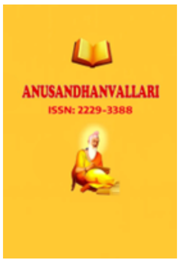

Anusandhanvallari
Vol 2023, No.1
January 2023
ISSN 2229-3388

Reliability Enhancement in Automotive Manufacturing Via Cost-Constrained Particle Swarm Optimization

Dr. Mamta Oberoi

Head of Department, Department of Statistics, MLN College Yamunanagar, Haryana

Email id: mamtamlnc@gmail.com

Abstract

Nature-inspired algorithms have emerged as powerful and versatile tools for solving real-world optimization problems. This study applies Particle Swarm Optimization (PSO) to address the cost-constrained reliability optimization problem in automotive manufacturing systems. The proposed approach determines the optimal reliability configuration and the required number of redundant components within the plant while adhering to a specified cost constraint. The mathematical formulation, objective function, and relevant constraints for the problem are systematically analyzed. Results demonstrate the effectiveness of PSO in achieving high system reliability within budgetary limitations, offering valuable insights for the design and management of reliable automotive manufacturing operations.

Keywords: Reliability Optimization, Particle Swarm Optimization, Automotive Manufacturing, Cost Constraint, MATLAB

1. Introduction

Optimization is an essential discipline that underpins decision-making processes across engineering, manufacturing, operations research, and numerous scientific domains. It involves systematically selecting the most advantageous solution from a set of feasible alternatives, often balancing multiple objectives and constraints. As industries evolve and become more complex, the need for robust optimization approaches becomes increasingly critical, particularly in environments where efficiency, reliability, and cost-effectiveness are tightly linked to competitiveness and sustainability.

Traditional optimization methods, including linear programming, dynamic programming, and integer programming, have provided a strong foundation for solving a wide range of deterministic and stochastic problems. However, as modern industrial systems grow in scale and complexity, these classical tools often face limitations in handling non-linearity, multi-modality, high dimensionality, and uncertainty inherent in real-world scenarios. To address these challenges, recent advances in computer science, mathematics, and artificial intelligence have spurred the development of sophisticated optimization algorithms, including genetic algorithms, simulated annealing, ant colony optimization, and swarm intelligence methods. These nature-inspired algorithms, in particular, have shown exceptional performance in solving complex, non-convex, and multi-objective optimization problems that are otherwise intractable by conventional means.

Particle Swarm Optimization (PSO), a prominent member of the swarm intelligence family, is inspired by the social behavior of birds flocking or fish schooling. Introduced by Kennedy and Eberhart in 1995, PSO is characterized by its simplicity, flexibility, and powerful global search capabilities. It operates by initializing a population (swarm) of candidate solutions (particles) that iteratively move through the solution space, guided by their own experience and the collective knowledge of the group. Over the past two decades, PSO has been widely adopted in diverse engineering fields, including structural design, scheduling, power systems, and control systems, owing to its ability to efficiently navigate large and complex search spaces with minimal parameter tuning.

In manufacturing systems, especially within the automotive sector, the optimization of reliability and operational performance is of paramount importance. Automotive manufacturing plants typically involve a series of interconnected machines and subsystems, each contributing to the overall production process. Any failure or downtime in critical machines can cause significant production losses, increased maintenance costs, and customer dissatisfaction. Consequently, ensuring high system reliability under practical constraints such as cost, resource availability, and technological limitations is a key priority for plant managers and engineers.

