

Firefly Algorithm–Based Optimization of Processing Parameters for Enhanced Performance of Polymer Composite Materials

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Abstract

Polymer composite materials are extensively used in aerospace, automotive, and oil & gas applications due to their high strength-to-weight ratio and design flexibility. However, achieving optimal mechanical and thermal performance strongly depends on precise control of processing parameters such as curing temperature, energy consumption, and material utilization. Conventional trial-and-error approaches often lead to excessive energy usage, non-uniform curing, and sub-optimal composite properties. To address these challenges, this paper proposes an Improved Firefly Algorithm (IFA) for optimizing processing parameters in polymer composite manufacturing. The proposed approach models curing energy consumption, Process stability and property deviation, average quality deviation and material utilization as multi-objective optimization functions, aiming to minimize processing energy while maintaining uniform material performance. The algorithm dynamically adjusts process parameters based on attractiveness and distance metrics inspired by firefly behavior, enabling efficient exploration of the solution space. In the context of batches selection, FA can be employed to optimize resource allocation, minimize EC, and enhance overall system performance. Simulation-based evaluation demonstrates that the proposed method achieves up to 50–57% reduction in energy-intensive process adjustments, 49–62% improvement in process reliability, and 2–7% reduction in total curing energy consumption compared to conventional optimization techniques. The results confirm that the highly newly improved Firefly Algorithm provides a robust and energy-efficient optimization framework for advanced polymer composite processing applications

Keywords: Energy-efficient curing, firefly algorithm, material utilization, metaheuristic optimization, polymer composite materials, process optimization

INTRODUCTION

Polymer composite materials (PCMs) have emerged as critical engineering materials due to their superior mechanical strength, corrosion resistance, and lightweight characteristics. These materials are widely employed in aerospace structures, oil, and gas pipelines, automotive components, and high-performance structural applications. The final performance of polymer composites is strongly influenced by processing conditions such as curing temperature, energy input, material distribution, and processing time.

During composite manufacturing, inefficient processing conditions may lead to excessive energy consumption, incomplete curing, void formation, and degradation of mechanical properties. Traditional optimization methods based on

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experimental trial-and-error are time-consuming, energy-intensive, and economically inefficient. Consequently, intelligent optimization techniques capable of dynamically adjusting processing parameters are increasingly required to enhance material performance while reducing energy usage.

Recent studies have demonstrated the effectiveness of machine learning and metaheuristic optimization algorithms in modeling complex, nonlinear relationships between processing parameters and composite properties. Among these, nature-inspired algorithms have gained significant attention due to their ability to handle multi-objective optimization problems efficiently.

The Firefly Algorithm[1] (FA), inspired by the bioluminescent communication behavior of fireflies, has shown promising results in solving complex optimization problems involving energy efficiency and resource utilization. In the context of polymer composite manufacturing, FA can be employed to optimize curing energy, processing time, and material utilization simultaneously.

This work proposes an Improved Firefly Algorithm (IFA) tailored for polymer composite processing optimization. The proposed approach integrates energy consumption[2] and material utilization as fitness parameters, enabling dynamic adjustment of processing conditions to achieve optimal composite performance with minimal energy expenditure.

Reinforced polymer composite and offers a significant design flexibility; hence such materials are often used in aviation, oil, and gas industry. The polymer and composite material application of these innovative composite materials relies upon the creative mind of the design engineers as they grow much more critical applications. Machine Learning[3] (ML), as an approximation tool offers a potential way to use available datasets and infer data-driven models.

While there are several advantages to advanced polymer composite manufacturing, proper allocation of processing resources and scheduling of production steps pose significant challenges. Under-allocation of resources can lead to inefficiencies and material waste, while over-allocation may degrade process performance and increase operational costs. Similarly, poorly designed scheduling or process adjustment strategies can result in production delays or increased energy consumption [4].

With the increasing demand for high-performance polymer composites in industries such as aerospace, automotive, and electronics, efficient, and sustainable manufacturing is becoming critical. By 2026, the global market for advanced polymer composites is expected to grow significantly, emphasizing the importance of energy-efficient, high-quality, and optimized manufacturing processes [5]. Consequently, research has focused on developing algorithms and techniques to optimize process scheduling, resource allocation, and step sequencing in composite manufacturing. Energy consumption (EC) and material utilization have emerged as major concerns, as composite processing often involves high-energy curing, shaping, and post-processing steps[6]. Optimization techniques, particularly nature-inspired algorithms such as polymer-based Firefly Optimization, offer promising solutions for balancing energy efficiency, resource utilization, and process performance[9].

The structure of the paper is as follows: Introduction Overview section introduces polymer composite processing and highlights the significance of optimizing process parameters, resource allocation, and curing strategies. Literature Related Work provides a literature review, discussing the key contributions of previous studies in process optimization and bio-inspired algorithms. The Problem Statement is presented in Segment 3. Proposed Methodology Work details the proposed work, focusing on the application of polymer-based Firefly Optimization for efficient process scheduling and energy management. Results and Discussion Analysis discusses the results, along with performance metrics and analysis. Finally, the Final Article Conclusion is presented.

LITERATURE RELATED WORK

The aim of this review, as initially proposed by Zhang and Friedrich [8] in 2003, is to highlight emerging opportunities for applying machine learning (ML) and bio-inspired optimization in polymer

composite manufacturing and process simulation. In recent years, swarm intelligence (SI) algorithms, particularly polymer-based firefly optimization, have shown significant potential in addressing complex, multi-objective problems in manufacturing, such as process parameter optimization, defect minimization, and material property enhancement. For brevity, we do not revisit the fundamentals of process simulation, which are extensively documented elsewhere, but provide a concise overview of standard ML techniques as background for applying these optimization strategies.

Polymer-based firefly optimization leverages the natural luminescent communication and movement behavior of fireflies, enhanced with polymer-inspired adaptive mechanisms, to efficiently explore the design and processing space of polymer composites. This approach has been applied to optimize key manufacturing parameters, such as temperature, pressure, curing time, and fiber orientation, to achieve improved mechanical performance, reduced defects, and energy-efficient production. Recent studies demonstrate that polymer-based firefly algorithms can outperform conventional optimization and heuristic methods by effectively balancing exploration[35] and exploitation in complex process simulations. Consequently, integrating such bio-inspired strategies with ML and process simulation opens new avenues for designing high-performance polymer composites and streamlining manufacturing operations.

