interests influenced the research design, implementation, or findings. All data generation, analysis, and interpretation were performed objectively, adhering to established scientific principles and ethical research practices.

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