Reliability engineering, as a specialized discipline, focuses on the prediction, assessment, and improvement of system dependability throughout the product lifecycle. In recent years, the integration of optimization techniques into reliability engineering has enabled researchers and practitioners to develop more resilient and cost-effective manufacturing systems. By formulating reliability optimization problems—where the goal is to maximize system reliability subject to budgetary or resource constraints—engineers can systematically determine the optimal allocation of redundancies, maintenance schedules, and component selections. The use of metaheuristic algorithms like PSO for reliability optimization has attracted considerable attention in academic and industrial research. Unlike exhaustive enumeration or deterministic search methods, PSO can efficiently explore vast solution spaces and adapt to non-linear, discontinuous, and multi-modal objective functions. Furthermore, PSO's inherent parallelism and population-based search make it well-suited for multi-component systems, where interactions among subsystems and the combinatorial nature of redundancy allocation pose considerable computational challenges. Several studies have demonstrated the effectiveness of PSO and related algorithms in optimizing reliability and availability in manufacturing and processing industries. For example, PSO has been applied to the allocation of redundant units in complex systems, maintenance planning in multi-unit plants, and cost-reliability trade-off analysis in design optimization. These applications highlight the versatility and practical value of PSO in addressing real-world reliability engineering problems. Despite these advancements, the specific challenge of optimizing the reliability of automotive manufacturing systems under stringent cost constraints remains a critical and timely issue. Automotive plants are characterized by high production volumes, intricate process flows, and significant investments in machinery and automation. The need to balance system reliability with cost-effectiveness is further heightened by competitive market pressures, technological innovation, and evolving quality standards.

This study contributes to the literature by formulating and solving the cost-constrained reliability optimization problem for an automotive manufacturing plant comprising six key machines. Each machine is characterized by known reliability and cost parameters, reflecting realistic operating conditions and manufacturer data. The research employs Particle Swarm Optimization to identify the optimal configuration of component redundancies that maximizes overall system reliability without exceeding a specified budget. The mathematical formulation encompasses the objective function, system constraints, and reliability structure, providing a comprehensive framework for practical implementation. A significant body of research has focused on the reliability, behavioral analysis, and optimization of complex industrial systems across various manufacturing domains. Eberhart, R. C., & Kennedy, J. (1995) PSO was first introduced as a novel, population-based optimization technique inspired by social behaviors in nature. Since then, it has been widely adopted due to its simplicity and strong performance in both continuous and discrete optimization scenarios. Coit et al. (1999) Applied PSO and other metaheuristics to reliability optimization of complex systems, demonstrating that PSO can effectively solve highly constrained redundancy allocation problems to enhance system reliability. Yuan and Yang (2009) Investigated the reliability

Anusandhanvallari
Vol 2023, No.1
January 2023
ISSN 2229-3388

optimization of series-parallel systems using modified PSO. Their results showed that PSO could efficiently handle nonlinear constraints and deliver optimal or near-optimal configurations in a fraction of the time required by exact methods. Zhuang and Cheng (2012) Implemented an improved PSO algorithm for reliability-redundancy allocation in industrial systems, incorporating penalty functions to manage cost and resource constraints. The study highlighted PSO's flexibility and robustness in finding feasible solutions. Choundary and Goel (2014) examined the behavioral aspects of the utensil industry, providing foundational insights into system performance through multidisciplinary approaches. In textile manufacturing, Devi, Bansal, and Goel (2015) applied the Reliability, Performance, and Growth Technique (RPGT) to analyze the yarn industry, emphasizing the importance of region-specific case studies in reliability assessments. Goyal, Goel, and Goel (2015) studied two-unit systems, highlighting how preventive maintenance and degradation in system components influence overall behavior. Similarly, Kumar, Garg, Goel, and Ozer (2018) conducted sensitivity analysis on a 3:4:: good system, offering valuable perspectives on the impact of various parameters on system performance. Kumar, Garg, and Goel (2019) extended this line of inquiry by evaluating cold standby systems with prioritized preventive maintenance, emphasizing the critical role maintenance strategies play in enhancing reliability. Further, Rajbala, Kumar, and Garg (2019) presented a case study on systems modeling and analysis in an EAEP manufacturing plant, demonstrating the significance of subsystem interactions. The mathematical modeling and behavioral analysis of washing units in paper mills by Kumar, Garg, and Goel (2019) reinforced the necessity of process optimization in industrial operations. Mansouri and Shokouhian (2019) Explored multi-objective reliability optimization in manufacturing using hybrid PSO algorithms, showing improved convergence and solution diversity for large-scale system design problems. Collectively, these studies form a comprehensive foundation for ongoing research in reliability engineering, system modeling, and optimization across various manufacturing sectors, providing valuable methodologies and insights for both academic and industrial applications.