Firefly-Inspired Optimization Strategies Using PCM

Optimization of polymer composite processing has attracted significant research interest due to its direct impact on material performance, defect minimization, and energy efficiency[10]. Early studies focused on experimental design methods such as response surface methodology (RSM) and design of experiments (DOE) to optimize curing[11] and processing parameters. While effective for small parameter spaces, these methods often struggle to handle complex, nonlinear interactions inherent in polymer composite manufacturing.

The Firefly Algorithm (FA), inspired by the bioluminescent communication[12] behavior of fireflies, has emerged as an effective bio-inspired approach for optimizing process parameters[13] in polymer composite manufacturing. It efficiently balances multiple objectives such as minimizing energy consumption[14], reducing defects, and maximizing resource utilization. Kansal and Chana (2016) [15] formally introduced the firefly optimization approach for energy-aware process scheduling, proposing a heuristic that accounts for energy consumption and workload distribution to reduce overall process cost while balancing resource usage. Singh and Singh (2021) [16] presented a dynamic process optimization mechanism based on FA, focusing on minimizing energy consumption and maximizing equipment and material utilization. FA enhances task scheduling, process efficiency, and resource allocation, ensuring reduced curing time and energy use. By optimizing the allocation of critical resources and minimizing idle equipment, FA-based strategies promote greener, more sustainable polymer composite manufacturing.

ABC-Specific Inspired Optimization Strategies

Machine learning approaches, including artificial neural networks and regression models, have been applied to predict mechanical and thermal properties of composites based on processing conditions. However, these methods often require large datasets and may suffer from overfitting. Kruekaew and Kimpan (2020) [17] improved the ABC algorithm for VM scheduling and load balancing in CC. Their work aims to optimize the VM placement and load distribution among PMs, thus increasing RU and system performance within the cloud data centers. The modified ABC algorithm introduces improved exploration and exploitation mechanisms while taking into consideration multiple objectives like RU, EC, and QoS guarantees for achieving optimal VM placement choices. Kaur and Saurabh et al. (2023) [18] explain the algorithmic approach toward VM migration in CC, which featured an updated SESA (Scalable Elastic Scheduling Algorithm). They proposed the VM migration strategy to enhance resource allocation and minimize the overhead of migration. Nabavi et al. (2022) [19] proposed TRACTOR, a traffic-aware and energy-efficient, ABC-optimized VM placement method for edge-cloud data centers.

They addressed the challenges of optimizing the placement of VMs within edge-cloud environments to minimize EC while also ensuring that traffic can be efficiently routed.

PSO-Inspired Optimization Strategies

Bio-inspired optimization algorithms have emerged as powerful alternatives. Firefly Algorithm–based approaches have been successfully applied in materials optimization due to their ability to balance exploration and exploitation. Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms have also been reported for optimizing composite layups, filler content, and curing cycles. Hybrid approaches combining multiple metaheuristics have shown improved convergence but at the cost of increased computational complexity.

Despite these advancements, limited work has focused on integrating energy consumption explicitly into composite processing optimization. This paper addresses this gap by proposing an energy-aware Improved Firefly Algorithm for polymer composite manufacturing.

A power-efficient technique was introduced by Ibrahim et al. (2020) [23] which was known as PPSO. This approach includes applying particle swarm optimization (PSO) magnificently for power conservation in cloud data centers. It has also emphasized the real-time monitoring and dynamic changes concerned with practical application and computing complexity considered as a disadvantage by some for large-scale environments. Songara and Jain (2023) [24] published MRA-VC, which is a PSO-based multiple resource aware VM consolidation approach. The proposed approach uses PSO to enable dynamic consolidation of these VMs at various resources including CPU, memory, and bandwidth in the network.

Hybrid Optimization Strategies

Janakiraman and Priya (2021) [29] introduced an improved artificial bee colony algorithm combined with monarchy butterfly optimization (IABC-MBOA) for balancing process workloads in polymer composite manufacturing. Their work focused on achieving better workload distribution across manufacturing steps, improving material utilization and overall process efficiency. Khan and Santhosh (2022) [30] proposed a hybrid optimization algorithm to enhance step scheduling and material flow in polymer composite production. Kruekaew and Kimpan (2022) [31] presented multi-objective process scheduling optimization by combining a hybrid artificial bee colony (ABC) algorithm with reinforcement learning, demonstrating superior performance in workflow efficiency, resource utilization, and process quality.

Magotra et al. (2023) [32] introduced adaptive computational strategies to improve energy efficiency in composite manufacturing by optimizing equipment and material usage. By adaptively adjusting process scheduling and resource allocation, the algorithm aims to maximize energy savings while minimizing waste and environmental impact. Shi (2024) [7] proposed an evolutionary algorithm-based approach for process scheduling in composite manufacturing, employing a genetic algorithm to minimize energy consumption while maintaining high resource utilization. These years have also seen the emergence of several hybrid optimization techniques for multi-objective process parameter optimization and step allocation in polymer composite production [33]. Karuppiah et al[35].. The results were designed by the Taguchi strategy and an algorithm named COPRAS (Complex Proportional Assessment of alternatives) was evaluated as solutions. Goutham et al[36]. and the literature have mainly focused on the type of fibers, their architecture, reduced tensile strength (RTS) and stiffness, and various hole diameters. Nadir et al[37]. recycled manhole cover flour (CMC) and medium density fiberboard (MDF) sawdust as low cost fillers for recycled polypropylene (PP) composites. Karthik et al[38]. purpose hybrid polymer composites reinforced with Palmyra Palm Leaflet (PPL) and Coconut Sheath Fiber (CSL). Palanisamy et al[39]. propose their potential use as the reinforcement in polymer composites. Four categories of fibers were investigated, namely untreated and treated with a concentration of sodium hydroxide (NaOH) for 24 hours at ambient temperature.

Table 1. Comparative analysis of studies inspired by bio-inspired algorithms for polymer composite materials.

