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A Review of the Tabu Search Algorithm for Industrial Applications

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Abstract. *The Tabu Search Algorithm (TSA) is a powerful optimization technique that has gained significant attention in industrial applications. This review paper aims to provide a comprehensive overview of the TSA, its key components, and its effectiveness in solving complex optimization problems in industrial settings. We discuss its application in areas such as production planning, scheduling, logistics, and resource allocation. Additionally, we analyze recent advancements, challenges, and future directions in the use of TSA for industrial applications. This review serves as a valuable resource for researchers and practitioners interested in utilizing the TSA to enhance industrial optimization processes*

Keywords: Tabu Search; Industrial Applications; Optimization Algorithms; Approximation Methods; Artificial Intelligence.

1. Introduction.

In today's competitive industrial landscape, companies face numerous complex optimization problems that require efficient and effective solutions [1][2]. These problems range from production planning and scheduling to logistics and resource allocation [3]. Traditional optimization techniques often struggle to handle the complexity and dynamic nature of these problems [4][5]. As a result, researchers have turned to metaheuristic algorithms, such as the Tabu Search Algorithm (TSA) [6], to address these challenges. The primary objective of this review paper is to provide a comprehensive understanding of the TSA and its application in industrial settings [7]. Specifically, the review aims to:

- Explore the key components of the TSA, including the tabu list, aspiration criteria, diversification and intensification strategies, and neighborhood structures.

- Discuss the effectiveness of the TSA in solving optimization problems in industrial applications, such as production planning, scheduling, logistics, and resource allocation.
- Analyze the performance of the TSA using evaluation metrics and compare it with other optimization techniques commonly employed in industrial settings.
- Highlight the advantages and limitations of the TSA in industrial applications.
- Discuss recent advancements in the field, such as hybridization with other metaheuristics, parallel and distributed implementations, memetic tabu search, and multi-objective optimization.
- Identify the challenges faced in implementing the TSA for industrial problems and propose future research directions to overcome these challenges.
- Provide a comprehensive conclusion summarizing the key findings and recommendations for future research.

By achieving these objectives, this review paper aims to serve as a valuable resource for researchers, practitioners, and decision-makers interested in utilizing the TSA to enhance industrial optimization processes [7]. The TSA is a metaheuristic optimization technique that has gained significant attention due to its ability to solve complex optimization problems in various industrial applications [8]. This review paper provides an overview of the TSA, its key components, and explores its effectiveness in solving industrial optimization problems [9]. We discuss the application of TSA in diverse areas such as production planning, scheduling, logistics, and resource allocation. Additionally, we analyze recent advancements, challenges, and future directions in the use of TSA for industrial applications [10].