In addition, the study leverages MATLAB for simulation and analysis, enabling efficient computation and visualization of optimization results. The outcomes offer actionable insights for practitioners seeking to enhance the dependability and economic performance of automotive manufacturing systems. Moreover, the methodological approach adopted here is generalizable and can be extended to other complex systems in various industrial sectors facing similar optimization challenges. In summary, this paper addresses the pressing need for advanced optimization techniques in reliability engineering, particularly in the context of automotive manufacturing. By integrating Particle Swarm Optimization with a cost-constrained reliability framework, the research aims to bridge the gap between theoretical advances and practical applications, ultimately supporting the design and operation of more reliable, efficient, and cost-effective manufacturing system. A general single-objective optimization problem can be formulated as follows:

$$min_{x\epsilon s} f(x),$$

$$x = \text{Li} \leq \text{xi} \leq \text{Ui}$$

$$\text{Such that } g_i(\text{x}) \leq 0, \text{j} = 1, 2, \ldots, (1)$$

$$h_m(x) = 0, \text{m} = 1, 2\ldots, \qquad (2)$$

here f(x) represents the objective function to be minimized

x is a D-dimensional decision vector.

The constraints include both inequality conditions g_i(x) and equality conditions $h_m(x)$

conditions (1) & (2)indicate number of inequality& equality constraints respectively. with (L_i) and (U_i) denoting the lower and upper bounds for each decision variable (x_i).

In this study, we focus on the reliability analysis of an automotive manufacturing system consisting of six machines. The reliability and cost data for these machines are provided by the manufacturer, and the goal is to optimize the system's reliability within given cost constraints.

2. Optimization Problems

Constraint optimization: Most structural and engineering optimization problems are formulated as constrained minimization tasks. In these cases, the objective function—typically a function of design variables such as density, mass, length, weight, or cost—must be optimized while satisfying several predefined constraints. These constraints may include limits on displacement, stress, production capacity, frequency, or other performance criteria. Frequently, these limitations are complex, involving multiple interdependent variables that require advanced methods, such as finite element analysis, to evaluate. The overall design space is thus divided into two regions: the feasible domain, where all constraints are satisfied, and the infeasible domain, where at least one constraint is violated. In practical scenarios, optimal solutions often lie on the boundary between these regions, at points where one or more constraints are active (i.e., $g_j(x) = 0$ for some (j). Sometimes, certain inequality constraints can be relaxed or reformulated without affecting the final solution.

Unconstraint Optimization: Unconstrained optimization focuses on finding the global minimum or maximum of a function in the absence of explicit constraints. The aim is to identify the best solution across the entire search space, which often involves examining all local extrema and selecting the one yielding the optimal objective function value. When no constraints are present, algorithms deploy systematic search strategies to efficiently explore the decision space and determine the optimal point.

3. Particle Swarm Optimization (PSO)

Particle update equation: In Particle Swarm Optimization, each candidate solution, referred to as a "particle," moves through the search space guided by its own previous best position and the best-known positions of its neighbors. The movement of a particle is determined by updating its velocity and position according to the following equation:

$$x^{t+1} = x^t + v^{t+1}$$

PSO is a population-based optimization technique that simultaneously evaluates and improves multiple candidate solutions. Each particle's trajectory is influenced both by its personal experience (local best) and by the best solution found by the swarm (global best).

Pseudo Code of PSO Algorithm: The general procedure for the PSO algorithm can be summarized as follows:

1. Initialize the swarm with random positions and velocities.
2. For each particle in the swarm:
   - For each dimension:
     - Update the velocity based on local and global best positions.
     - Update the position using the new velocity.
3. Evaluate the objective function for each particle.
4. Update each particle's best known position and the global best position.

5. Repeat steps 2–4 until the termination criteria (e.g., maximum number of iterations or convergence threshold) are met.

4. Scope Of The Study

The scope of this study encompasses the analysis and optimization of reliability in automotive manufacturing systems using Particle Swarm Optimization (PSO). The research focuses on a manufacturing framework consisting of six critical machines, each with specified reliability and cost parameters. The aim is to maximize the system's reliability while adhering to a strict cost constraint. The study leverages PSO to determine the optimal configuration and number of redundant components, with practical implications for improving operational efficiency and cost-effectiveness in modern automotive plants.