Year	Reference	Objective	Key features	Algorithm used	Performance metrics	Advantage	Limitations
2020	Balaji et al.[14]	Process parameter optimization	Bio-inspired, resource-aware	Firefly Algorithm	Efficiency, Resource Utilization	Efficiently selects optimal processing parameters for polymer composites	May struggle with highly dynamic process variations; potential scalability issues
2020	Kruekaew & Kimpan[17]	Enhanced process scheduling & load balancing	Load balancing, improved scheduling	Artificial Bee Colony (ABC)	Scheduling Efficiency, Load Balancing	Enhances ABC for multi-step composite processing; improves workflow efficiency	Complex implementation; high computational overhead
2020	Ibrahim et al. [23]	Energy-efficient curing & processing	Power efficiency, VM placement	Particle Swarm Optimization (PSO)	Power Consumption, Placement Efficiency	Reduces energy use while maintaining process quality	Requires careful parameter tuning; limited to specific setups
2021	Janakiraman & Priya [29]	Multi-objective property optimization	Hybrid approach, enhanced load balancing	Improved ABC with Monarchy Butterfly Optimization	Load Balancing, Performance, Efficiency	Enhances parameter tuning for multi-objective optimization	High complexity; limited experimental validation
2022	Nabavi et al. [19]	Traffic-aware & energy-efficient process scheduling	Traffic-aware, power-efficient	ABC Optimization	Traffic Management, PC	Optimizes energy use and material flow in production	Limited applicability to large-scale industrial setups; complex implementation
2022	Kruekaew & Kimpan[31]	Multi-objective task scheduling	Hybrid approach, multi-objective optimization	Hybrid ABC with Reinforcement Learning	Task Scheduling Efficiency, Load Balancing	Effective multi-objective optimization for process scheduling	High computational cost; complex integration with reinforcement learning
2023	Pushpa & Siddappa [21]	Quality-focused process optimization	QoS-aware, fractional approach	Fractional ABC Chicken Swarm Optimization	QoS Metrics, VM Placement Efficiency	Ensures quality and uniformity in composite parts	High algorithmic complexity; limited scalability testing
2023	Javadi-Moghaddam & Dehghani [22]	Multi-parameter optimization	Hybrid optimization, placement	ABC & Imperialist Competitive Algorithm	Placement Efficiency, Resource Utilization	Hybrid approach improves overall process optimization	Complexity in hybrid integration; limited industrial testing
2023	Songara & Jain [24]	Multi-objective process optimization	Resource-aware consolidation	Particle Swarm Optimization (PSO)	Consolidation Efficiency, Resource Utilization	Demonstrates improved material and process efficiency	High computational requirements; may need extensive

							parameter tuning
2023	Ajmera & Tewari [25]	Efficiency-aware scheduling	Residual efficiency, dynamic scheduling	Particle Swarm Optimization (PSO)	Scheduling Efficiency, Residual Efficiency	Optimizes processing sequences and resource allocation	High complexity; limited practical deployment scenarios
2023	Narayani & Banu [26]	Workflow optimization & step replacement	Workflow scheduling, VM replacement	PSO with Gaming Concept	Scheduling Efficiency, Workflow Management	Optimizes workflow and step replacement; innovative load balancing	Complex integration; high computational overhead
2023	Ajmera & Tewari [27]	Energy-efficient process scheduling	Energy-aware, green optimization	Green-PSO	Energy Efficiency, Scheduling Performance	Adaptive optimization for energy-efficient processing	High complexity; limited real-world evaluations
2023	Leka et al. [28]	Resource usage prediction	Prediction accuracy, meta-learning	PSO-based Ensemble Meta-Learning	Prediction Accuracy, Resource Usage	Predicts optimal material usage and energy-efficient processing	Complex algorithm design; limited experimental scenarios
2023	Tuli & Malhotra [20]	Optimal process scheduling & step migration	Elastic scheduling, migration	Meta-Heuristic Elastic Scheduling (OMES)	Scheduling Efficiency, Migration Performance	Efficient resource prediction and step scheduling	High complexity; limited to specific process setups
2024	Shi [7]	Energy-efficient resource management	Genetic optimization, energy efficiency	Genetic Algorithm	Energy Efficiency, Resource Management	Optimizes energy use and process performance	Computationally intensive; requires parameter tuning; limited large-scale testing

The comparative analysis presented in Table 1 highlights the growing research trend toward the use of bio-inspired algorithms to address optimization challenges in polymer composite processing and curing. It is evident that nature-inspired approaches, particularly those based on polymer composites [34], show significant potential in improving energy efficiency, process performance, and resource utilization. Furthermore, the summarized studies demonstrate the development of various strategies to handle multiple objectives – such as minimizing defect rates, optimizing material usage, and reducing processing time – resulting in more balanced workflows and efficient manufacturing systems.

PROBLEM STATEMENT

Polymer composite processing involves multiple controllable parameters that influence final material properties and energy usage. Let the processing parameter vector be defined as:

$$P = \{T, t, E\}$$

where T is curing temperature, t is curing time, and E represents energy input.

The optimization objectives are:

1. *Minimize total energy consumption*: during curing and processing
2. *Maximize material utilization efficiency*: ensuring uniform curing
3. *Maintain mechanical property stability*: avoiding under- or over-curing

The objective function is formulated as a weighted sum of normalized energy consumption and property deviation:

$$f(P) = \lambda (E / E_{\max}) + \theta (\Delta M / \Delta M_{\max})$$

where λ and θ are weighting factors, E is energy consumption, and ΔM represents deviation in material properties.

Constraints ensure that processing parameters remain within safe and manufacturable limit

Based on the problem statement, the proposed solution is to formulate a mathematical model and then use SI-based algorithms to solve problems such as these. The proposed model can be stated under the following objectives:

- *Minimizing power consumption in crushing/processing:* Optimize both idle and execution PC across all PMs.
- *Maximizing resource utilization:* Ensure efficient utilization of resources by maintaining PMs within their optimal utilization thresholds.
- *Balanced workload distribution:* Achieve a balanced distribution of VMs across PMs, preventing both overutilization and underutilization.