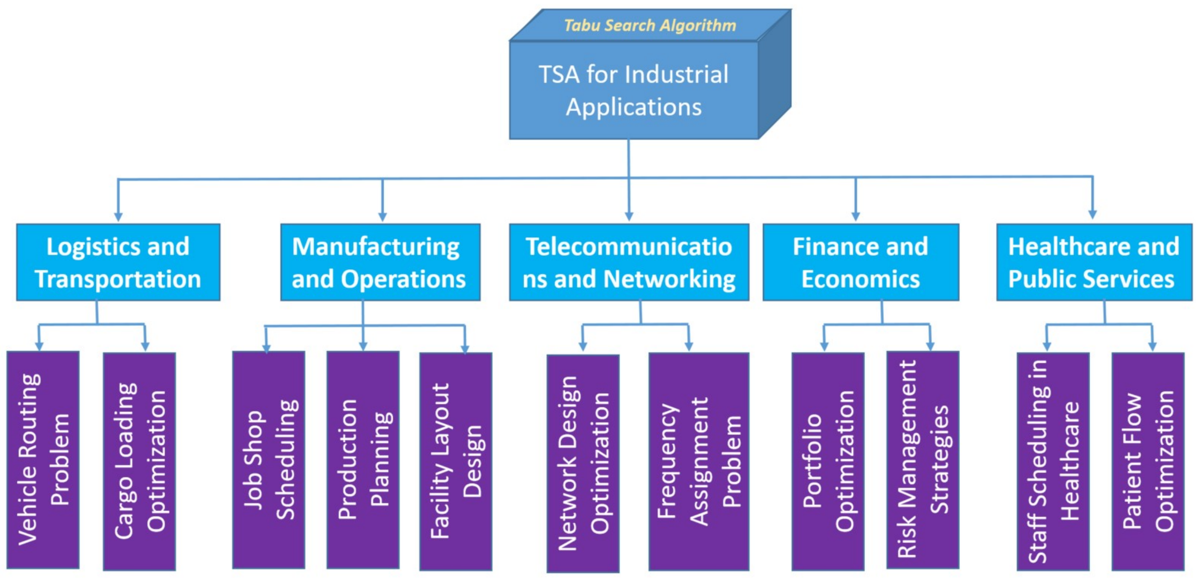

FIGURE 1. Applications of Tabu Search Algorithm in Industry.

Figure 1 illustrates the diverse applications of the Tabu search algorithm across five key industry sectors: Logistics and Transportation, Manufacturing and Operations, Telecommunications and Networking, Finance and Economics, and Healthcare and Public Services. This overview highlights the algorithm's versatility and effectiveness in solving complex optimization problems, showcasing its role in enhancing operational efficiency and informed decision-making within various industrial contexts.

Scope of the review as it is essential to note the content of this review paper[7]. While the TSA has been applied in various industrial domains, this review will primarily focus on its application in production planning [11], scheduling, logistics, and resource allocation [12]. These areas are of significant importance in industrial settings and have been extensively studied in the context of the TSA. We will also discuss the performance evaluation metrics used to assess the efficiency of the TSA and compare its performance with other optimization techniques commonly used in industrial applications [13]. The methodology is used to accomplish the objectives of this review; a systematic literature review methodology will be employed. Relevant research articles, conference papers, and books will be identified through comprehensive searches in electronic databases [14]. The selected literature will be critically analyzed and synthesized to comprehensively overview the TSA and its application in industrial settings [10]. The analysis will include discussions on the critical components of the TSA, its effectiveness in solving optimization problems, performance evaluation metrics, comparative analysis with other optimization techniques, advantages and limitations, recent advancements, challenges, and future directions.

2. **Tabu Search Algorithm.** The TSA is a metaheuristic optimization technique that Fred Glover introduced that is inspired by the concept of "tabu" from the field of operations research, which refers to actions or solutions that are temporarily prohibited to avoid getting trapped in local optima [6]. The TSA aims to explore the solution space efficiently by maintaining a memory structure that guides the search process [15]. Figure 2 illustrates a graph curve example of the TSA optimization principle process.

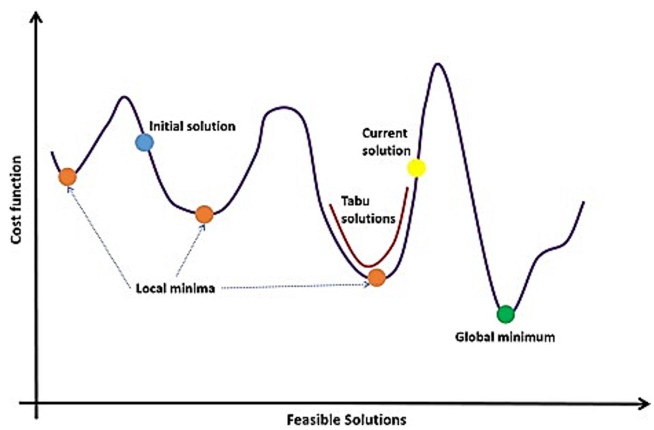

FIGURE 2. A graph curve example of the TSA optimization principle process

The components of TSA include items as follows.