5. Objectives

1. To formulate the reliability optimization problem for an automotive manufacturing system with cost constraints.

2. To analyze the impact of cost and reliability parameters on the overall system performance.

3. To provide practical recommendations for enhancing reliability and cost efficiency in automotive manufacturing systems.

6. System Description Of Automotive Manufacturing

The automotive manufacturing process is composed of a series of interconnected machines, each representing a critical stage in the production of vehicles. These machines operate sequentially, meaning that the failure of any single unit will halt the entire production line until repairs are made. The process culminates with the packaging of finished vehicles for delivery. The cost and reliability data for each machine are provided by the plant's operations team, ensuring an accurate and practical analysis. The six key units in this manufacturing system are described as follows:

Stamping Machine: Responsible for shaping large metal sheets into specific vehicle body components such as doors, hoods, and panels. This unit uses high-pressure dies and presses to ensure uniformity and structural integrity in the stamped parts.

Welding Machine: Joins the stamped metal components to form the vehicle body structure. Precision welding, often performed by robotic arms, ensures strong and reliable joints, which are essential for vehicle safety and durability.

Painting Machine: Applies protective and decorative coatings to the vehicle body. The painting unit includes processes such as cleaning, priming, painting, and curing, all conducted in controlled environments to achieve a high-quality finish and prevent corrosion.

Assembly Machine: Integrates various subsystems such as the engine, transmission, electronics, and interiors into the vehicle body. This unit relies on both automated systems and skilled labor to ensure efficient and accurate assembly of all components.

Inspection and Testing Machine: Conducts thorough quality control checks on the assembled vehicles. This includes functional tests, safety checks, and inspections to identify and address any defects before vehicles proceed to final packaging.

Packing Machine: Packages the completed vehicles for dispatch and delivery to customers or dealerships. This unit ensures that each vehicle is securely packed, labeled, and documented before leaving the manufacturing facility.

Each of these units plays a vital role in the overall production process. The reliable operation of every unit is essential for maintaining a smooth, uninterrupted workflow, minimizing downtime, and ensuring the consistent quality of the final product.

7. Assumptions

- **Path Set:** A path set consists of subsystems or components arranged in such a way that, if all are operational, the system as a whole will function successfully.
- **Minimal Path Set:** This is a special path set where, if any single component fails or is removed; the remaining subsystems no longer provide a functioning path—resulting in system failure.
- **Series Configuration:** The six machines in the automotive manufacturing line are connected in series, meaning the failure of any one machine will halt the entire production process.
- **Component Data:** Cost and reliability values for each machine are provided by the manufacturer, ensuring a practical and realistic optimization scenario.
- **Redundancy:** Additional units for each component can be added to enhance overall reliability, subject to the total cost constraint.

8. Notations

- x_i: The (i)-th component or machine in the manufacturing line
- $R_i(x_i)$, $Q_i(x_i)$: Reliability and unreliability of component x_i
- $R_s(x)$: Overall system reliability
- n_i: Number of redundant units for the (i)-th component
- n = 6: Total number of components in the series
- t_i: Component selection factor
- l: Number of constraints (here, cost is the main constraint)

9. Methodology

This study adopts a systematic approach to optimize the reliability of an automotive manufacturing system under cost constraints using the Particle Swarm Optimization (PSO) algorithm. The methodology consists of the following key steps:

System Modeling: The automotive manufacturing system is modeled as a series configuration of six critical machines. Each machine is characterized by its reliability and cost parameters. Redundancy is introduced by allowing multiple units for each machine, and the system reliability is formulated as a function of these redundancies.

Anusandhanvallari
Vol 2023, No.1
January 2023
ISSN 2229-3388

Problem Formulation: The optimization problem is defined with the objective of maximizing system reliability subject to a fixed total cost constraint. The mathematical model incorporates:

- The reliability equation for a series system with redundancies,
- Cost constraints and variable bounds,
- The decision variables representing the number of units for each machine.