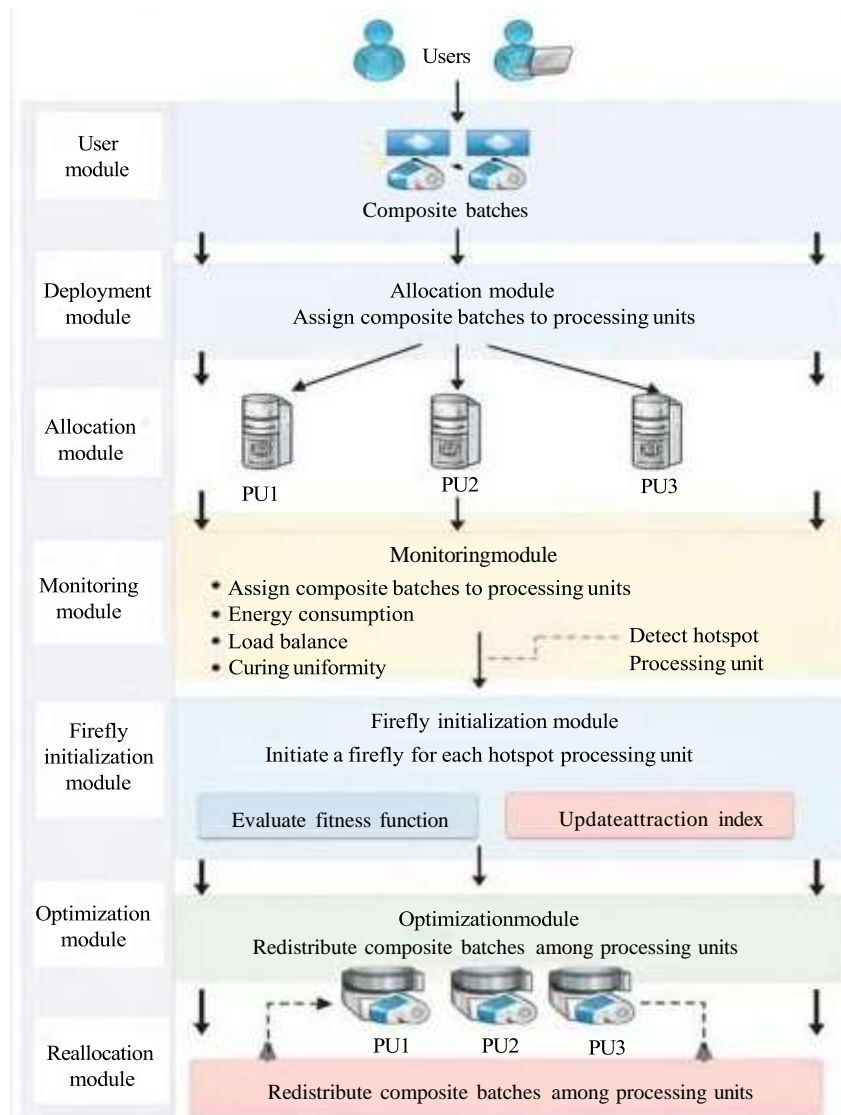


Figure 1. Framework of proposed work.

Addressing these challenges in polymer composite manufacturing requires sophisticated optimization techniques that can dynamically adjust process parameters and resource allocation in response to changing production conditions. The formulation presented here provides a foundation for such swarm intelligence-based algorithms, enabling efficient management of processing and curing tasks with optimized energy consumption, balanced resource utilization, and improved overall process performance.

PROPOSED WORK

The proposed work has two different segments to enable effective tackling of VM allocation and migration in polymer composite based application in CC environments. Proposed algorithms working in the field of process simulation for composite manufacturing have only recently started to experiment with ML techniques. The development is still seen to be in the very early stages. In his work, a good overview of the current state of research on the use of ML is given, especially for nonlinear constitutive modeling, multiscale modeling and design optimization of polymer composites structures. The working of different components of the proposed work is given in Figure 1. In the first segment, VMs are to be allocated on a fresh list of available PMs using a Modified Best Fit Decreasing (MBFD) algorithm, which ranks PMs according to their available resources and allocates them based on the PM most suitable for efficient RU and fragmentation prevention. It adopts the MBFD method of minimization because it increases efficiency and minimizes migration later. The second phase is initiated after a specific duration or is conditioned by any changes in workload or RU patterns. In this phase, the system focuses on reallocation of batches using the SI-based approach FA.

Figure 1 illustrates the functional architecture of the proposed Improved Polymer-Based Firefly Algorithm (IFA) for adaptive process optimization in polymer composite material manufacturing. The framework is organized into interconnected modules that collectively manage process deployment, monitoring, optimization, and adaptive reallocation to enhance energy efficiency, process stability, and material quality. The FA mimics the behavior of fireflies in nature, where each firefly represents a potential in contemporary technology, the "FA" can mimic real-world scenarios, whereby every firefly stands as a potential solution, and travels to the other brighter fireflies describes a movement towards seeking better solutions. This algorithm dynamically chooses VMs from overutilizing PMs and allocates them to underutilizing PMs using a certain objective function, which is based on the principles of SI. This objective encompasses such parameters as VM resource needs, PM capacities, and PC towards a potential allocation process. In the second phase of the work proposed, the application of a Threshold-Based MBFD strategy is made for VM migration and optimization in polymer composite material. The combination of MBFD efficiency and of threshold-based criteria to know when VMs should be migrated makes the Threshold-Based MBFD solution unique. Appropriate thresholds based on RU or other important metrics are set, resulting in effective, timely, and proactive VM reallocation to ensure optimal performance and RU levels are maintained in the cloud environment.