Tabu List: is a component that is the tabu list is a memory structure that keeps track of recently visited solutions or actions. It prevents the algorithm from revisiting these solutions shortly, allowing for diversification and exploration of the search space. The tabu list is typically implemented as a queue or a dynamic memory structure with a limited capacity. The length of the tabu tenure, i.e., the number of iterations a solution remains in the tabu list, is an important parameter affecting search behavior. *Aspiration Criteria:* as aspiration criteria relax the tabu restrictions under certain conditions. They allow the algorithm to consider solutions that are in the tabu list if they provide an improvement over the current best solution. Aspiration criteria prevent the algorithm from being overly conservative and potentially missing better solutions.

Diversification and Intensification Strategies: is diversification and intensification strategies balance exploration and exploitation in the search process. Diversification aims to explore new regions of the search space by introducing random perturbations or diversifying the search trajectory. Intensification, conversely, focuses on exploiting promising areas by intensifying the search for suitable solutions. The balance between diversification and intensification is crucial for the effectiveness of the TSA.

Neighborhood Structures: Neighborhood structures define the neighboring solutions generated from a given key. The neighborhood search process involves exploring these neighboring solutions to find better solutions. The choice of neighborhood structures depends on the problem at hand and can significantly impact the efficiency and effectiveness of the TSA.The proces steps below provides a high-level representation of the TSA: Step 1. Initialize the current solution as the initial solution. Step 2. Initialize the tabu list. Step 3. Set the current solution as the best solution found so far. Step 4. while (stopping condition is not met) do

- Generate a set of neighboring solutions.
- Evaluate the neighboring solutions.
- Choose the best non-tabu solution as the next solution.
- Update the tabu list.
- Update the best solution if the next solution is better.
- Apply diversification and intensification strategies.

Step 5. Return the best solution found. Algorithm 1 displays a pseudocode of the Tabu Search algorithm (TSA).

Algorithm1. Pseudo code of the Tabu Search algorithm (TSA)

```
function [bestSolution, bestFitness] =
tabuSearch(initialSolution, fitnessFunction, tabuListSize,
numIterations)
    currentSolution = initialSolution
    bestSolution = currentSolution
    bestFitness = fitnessFunction(currentSolution)
    tabuList = {}

    for iteration = 1 to numIterations
        neighborhood = generateNeighborhood(currentSolution)

        neighborFitness = []
        for each neighbor in neighborhood
            neighborFitness = fitnessFunction(neighbor)
        end

        bestNeighbor = null
        bestNeighborFitness = infinity
        for each neighbor in neighborhood
            if neighbor is not in tabuList and
                neighborFitness < bestNeighborFitness
                bestNeighbor = neighbor
                bestNeighborFitness = neighborFitness
            end
        end

        currentSolution = bestNeighbor
        add currentSolution to tabuList
        if length(tabuList) > tabuListSize
            remove the oldest entry from tabuList
        end

        if bestNeighborFitness < bestFitness
            bestSolution = bestNeighbor
            bestFitness = bestNeighborFitness
        end
    end
end
```

This pseudocode provides a general framework for implementing the TSA. However, the specific implementation details may vary depending on the problem domain and the specific requirements of the optimization problem. The TSA's key components, such as

Table 1. A summarizing the industrial applications of the TSA, including the year, application, and description