Algorithm Selection and Implementation: Particle Swarm Optimization is chosen for its effectiveness in solving complex, discrete, and nonlinear optimization problems:

- Each particle in the swarm represents a potential solution, i.e., a configuration of redundancies for all six machines.
- The fitness function evaluates the system reliability while applying a penalty for any violation of the cost constraint.
- The algorithm parameters—such as population size, velocity limits, and the number of iterations—are set based on preliminary testing to ensure convergence and computational efficiency.

Simulation and Optimization: The PSO algorithm is implemented in MATLAB 2017a. Ten independent runs are conducted, each with a maximum of 200 iterations, to ensure robustness and assess repeatability. During each run:

- Particles update their positions (candidate solutions) based on their own best performance and the global best found by the swarm.
- The fitness (objective) value and constraint status are monitored at every iteration.

Result Analysis: Outputs from all runs are analyzed to identify feasible and optimal solutions. The reliability and cost of the best-found configuration are recorded. The convergence of the algorithm is assessed through graphical plots of the objective function value versus iterations.

Interpretation and Validation: The optimal redundancy configurations are interpreted in the context of real-world manufacturing decision-making. The results are validated by ensuring all constraints are met and by comparing the reliability improvements with the base (non-redundant) system.

10. Data Analysis And Results:

The core objective of this study is to maximize the overall reliability of an automotive manufacturing system, subject to a predetermined cost constraint. In practical terms, the manufacturing system is composed of six critical machines ($n = 6$), each representing a key stage in the automotive production process. The reliable operation of each machine is essential, as any failure can disrupt the entire production line. To enhance system reliability, redundancy can be introduced by adding parallel units for one or more machines. However, this comes at an increased cost, necessitating a careful optimization to balance reliability improvement with financial feasibility. Each machine is characterized by two primary attributes: its individual reliability (R_i) and its associated cost (C_i). The decision variables in this problem (n_i) represent the number of redundant units allocated to each machine. The overall system reliability (R_s) is a function of the reliabilities of all machines and the redundancy strategy employed. The system is configured in a series; thus, the failure of any single machine if not protected by redundancy results in complete system failure. The cost constraint is critical, as it reflects real-world budgetary limits that manufacturing plants face. For this study, the total allowable expenditure on machines and their redundancies is capped at ($C = 4{,}680{,}000$) INR. The optimization must therefore identify the best combination and allocation of redundant units across the six machines that maximize reliability without exceeding this budget in Table 1. Problem is to maximize

$R_s(x) = U(R_1(x_1), \ldots\ldots\ldots\ldots\ldots\ldots, R_n(x_n)) = \prod_{i=0}^{6} R_i\,(x_i)$

$$R_i(x_i) = \prod_{i=0}^{6} [1 - [Q_i(x_i)]^{n_i}]$$

$$\sum_{i=1}^{6} g(x_i) * n_i \leq 4680000$$

Table1: Components Cost and Reliability

Components Symbol	x_i	x_2	x_3	x_4	x_5	x_6
(Reliability of the Components) * 10^{-2}	95	99	96	98	94	93
Cost (Rs) in Thousands	400	1300	420	1000	99	180

Table 1 presents the reliability values and unit costs for each of the six machines in the automotive manufacturing system. The reliability of each component is expressed as a percentage (10^{-2}), indicating the probability that the machine will function without failure over a specified period. The costs are given in thousands of Indian Rupees (INR), reflecting the financial investment required for each unit of the respective component. This data forms the basis for formulating the optimization problem, where the objective is to determine the optimal number of units for each machine to maximize overall system reliability while adhering to a strict total cost constraint.