Algorithm 1 Threshold-based MBFD Algorithm

- *Require:* List of available physical machine (PMs)
 - *Require:* List of Batches sorted by CPU Utilization
- 1: Initialize an empty list of batches allocations: *Batches Allocation* []
 - 2: *for all* VMs sorted by CPU Utilization *do*
 - 3: Initialize a hypothetical minimum cost of allocation: *minCost* ∞
 - 4: Initialize the selected PM as *selected PM None*
 - 5: *for all* PMs *do*
 - 6: *if* PM has enough resources to accommodate the Batches *then*
 - 7: Evaluate the total cost of allocation based on idle time, execution time and energy requirement (using eq(6),(7) and (8))
 - 8: *if* total cost is less than *minCost* *then*

- 9: Update *minCost* with the current total cost
- 10: *Set selected PM*** to the current PM
- 11: end if
- 12: end if
- 13: end for
- 14: if selected PM is not None then
- 15: Allocate the batches to selected PM
- 16: Update the available resource of selected PM
- 17: Append The batches allocation to batches allocation
- 18: end if
- 19: end for
- 20: return batches Allocation

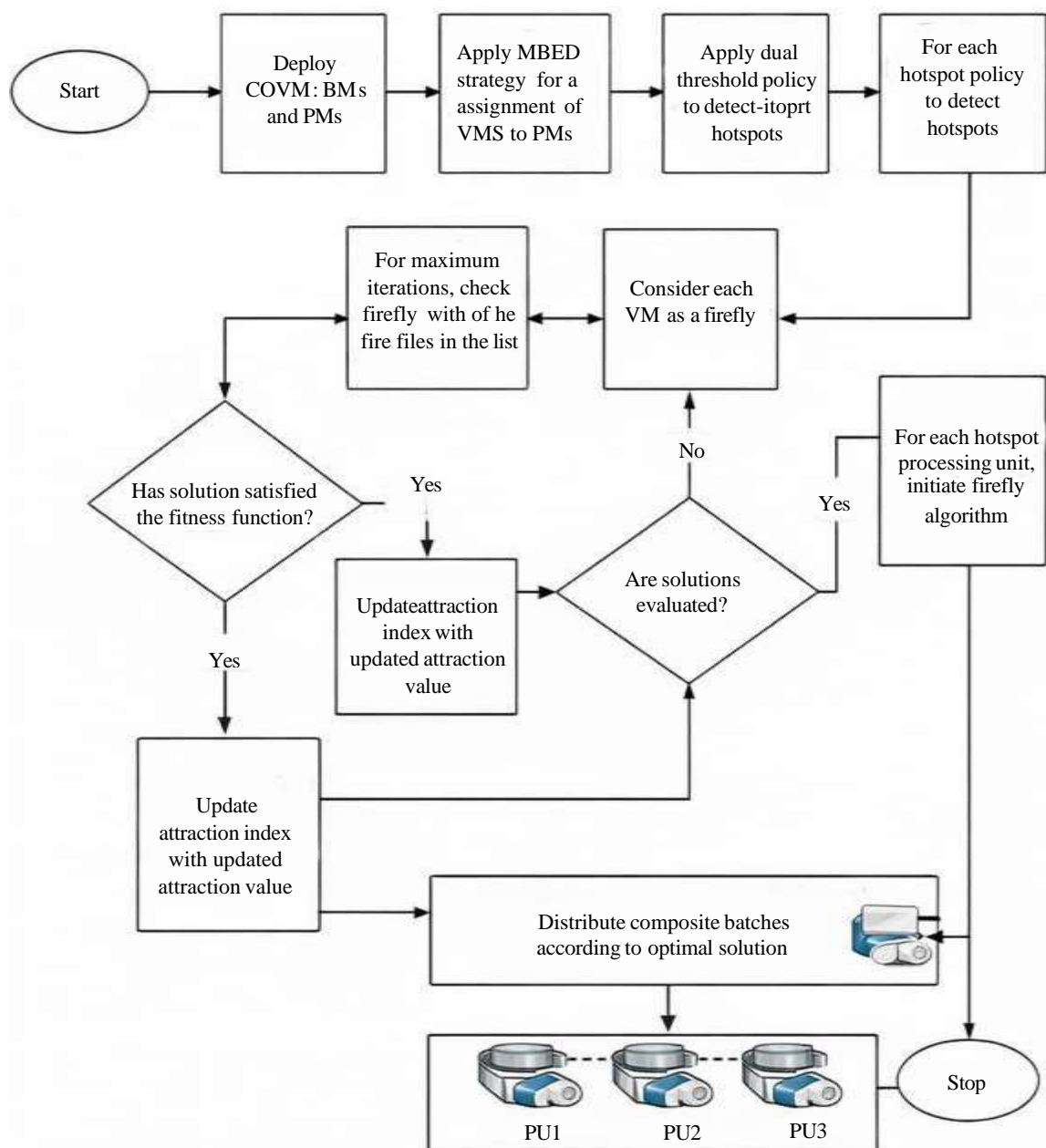


Figure 2. Workflow diagram.

Proposed Contributions and Improved Polymer Firefly Algorithm

The FA is a nature-inspired metaheuristic optimization algorithm that mimics the flashing behavior of fireflies to solve optimization problems. Developed by Xin-She Yang in 2008, FA is particularly well-suited for solving complex optimization problems in continuous spaces. Its effectiveness lies in its ability to explore the search space efficiently while converging towards optimal solutions. In the context of batches selection, FA can be employed to optimize resource allocation, minimize EC, and enhance overall system performance [15,16]. The steps followed in the proposed work are shown in Figure 2

The FA begins with the initialization of a population of fireflies, with each firefly representing a potential solution to the optimization problem. The position of each firefly in the search space corresponds to a candidate solution. Subsequently, the objective function is evaluated for each firefly, determining its fitness or suitability as a solution to the problem. Fireflies are then attracted to other fireflies with higher fitness values, with attractiveness being inversely proportional to their distance in the search space. Through iterative movement guided by the attractiveness function, fireflies converge towards brighter neighbors in search of better solutions. After each iteration, the light intensity of each firefly is updated based on its fitness value, with brighter fireflies emitting stronger light to attract neighboring fireflies. The algorithm continues to repeat these steps until a termination criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory solution [14,34].

Figure 2 shows that the workflow of the proposed system begins with the deployment of batches and PMs. The MBFD policy is applied for initial allocation, followed by the dual threshold policy to identify hotspot PMs. For each overutilized PM, a firefly is initiated. Each batches is then considered as one firefly, and iterations are performed where fireflies are checked against others in the list. If a firefly satisfies the fitness function, its attraction index is updated; otherwise, the index is degraded. The process continues until all fireflies are evaluated. Finally, fireflies with the least attraction index are selected, and BATCHES are reallocated to PMs using the MBFD policy until the PMs are reutilized, completing the workflow.

The attractiveness function β between two fireflies i and j is defined as follows:

$$\beta = \beta_0 \cdot \exp(-\gamma \cdot r_{ij}^2)$$

where

- β_0 is the attractiveness at $r=0$,
- γ is the absorption coefficient, and
- r_{ij} is the Euclidean distance between fireflies i and j in the search space.