#	Application	Description features	Note
1	Production Planning [16]	Optimizing production schedules, batch sizing, lot-sizing, and inventory management to minimize costs and maximize efficiency .	Improved on-time delivery performance [17].
2	Scheduling [18][19]	Solving complex scheduling problems such as job shop scheduling, flow shop scheduling, project scheduling, and vehicle routing [20].	Reduced makespan and improved resource utilization [21].
3	Logistics [22][23]	Optimizing delivery routes, inventory management, facility location, and distribution network design to minimize costs and improve efficiency [24].	Achieved significant cost savings and improved customer satisfaction [24].
4	Resource Allocation [25][26]	Efficiently allocating limited resources in industries such as telecommunications, healthcare, energy, and finance to achieve desired objectives [11] [27].	Maximized resource utilization and productivity [13][28].
5	Case Studies [29][30]	Real-world examples demonstrating the effectiveness of the TSA in solving industrial problems, such as production planning and vehicle routing [31][32].	Highlighted the versatility and effectiveness of the algorithm in diverse industrial applications [33].

the tabu list, aspiration criteria, diversification and intensification strategies, and neighborhood structures, work together to guide the search process and explore the solution space effectively.

3. TSA's Industrial Applications and Effectiveness.

3.1. Industrial Applications of Tabu Search Algorithm. Table 1 provides a chronological overview of the industrial applications of the TSA [6], along with a brief description of each application and a note highlighting the specific outcomes or benefits achieved in each case.

Production Planning: Production planning involves determining the optimal allocation of resources, such as materials, machines, and labor, to meet production targets while minimizing costs and maximizing efficiency. The TSA has been successfully applied to various production planning problems, including production scheduling, batch sizing, lot-sizing, and inventory management. It helps in optimizing production schedules, minimizing setup times, reducing inventory levels, and improving overall production efficiency. Scheduling: Scheduling is a critical task in industries that involve time-dependent activities, such as manufacturing, transportation, healthcare, and project management. The TSA has been widely used to solve complex scheduling problems, such as job shop scheduling, flow shop scheduling, project scheduling, and vehicle routing. It helps in optimizing the sequence of tasks, minimizing makespan, reducing waiting times, and improving resource utilization [30].

Logistics: Logistics optimization involves managing the flow of goods, information, and resources across the supply chain to minimize costs and maximize customer satisfaction. The TSA has been applied to various logistics problems, including vehicle routing, inventory management, facility location, and distribution network design. It helps in optimizing delivery routes, minimizing transportation costs, reducing inventory holding costs, and improving overall supply chain efficiency. Resource Allocation: Resource allocation problems arise in various industries, including telecommunications, healthcare, energy, and finance, where limited resources need to be allocated efficiently to achieve desired objectives. The TSA has been used to solve resource allocation problems, such as task allocation, workforce scheduling, equipment allocation, and portfolio optimization. It helps in optimizing resource utilization, minimizing costs, maximizing productivity, and improving overall performance. Case Studies: Several case studies demonstrate the effectiveness of the TSA in solving real-world industrial problems. For example, in a case study on production planning in a manufacturing company, the TSA was used to optimize the production schedule, resulting in reduced setup times and improved on-time delivery performance. In another case study on vehicle routing for a logistics company, the TSA was applied to optimize the delivery routes, leading to significant cost savings and improved customer satisfaction [30]. These case studies highlight the versatility and effectiveness of the TSA in solving a wide range of industrial optimization problems. The algorithm's ability to handle complex constraints, explore diverse solutions, and balance exploration and exploitation makes it a valuable tool for industrial applications.

3.2. **Effectiveness of TSA in Industrial Applications.** Performance Evaluation Metrics is used to assess the effectiveness of the TSA in industrial applications, several performance evaluation metrics can be used. These metrics include:

* Solution quality: Measures the optimality of the solutions generated by the algorithm, such as minimizing costs, maximizing efficiency, or meeting specific objectives.
* Convergence speed: Evaluates how quickly the algorithm converges to a near-optimal solution.
* Computational time: Measures the time required by the algorithm to find a solution.
* Scalability: Assesses the algorithm's ability to handle larger problem sizes and datasets.
* Robustness: Measures the algorithm's ability to handle uncertainties, variations, or disruptions in the industrial environment.