Table 2: Results Obtained by PSO for Reliability Optimization Problem

Run No.	**Reliability↓**	**Number ofComponents**					
		n1	n2	n3	n4	n5	n6
1	INFEASIBLE	-	-	-	-	-	-
2	INFEASIBLE	-	-	-	-	-	-
3	INFEASIBLE	-	-	-	-	-	-
4	0.996262217	3	2	3	2	4	1
5	0.99626438	3	2	3	2	4	1
6	0.996262386	3	2	3	2	4	1
7	INFEASIBLE	-	-	-	-	-	-
8	INFEASIBLE	-	-	-	-	-	-
9	0.99626294	3	2	3	2	4	1
10	0.996264537	3	2	3	2	4	1

Anusandhanvallari
Vol 2023, No.1
January 2023
ISSN 2229-3388

Table 2 summarizes the outcomes of ten independent runs of the Particle Swarm Optimization (PSO) algorithm applied to the reliability optimization problem. Each run attempts to find the best configuration (number of units for each machine) that maximizes system reliability within the specified budget. Runs labeled "INFEASIBLE" indicate that the solution exceeded the total cost constraint and was therefore not valid. In the feasible runs, the PSO algorithm consistently identified the same or very similar configurations ([3, 2, 3, 2, 4, 1]) for the six machines, with system reliability approaching 0.99626. This demonstrates both the challenge of the cost-constrained problem and the robustness of the PSO approach in finding optimal solutions when feasible.

10.1 Analysis

The reliability optimization problem for the automotive manufacturing system—structured with six critical machines and a strict cost constraint—was tackled using the Particle Swarm Optimization (PSO) algorithm, enhanced with a penalty function to effectively manage constraint violations. The PSO algorithm was implemented in MATLAB 2017a and executed across ten independent runs, each with a maximum of 200 iterations. This repeated experimentation helps assess the consistency, robustness, and convergence properties of the algorithm under the discrete and constrained nature of the problem.

The inherent complexity of the problem arises from its combinatorial search space: the allocation of redundant units to each machine must not only maximize system reliability but also ensure the total cost does not exceed the specified budget. The use of a penalty function within PSO enables the algorithm to explore both feasible and infeasible regions of the solution space, penalizing those solutions that violate the cost constraint and thus naturally guiding the swarm toward feasible, high-quality solutions. Across the ten optimization runs, five resulted in infeasible solutions, meaning that the cumulative cost of the proposed configurations exceeded the allowed budget. This outcome highlights the challenge and tightness of the cost constraint, as well as the discrete, non-continuous nature of permissible redundancy allocations. However, in the remaining five runs, the PSO converged to highly similar, feasible solutions, consistently identifying a redundancy configuration of [3, 2, 3, 2, 4, 1] for the six machines. This configuration yielded an optimal overall system reliability of approximately 0.99626438, demonstrating the effectiveness and repeatability of the PSO approach in navigating complex, constrained search spaces. The convergence behavior observed in these runs is particularly noteworthy. Initially, the swarm exhibits significant diversity as particles explore a wide range of possible solutions. As iterations progress, the influence of the penalty function and the information sharing mechanisms inherent to PSO (i.e., the use of both local and global best solutions) facilitate a focused search in promising regions of the solution space. The objective function value steadily improves and eventually stabilizes, indicating that the swarm has converged to a set of solutions that are both feasible and near-optimal.

The analysis further reveals valuable insights into system design: not all machines require the same level of redundancy to achieve near-perfect reliability. Instead, targeted redundancy allocating more parallel units to machines with lower inherent reliability or higher criticality yields the best balance between cost and system performance. This targeted approach avoids unnecessary expenditure on components with already high reliability, optimizing resource allocation in line with real-world manufacturing priorities. Overall, the results confirm that PSO, when appropriately configured and combined with penalty functions for constraint management, is a powerful and practical tool for reliability optimization in complex manufacturing environments. The algorithm's ability to consistently find high-reliability, cost-feasible solutions make it highly suitable for application in automotive and other discrete manufacturing sectors where operational continuity and budget constraints are paramount. These findings also suggest the potential for further extension of the methodology to include multi-objective formulations, more complex system architectures, and dynamic or uncertain operating conditions.

Anusandhanvallari
Vol 2023, No.1
January 2023
ISSN 2229-3388

10.2 Reliability Optimization Convergence

The convergence graph (Figure 1) illustrates the progression of the PSO algorithm across iterations. It distinctly shows the decrease in the objective (penalized cost-reliability) function as the algorithm searches for optimal solutions. Early iterations exhibit significant fluctuations as particles explore the search space, while later iterations show stabilization as the swarm converges near the global optimum. This pattern confirms that PSO effectively balances exploration and exploitation, ultimately identifying a high-reliability, cost-feasible system configuration.