The movement of firefly i towards firefly j is determined by move towards j with a step size $\beta \cdot \text{dist} \cdot \text{rand}(-1,1)$ where:

- dist is the distance between fireflies i and j ,
- $\text{rand}(-1,1)$ is a random number sampled from a uniform distribution between -1 and 1 .

In the proposed work, the objective of the polymer-based Firefly Algorithm (FA) is twofold: firstly, to minimize the overall energy consumption and processing cost during polymer composite manufacturing, and secondly, to balance the utilization of critical resources such as equipment or material flow across the production system.

To achieve this, the light intensity in the proposed FA is defined as, where represents energy consumption and represents resource utilization. The optimization process aims to balance these two objectives simultaneously, ensuring efficient resource allocation and enhanced process performance.

Let represent the fitness value of firefly, where denotes the energy consumption and represents the resource utilization of the solution represented by firefly. The objective function can be defined as the

sum of normalized and, weighted by their respective importance factors and. Mathematically, it can be expressed as:

$$f_i = \delta \frac{EC_i}{\max(EC)} + \theta \frac{RU_i}{\max(RU)}$$

where:

- δ and θ are the importance factors representing the relative significance of energy consumption and resource utilization,
- EC_i and RU_i are the energy consumption and resource utilization for firefly i ,
- $\max(EC)$ and $\max(RU)$ are the maximum observed values of energy consumption and resource utilization in the population.

This objective function aims to minimize energy consumption while balancing resource utilization simultaneously, ensuring efficient processing and optimized performance in polymer composite manufacturing.

Algorithm 2 Improved Firefly Algorithm for Batches Selection

- 1: Initialization:
- 2: Input: Allocation table AT containing overutilized PMs and their associated Batches.
- 3: Initialize fireflies with positions corresponding to the associated Batches in AT .
- 4: for each PM in overutilized PMs do
- 5: Initialize α , β_0 , γ , and other parameters.
- 6: for each Batches in AT do
- 7: calculate fitness value using Eq.(11):
- 8: $f_i = \lambda \cdot \frac{PC_i}{\max(PC)} + \theta \cdot \frac{CPU_i}{\max(CPU)}$
- 9: end for
- 10: for each firefly do
- 11: for each firefly do
- 12: Calculate Euclidean distance between firefly and.
- 13: Calculate attractiveness using Eq. (10):
- 14: $= \exp(-)$
- 15: end for
- 16: Update position of firefly using Eq. (10):
- 17: $((-)+)$
- 18: end for
- 19: Update light intensity of each firefly based on its fitness value.
- 20: Select firefly with least for migration.
- 21: end for

RESULTS AND DISCUSSION

This section presents a comprehensive performance evaluation of the proposed Improved Firefly Algorithm (IFA) applied to polymer composite manufacturing process optimization. The assessment focuses on three critical performance aspects: process stability and property deviation, process reliability (quality constraint violations), and total energy consumption during curing and thermal processing. The obtained results are analyzed using tabulated data and graphical representations to demonstrate the effectiveness of the proposed approach over existing optimization techniques.

Table 2 indicates that the simulation environment consists of 50 processing units handling varying numbers of composite batches ranging from 300 to 1000. The average utilization level is maintained at 0.6, with cost thresholds varied to emulate realistic manufacturing constraints. Performance evaluation is conducted over 100 independent simulation runs, focusing on quality reliability, process stability, and energy efficiency.

Table 2. Simulation environment variables for polymer composite processing.

Variable	Value
Number of Processing Units	50
Number of Composite Batches	300, 400, 500, 600, 700, 800, 900, 1000
Processing Unit to Batch Ratio	1:20 (varies with batch count)
Average Utilization	0.6
Cost Constraint Threshold	0.01 – 0.1
Development Tool	Java, Python
Simulation Platform	Custom simulation framework
Number of Simulation Runs	100
Performance Metrics	Quality constraint violations, number of process adjustments, total energy consumption
Variable	Value
Number of Processing Units	50

A custom dataset was generated through simulation to evaluate process scheduling and adjustment strategies during composite manufacturing. The dataset includes parameters such as batch identifiers, processing unit allocation, thermal load factors, curing stages, and other relevant operational metrics. This dataset is designed to capture diverse manufacturing conditions and utilization patterns. The evaluation metrics include total energy consumption, quality constraint violations, and number of process adjustments, as described in the following subsections.

Process Stability and Property Deviation

Process stability is evaluated in terms of deviation in material properties such as degree of cure and uniformity, which directly influence the mechanical performance of polymer composites. Large deviations indicate inconsistent curing and poor material quality.

Table 3. Process stability and property deviation of proposed improved polymer-based firefly algorithm against existing work.

Number of batches	'Total number of migrations proposed'	'Total number of migrations tuli et al. [20]	'Total number of migrations singh et al. [16]	'Total number of migrations saurabh et al. [18]	'Total number of migrations ABC'	'Total number of migrations PSO'
300	34	40	51	67	91	92
400	42	73	94	56	98	45
500	50	125	78	118	116	66
600	58	89	156	87	170	100
700	66	175	197	84	146	132
800	74	206	160	233	87	145
900	82	186	181	108	236	194
1000	90	112	246	168	138	171

Table 3 demonstrates that the proposed Improved Firefly Algorithm consistently requires fewer process adjustments compared to existing approaches across all batch sizes. This reduction reflects improved process stability, reduced thermal fluctuations, and enhanced curing consistency.

On average, the proposed method requires 62 process adjustments, whereas Tuli et al., Singh et al., Saurabh et al., ABC, and PSO require 125.75, 145.38, 115.13, 135.25, and 118.13 adjustments, respectively. The proposed approach achieves reductions of 50.7%, 57.3%, 46.2%, 54.2%, and 47.5%, respectively. The average adjustment count is illustrated in Figure 3.