By analyzing these metrics, it is possible to evaluate the performance of the TSA and compare it with other optimization techniques. Comparative Analysis with Other Optimization Techniques is used to assess the effectiveness of the TSA, it is important to compare its performance with other optimization techniques commonly used in industrial applications. Some popular comparative techniques include:

- Genetic algorithms: These algorithms use evolutionary principles to search for optimal solutions.
- Simulated annealing: This technique is inspired by the annealing process in metallurgy and explores the solution space by accepting worse solutions to escape local optima.
- Particle swarm optimization: This algorithm is based on the behavior of social organisms and simulates the movement of particles in a search space.
- Ant colony optimization: Inspired by the behavior of ants, this technique uses pheromone trails to guide the search for optimal solutions.

Comparative analysis helps in understanding the strengths and weaknesses of the TSA and identifying scenarios where it outperforms or falls short compared to other techniques.

Table 2. Phases for knowledge acquisition and representation in predictive socioeconomic indicator analysis [17].

#	Advantages	Limitations	Note
1	- Flexibility in handling various problem types, constraints, and objective functions [34].	- Parameter tuning required for optimal performance [35].	- The TSA strikes a balance between exploration and exploitation, making it suitable for a wide range of industrial problems [25].
2	- Enhanced local search by avoiding previously visited solutions [36].	- Computational complexity increases for large-scale problems [37].	- Careful problem representation and encoding are important for optimal results [26]..
3	- Robustness in handling uncertainties and disruptions in the industrial environment [35].	- Sensitivity to problem representation and encoding [38].	

Advantages and Limitations is presented with TSA offers several advantages in industrial applications:

- Flexibility: It can handle various problem types, constraints, and objective functions.
- Exploration and exploitation: It balances exploration of new solutions and exploitation of promising solutions.
- Local search enhancement: It improves local search by avoiding previously visited solutions.
- Robustness: It can handle uncertainties and disruptions in the industrial environment. However, the TSA also has limitations:
- Parameter tuning: It requires careful selection of parameters, such as tabu tenure and aspiration criteria, to achieve optimal performance.
- Computational complexity: It may become computationally expensive for large-scale problems with complex constraints.
- Sensitivity to problem representation: The algorithm's performance can vary depending on how the problem is represented and encoded.

Table 2 provides a concise overview of the advantages and limitations of the TSA, along with a note emphasizing its flexibility, local search enhancement, and robustness. It also highlights the need for parameter tuning, the potential computational complexity for large-scale problems, and the importance of careful problem representation and encoding. Understanding these advantages and limitations helps in effectively applying the TSA in industrial settings and selecting appropriate alternatives when necessary.

4. **Recent Advancements in TSA for Industrial Applications.** Hybridization with Other Metaheuristics: Recent advancements in the TSA involve hybridizing it with other metaheuristics to improve its performance and effectiveness in solving complex industrial problems [7]. Hybridization techniques combine the strengths of multiple algorithms to create a more powerful optimization approach. For example, hybridizing Tabu Search with Genetic Algorithms or Particle Swarm Optimization can enhance the exploration

Table 3. Recent advancements in the TSA for industrial applications

Advancement	Description features
Hybridization with Other Metaheuristics [40]	The TSA is combined with other metaheuristics, such as Genetic Algorithms or Particle Swarm Optimization, to leverage their strengths and improve solution quality and convergence speed in solving complex industrial problems.
Parallel and Distributed Tabu Search [41]	Parallel and distributed computing techniques are applied to the TSA to accelerate its performance and handle larger-scale industrial problems. By dividing the search process among multiple processors or machines, parallel and distributed TSAs can explore the solution space in parallel, leading to faster convergence and improved solution quality.
Memetic Tabu Search [42]	Memetic algorithms integrate evolutionary algorithms with local search methods to enhance the exploration and exploitation capabilities. In the context of the TSA, memetic Tabu Search incorporates local search operators within the framework, allowing for more efficient exploration of the search space and improved convergence to optimal or near-optimal solutions in industrial applications.
Multi-objective Tabu Search [43]	Multi-objective TSAs extend the TSA to handle multi-objective industrial problems. These algorithms employ techniques such as Pareto dominance, diversity preservation, and adaptive memory structures to efficiently explore and maintain a diverse set of Pareto-optimal solutions, providing decision-makers with a range of trade-off solutions.