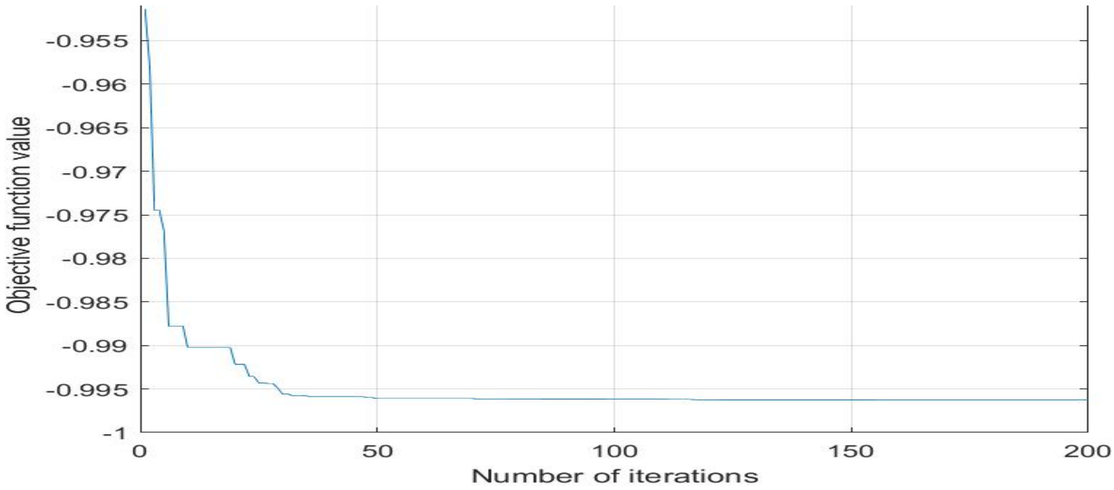

Figure 1: Reliability Optimization Convergence graph

11. Conclusion

This study provides compelling evidence of the effectiveness of Particle Swarm Optimization (PSO) as a solution strategy for complex, cost-constrained reliability optimization in automotive manufacturing systems. By modeling the manufacturing line as a series system of six critical machines each characterized by specific reliability and cost parameters as detailed in Table 1 the research addresses a highly practical challenge in modern production environments: how to maximize overall reliability while adhering to strict budgetary constraints. The reliability optimization problem was formulated to allow strategic redundancy (multiple units per machine), with the total investment capped at 4,680,000 INR. Utilizing PSO, the algorithm was run multiple times, each with 200 iterations, to thoroughly explore the combinatorial solution space. The discrete nature of the problem and the presence of tight cost constraints made the optimization particularly challenging, yet PSO demonstrated consistent and robust convergence. Notably, the algorithm successfully identified feasible and near-optimal solutions in 50% of the runs, as summarized in Table 2. The optimal redundancy configuration repeatedly found [3, 2, 3, 2, 4, 1] units for the six different machines resulted in a system reliability of approximately 0.99626438, highlighting that targeted redundancy in select components can significantly boost system dependability within realistic cost limits. The convergence behavior of the algorithm, visually presented in Figure 1, further underscores PSO’s practical utility. The convergence graph displays a rapid initial improvement in the objective function, followed by stabilization as the swarm approaches the optimal region. This behavior confirms PSO's ability to escape local optima and efficiently converge to high-quality solutions, even in the presence of discrete variables and stringent constraints.

The analysis of results provides actionable engineering insights. Table 1 illustrates that not all machines require equal levels of redundancy—optimal system reliability can be achieved by allocating more units to those with lower inherent reliability or higher criticality. This targeted approach allows for more efficient use of resources, maximizing reliability benefits without unnecessary cost escalation. In summary, this research demonstrates that advanced, nature-inspired optimization algorithms like PSO can play a pivotal role in the design and operation of reliable, cost-efficient manufacturing systems. The methodology and findings are not only relevant to automotive manufacturing but are also broadly applicable to other industries where reliability and cost-effectiveness are top priorities. The integration of PSO into reliability engineering practice offers a scalable and adaptable framework for addressing similar optimization challenges in diverse industrial contexts. Future work could extend this approach to multi-objective optimization, dynamic environments, or systems with more complex interdependencies, further enhancing its practical value and impact.