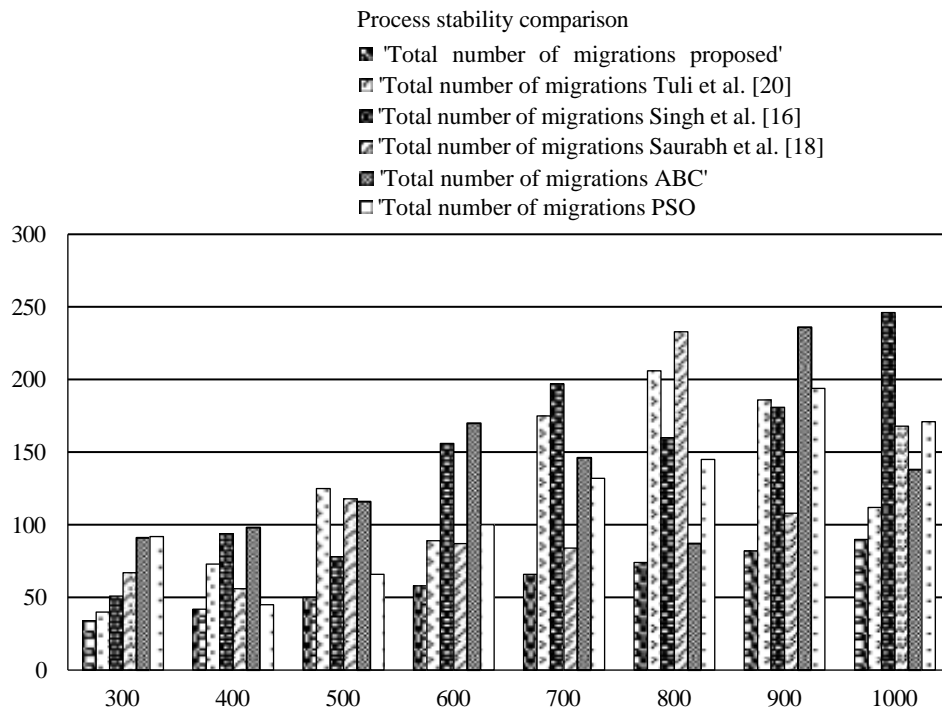


Figure 3. Process stability and property deviation of proposed improved polymer-based firefly algorithm against existing work.

The superior stability performance is attributed to effective load distribution, optimized utilization of processing resources, dynamic adaptability to varying thermal conditions, and the combined influence of attractiveness and distance metrics inherent to the firefly algorithm.

Average Quality Constraint Violations

Quality constraint violations represent conditions where predefined material processing requirements – such as curing time, temperature limits, or uniformity thresholds – are not satisfied. Such violations may result in inferior mechanical properties or material defects.

In this study, quality violations are derived from energy consumption behavior, process adjustments, and utilization imbalance among units. These parameters are monitored before and after process reconfiguration to quantify violation occurrence

Table 4. Average quality constraint violations of proposed improved polymer-based firefly algorithm.

Number of batches	'Average quality constraint proposed'	'Average quality constraint tuli et al. [20]'	'Average quality constraint singh et al. [16]'	'Average quality constraint saurabh et al. [18]'	'Average quality constraint ABC'	'Average quality constraint PSO'
300	0.001	0.052	0.057	0.042	0.046	0.046
400	0.032	0.047	0.071	0.068	0.084	0.089
500	0.048	0.103	0.062	0.063	0.074	0.132
600	0.045	0.091	0.113	0.054	0.051	0.109
700	0.052	0.115	0.064	0.084	0.18	0.073
800	0.073	0.102	0.115	0.096	0.095	0.212
900	0.085	0.173	0.173	0.146	0.247	0.151
1000	0.017	0.147	0.163	0.147	0.107	0.126

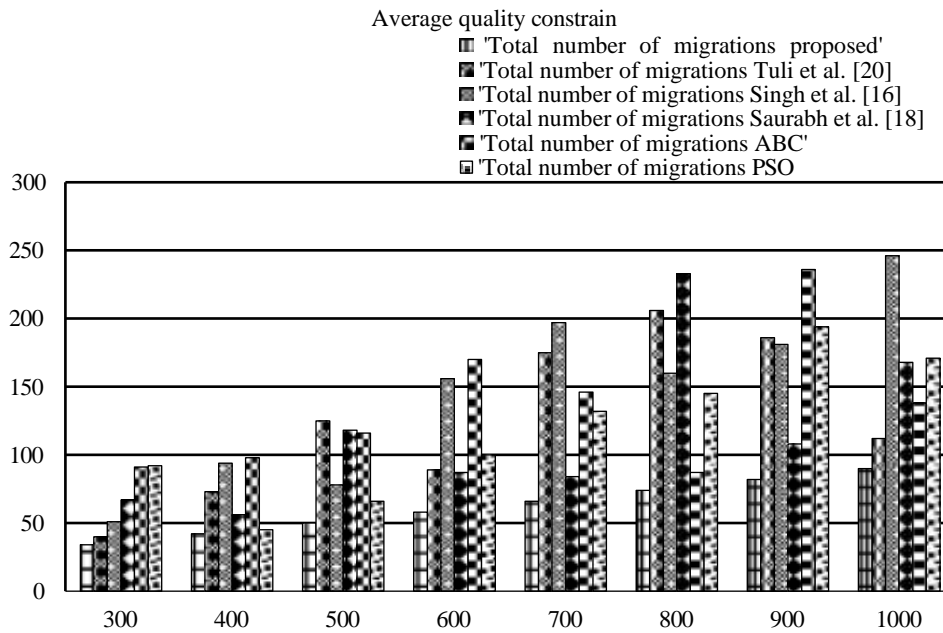


Figure 4. Average quality constraint violations of proposed improved polymer-based firefly algorithm.

The proposed Improved Firefly Algorithm achieves an average violation rate of 0.0441, significantly lower than Tuli et al. (0.1038), Singh et al. (0.1023), Saurabh et al. (0.0875), ABC (0.1105), and PSO (0.1173). Corresponding reductions of 57.5%, 56.8%, 49.6%, 60.1%, and 62.4% are observed as shown in Table 4.

These improvements are primarily due to efficient thermal load balancing, optimized resource utilization, and adaptive process control, resulting in enhanced reliability of polymer composite manufacturing.