and exploitation capabilities, leading to better solutions in industrial applications. Parallel and Distributed Tabu Search: Parallel and distributed computing techniques have been applied to the TSA to accelerate its performance and handle larger-scale industrial problems. By dividing the search process among multiple processors or machines, parallel and distributed TSAs can effectively explore the solution space in parallel, leading to faster convergence and improved solution quality. Memetic Tabu Search: Memetic algorithms combine evolutionary algorithms with local search methods to enhance the exploration and exploitation capabilities. In the context of the TSA, memetic Tabu Search incorporates local search operators within the Tabu Search framework. This integration allows for more efficient exploration of the search space and improved convergence to optimal or near-optimal solutions in industrial applications. Multi-objective Tabu Search: Multi-objective optimization involves optimizing multiple conflicting objectives simultaneously. Recent advancements in the TSA have focused on extending it to handle multi-objective industrial problems. Multi-objective TSAs employ techniques such as Pareto dominance, diversity preservation, and adaptive memory structures to efficiently explore and maintain a diverse set of Pareto-optimal solutions, providing decision-makers with a range of trade-off solutions [39]. Table 3 shows recent advancements in the TSA for industrial applications. The table provides a concise overview of recent advances in the TSA for industrial applications, including hybridization with other metaheuristics, parallel and distributed computing techniques, memetic Tabu Search, and multi-objective Tabu Search. These advancements improve solution quality, convergence speed, and scalability in solving complex industrial optimization problems.

These recent advancements in the TSA highlight the ongoing research efforts to enhance its performance and applicability in industrial settings. By combining it with other

Table 4. Overview of the challenges and future directions for the TSA in industrial applications

Challenge / Future Direction	Description
Scalability Issues	The TSA faces challenges in handling large-scale problems due to its computational complexity. Future research should focus on developing scalable variants of the algorithm that can efficiently handle larger problem instances [43].
Handling Large-scale Problems	In addition to scalability, the TSA needs to effectively handle memory requirements and computational time for large-scale problems. Future directions should explore techniques such as parallel and distributed computing, as well as approximation methods, to address the computational complexity and memory limitations associated with large-scale problems [40].
Incorporating Uncertainty	Many real-world industrial problems involve uncertainty. Future research should extend the TSA to handle uncertainty by incorporating robust optimization techniques, stochastic programming, or fuzzy logic. This would enable the algorithm to provide more robust and reliable solutions in the face of uncertain conditions [44].
Real-time Applications	Developing real-time versions of the TSA is a future direction to handle dynamic and time-sensitive industrial applications. This involves adapting the algorithm to quickly respond to changes in the problem environment and generate solutions in real-time or near real-time. Real-time Tabu Search can find applications in areas such as scheduling, routing, and resource allocation [45].
Hybridization with Artificial Intelligence Techniques	Integrating Tabu Search with artificial intelligence techniques, such as machine learning and deep learning, can enhance its performance and applicability. Future research should explore the potential of combining Tabu Search with techniques like reinforcement learning, neural networks, or expert systems to enable more intelligent exploration and exploitation of the solution space [45].

metaheuristics, parallelizing and distributing its computation, incorporating local search operators, and extending it to handle multi-objective problems, researchers aim to improve solution quality, convergence speed, and scalability in solving complex industrial optimization problems.