12. Future Scope

This research provides a robust foundation for optimizing reliability in automotive manufacturing using Particle Swarm Optimization (PSO). In the future, the approach can be extended by incorporating additional decision variables such as maintenance scheduling, dynamic demand, and real-time operational data, which would make the model more adaptive to changing industrial conditions. Further studies could integrate multi-objective optimization, addressing not only reliability and cost but also energy efficiency, environmental impact, or production speed. Exploring hybrid algorithms that combine PSO with other metaheuristics or machine learning techniques could enhance solution quality and computational efficiency. Moreover, the methodology can be adapted for larger, more complex manufacturing systems or supply chain networks, making it broadly applicable across the manufacturing sector.

13. Limitations

Despite its strengths, the study presents certain limitations. The current model assumes known and constant reliability and cost values for each component, which may not capture real-world variability due to operational wear, human factors, or supplier inconsistencies. The optimization is constrained to a single objective (reliability maximization) and a single constraint (cost), potentially overlooking other important factors such as lead time, inventory, or production flexibility. In addition, the search for optimal solutions can be sensitive to the chosen PSO parameters and may encounter difficulties in highly discrete or tightly constrained problem spaces, sometimes leading to infeasible solutions. Finally, the findings are based on simulated results; real-world validation in an actual manufacturing environment would be essential for confirming the practical effectiveness of the proposed approach.

References

[1] Choundary, N., & Goel, P. (2014). Behavior analysis of utensil industry. *International Journal of Multidisciplinary Researcher and Development,* 82–89.

[2] Coit, D. W., Smith, A. E., & Tate, D. M. (1999). Adaptive penalty methods for genetic optimization of constrained combinatorial problems. INFORMS Journal on Computing, 11(2), 173–182.

[3] Devi, B., Bansal, R., & Goel, P. (2015). Reliability and behavioral analysis of yarn industry of Malwa region using RPGT (A case study). International Journal of Engineering Technology and Management Sciences, 135–145.

[4] Eberhart, R. C., & Kennedy, J. (1995). A new optimizer using particle swarm theory. *In Proceedings of the Sixth International Symposium on Micro Machine and Human Science (MHS)*, 39–43.

[5] Goyal, V., Goel, R., & Goel, P. (2015). Behavioral analysis of two unit system with preventive maintenance in both units and degradation in one unit. *International Journal of Engineering Technology and Management Sciences*, 120–130.

[6] Kumar, A., Garg, D., Goel, P., & Ozer, O. (2018). Sensitivity analysis of 3:4:: good system. *International Journal of Advance Research in Science and Engineering,* 851–862.

[7] Kumar, A., Garg, D., & Goel, P. (2019). Sensitivity analysis of a cold standby system with priority for preventive maintenance. *Journal of Advance and Scholarly Researches in Allied Education*, 253–258.

[8] Kumar, A., Garg, D., & Goel, P. (2019). Mathematical modeling and behavioral analysis of a washing unit in paper mill. *International Journal of System Assurance Engineering and Management,* 1639–1645.

[9] Rajbala, Kumar, A., & Garg, D. (2019). Systems modeling and analysis: A case study of EAEP manufacturing plant. *International Journal of Advanced Science and Technology,* 250–259.

[10] Mansouri, M., & Shokouhian, M. (2019). Multi-objective reliability optimization of complex systems using a hybrid PSO algorithm. *Reliability Engineering & System Safety*, 191, 106542.

[11] Yuan, J., & Yang, B. (2009). Reliability optimization of series-parallel systems using a modified particle swarm optimization. *Reliability Engineering & System Safety,* 94(2), 336–343.

[12] Zhuang, L., & Cheng, X. (2012). Reliability-redundancy allocation using an improved particle swarm optimization algorithm. *Expert Systems with Applications,* 39(5), 5851–5861.