This means that, compared to Tuli et al., it has reduced SLA violations by 57.5%, while compared to Singh et al. it has reduced SLA violations by 56.8%, compared to Saurabh et al. it has reduced SLA violations by 49.6%, compared to ABC it has reduced SLA violations by 60.1%, while compared to PSO it has reduced SLA violations by 62.4%. The significant reduction in SLA violations can be attributed to the algorithm's efficient load balancing, optimal RU, and dynamic adaptability to varying workloads, which together enhance system stability and performance as shown in Figure 4.

Table 5. Average power consumption of proposed improved polymer-based firefly algorithm against existing work.

Number of batches	'Average consumed power proposed'	'Average consumed power tuli et al. [20]	'Average consumed power singh et al. [16]	'Average consumed power saurabh et al. [18]	'Average consumed power ABC'	'Average consumed power PSO'
300	5368	5477.98871	6045.31847	6035.94938	5706.71454	5926.46772
400	5380	5573.67994	5412.29227	5447.93397	5955.92641	5865.96314
500	5392	5475.41261	5741.33327	6064.74213	5630.59678	5802.24928
600	5404	5542.1121	5580.39143	5836.78371	5736.49488	5651.04784
700	5416	5424.38001	5653.36131	5530.18932	5975.23986	5635.12029
800	5428	5503.25846	6106.75376	5431.27009	5974.80782	6004.72184
900	5440	5688.19352	5802.97007	5724.15864	5493.72364	5609.6687
1000	5452	5520.36311	5545.53739	6119.68778	6129.66992	5859.68484

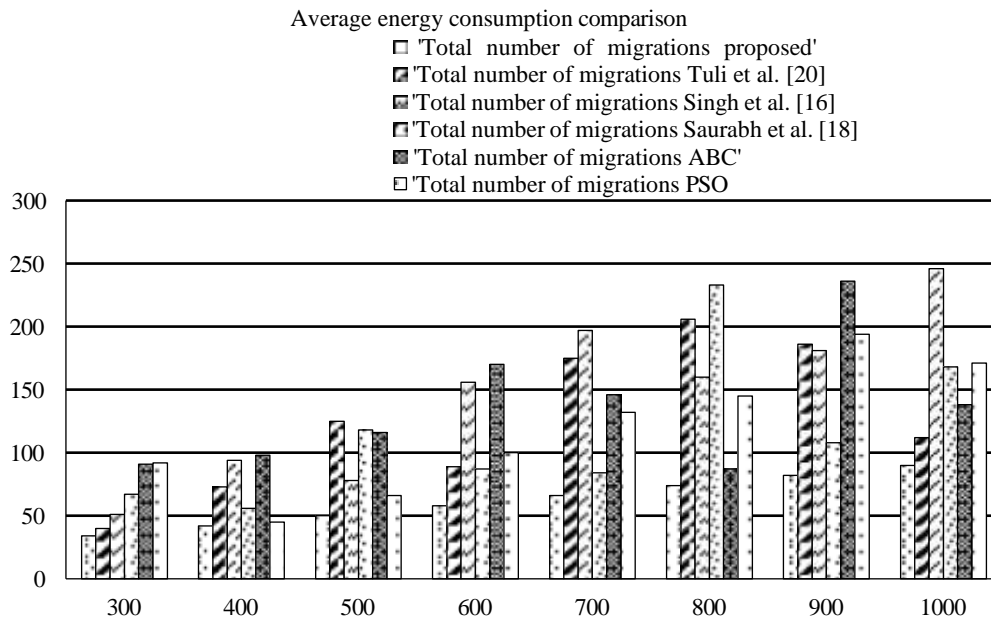


Figure 5. Average power consumption of proposed improved polymer-based firefly algorithm against existing work.

Total Power Consumption Analysis

Energy consumption is a critical parameter in polymer composite processing, particularly during curing and thermal treatment stages. Excessive energy input increases production costs and may cause over-curing or material degradation.

The total energy consumption is calculated by aggregating energy used during idle heating and active curing cycles. The proposed Improved Firefly Algorithm records an average energy consumption of 5410 W, which is significantly lower than competing approaches (Table 5).

The improved power efficiency in polymer composite material is primarily due to the algorithm's ability to migrate fewer VMs while still effectively neutralizing the load across PMs, thus consuming less power overall.

The proposed approach achieves energy reductions of 2.1% (Tuli et al.), 5.7% (Singh et al.), 6.3% (Saurabh et al.), 7.1% (ABC), and 6.6% (PSO). This improvement is attributed to the algorithm's ability to minimize unnecessary process reconfigurations while maintaining uniform load distribution across processing units.

Figure 5 illustrates that the proposed method consistently maintains lower energy consumption as the batch size increases, highlighting its suitability for large-scale polymer composite manufacturing environments.

CONCLUSION

The Improved polymer-based Firefly Algorithm (IFA) proposed in this study effectively enhances process optimization and resource utilization in polymer composite material manufacturing, while significantly reducing operational overhead. Inspired by the natural luminescent behavior of fireflies, the algorithm incorporates advanced features such as intelligent initialization of processing tasks, a multi-objective fitness function based on energy consumption and processing load, attractiveness modeling using Euclidean-distance-based similarity, and dynamic adaptive updates for optimal process

balancing. Comprehensive empirical evaluations demonstrate that the proposed polymer-based IFA substantially reduces the number of process adjustments, with an average of approximately 62 adjustments, compared to existing optimization techniques such as those proposed by Tuli, Singh, Saurabh, ABC, and PSO, which require between ~115 and ~145 adjustments on average. This corresponds to an improvement rate ranging from 50.7% to 57.3%, highlighting the superior process stability achieved by the proposed method.

Furthermore, quality constraint violations are significantly minimized, with the proposed approach achieving an average violation rate of 0.0441, representing an improvement of 49.6% to 62.4% over the benchmark methods. In terms of energy efficiency, the proposed algorithm achieves a reduction in total power consumption of 2.1% to 7.1%, primarily due to fewer process reconfigurations and more uniform load distribution during curing and thermal processing stages.

In conclusion, the Improved polymer-based Firefly Algorithm ensures a robust, adaptive, and low-variability optimization framework for polymer composite manufacturing processes. Its ability to simultaneously enhance process stability, reduce energy consumption, and improve quality consistency makes it a promising and effective solution for intelligent resource and process management in advanced polymer composite material applications.

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