5. **Challenges and Future Directions.** One of the major challenges in the TSA is its scalability to handle large-scale problems. As the problem size increases, the computational complexity of Tabu Search can become a limiting factor. Future research should focus on developing scalable variants of the algorithm that can efficiently handle larger problem instances. Handling Large-scale Problems is presented with related to scalability, another challenge is effectively handling large-scale problems in terms of memory requirements and computational time. Future directions should explore techniques such as parallel and distributed computing, as well as approximation methods, to address the computational complexity and memory limitations associated with large-scale problems. Incorporating Uncertainty is presented with many real-world industrial problems involve uncertainty, such as uncertain demand, resource availability, or machine breakdowns. Future research should focus on extending the TSA to handle uncertainty by incorporating

robust optimization techniques, stochastic programming, or fuzzy logic. This would enable the algorithm to provide more robust and reliable solutions in the face of uncertain conditions.

Real-time Applications: another future direction is to develop real-time versions of the TSA that can handle dynamic and time-sensitive industrial applications. This would involve adapting the algorithm to quickly respond to changes in the problem environment and generate solutions in real-time or near real-time. Real-time Tabu Search can find applications in areas such as scheduling, routing, and resource allocation.

Hybridization with Artificial Intelligence Techniques: the integration of Tabu Search with artificial intelligence techniques, such as machine learning and deep learning, holds promise for further enhancing its performance and applicability. Hybridization can leverage the strengths of both approaches, allowing for more intelligent exploration and exploitation of the solution space. Future research should explore the potential of combining Tabu Search with techniques like reinforcement learning, neural networks, or expert systems.

These challenges and future directions highlight the ongoing research efforts to overcome scalability issues, handle large-scale problems, incorporate uncertainty, develop real-time applications, and hybridize Tabu Search with artificial intelligence techniques. Addressing these challenges and exploring these directions will further enhance the effectiveness and applicability of the TSA in solving complex industrial optimization problems. Table 4 shows a concise overview of the challenges and future directions for the TSA in industrial applications, including scalability issues, handling large-scale problems, incorporating uncertainty, developing real-time applications, and hybridizing artificial intelligence techniques. Addressing these challenges and exploring these directions will further enhance the effectiveness and applicability of the TSA algorithm in solving complex industrial optimization problems.

Based on the challenges and future directions discussed, we recommend the following areas for future research on the Tabu Search Algorithm: Develop scalable algorithm variants that can efficiently handle more significant problem instances by exploring parallel and distributed computing techniques. Investigate approximation methods and procedures to address the computational complexity and memory limitations associated with large-scale problems. Extend the Tabu Search Algorithm to handle uncertainty by incorporating robust optimization techniques, stochastic programming, or fuzzy logic to provide more reliable solutions in uncertain conditions. Explore the development of real-time versions of the Tabu Search Algorithm to handle dynamic and time-sensitive industrial applications, such as scheduling, routing, and resource allocation.

6. **Conclusion.**

This review paper provided a comprehensive analysis of the TSA for industrial applications. It is a valuable resource for researchers, practitioners, and decision-makers interested in utilizing the TSA for solving complex optimization problems in various industrial domains. This comprehensive review paper aims to thoroughly understand the TSA and its application in various industrial settings. The report covers the key components of the TSA, including the tabu list, aspiration criteria, diversification and intensification strategies, and neighborhood structures. Furthermore, it explores the effectiveness of the TSA in solving optimization problems related to production planning, scheduling, logistics, and resource allocation. The review also discusses the performance evaluation metrics used to assess the efficiency of the TSA and compares its performance with other optimization techniques commonly employed in industrial applications. It highlights the advantages and limitations of the TSA, providing valuable insights for practitioners and researchers.

Moreover, recent advancements in the field, such as hybridization with other metaheuristics, parallel and distributed implementations, memetic tabu search, and multi-objective optimization, are discussed. These advancements have contributed to enhancing the performance and applicability of the TSA in industrial scenarios. The paper also addresses the challenges faced in implementing the TSA for large-scale problems, scalability issues, handling uncertainty, real-time applications, and the potential of hybridization with artificial intelligence techniques. It provides recommendations for future research directions to overcome these challenges and further improve the application of the TSA in industrial settings.

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REFERENCES

[1] S. Ruder, "An overview of gradient descent optimization algorithms," *arXiv preprint arXiv:1609.04747*, 2016.
[2] J.-S. Pan, T.-K. Dao, T-S. Pan, T.-T. Nguyen, S.-C. Chu, and J. F. Roddick, "An Improvement of Flower Pollination Algorithm for Node Localization Optimization in WSN," *Journal of Information Hiding and Multimedia Signal Processing,* vol. 08, no. 02, pp. 500–509, 2017.
[3] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review," *Archives of computational methods in engineering,* vol. 29, no. 5, pp. 2531–2561, 2022.
[4] T. K. Dao, T. S. Pan, T. T. Nguyen, and S. C. Chu, "A compact Articial bee colony optimization for topology control scheme in wireless sensor networks," *Journal of Information Hiding and Multimedia Signal Processing,* vol. 6, no. 2, pp. 297–310, 2015.
[5] T.-T. Nguyen, Y. Qiao, J.-S. Pan, T.-K. Dao, T.-T.-T. Nguyen, and C.-J. Weng, "An Improvement of Embedding Efficiency for Watermarking Based on Genetic Algorithm," *Journal of Information Hiding and Multimedia Signal Processing,* vol. 11, no. 02, pp. 79–89, 2020.
[6] F. Glover, "Tabu search, Part I," *ORSA Journal of Computing,* vol. 1, no. 3, pp. 190–206, 1989.
[7] F. Glover and M. Laguna, *Tabu search.* Springer, 1998.
[8] J.-F. Cordeau and G. Laporte, *Tabu search heuristics for the vehicle routing problem.* Springer, 2005.
[9] F. Glover, "Tabu Search: A Tutorial," *Interfaces,* vol. 20, no. 4, pp. 74–94, 1990, doi: 10.1287/inte.20.4.74.
[10] F. Glover, "Tabu search—part II," *ORSA Journal on computing,* vol. 2, no. 1, pp. 4–32, 1990.
[11] T.-K. Dao, T.-T. Nguyen, V.-T. Nguyen, and T.-D. Nguyen, "A Hybridized Flower Pollination Algorithm and Its Application on Microgrid Operations Planning," *Applied Sciences,* vol. 12, no. 13, p. 6487, Jun. 2022, doi: 10.3390/app12136487.
[12] Z. Fu, R. Eglese, and L. Y. O. Li, "A new tabu search heuristic for the open vehicle routing problem," *Journal of the operational Research Society,* vol. 56, no. 3, pp. 267–274, 2005.
[13] T.-T. Nguyen, T.-K. Dao, M.-F. Horng, and C.-S. Shieh, "An Energy-based Cluster Head Selection Algorithm to Support Long-lifetime in Wireless Sensor Networks," *Journal of Network Intelligence,* vol. 1, no. 1, pp. 23–37, 2016.
[14] J. S. Pan, T. K. Dao, T. S. Pan, T. T. Nguyen, S. C. Chu, and J. F. Roddick, "An improvement of flower pollination algorithm for node localization optimization in WSN," *Journal of Information Hiding and Multimedia Signal Processing,* vol. 8, no. 2, pp. 486–499, 2017.
[15] R. Battiti and G. Tecchiolli, "The reactive tabu search," *ORSA journal on computing,* vol. 6, no. 2, pp. 126–140, 1994.
[16] M. Chen and D. Cao, "Coordinating production planning in cellular manufacturing environment using Tabu search," *Computers & Industrial Engineering,* vol. 46, no. 3, pp. 571–588, 2004.
[17] T.-T. Nguyen, T.-G. Ngo, T.-K. Dao, and T.-T.-T. Nguyen, "Microgrid Operations Planning Based on Improving the Flying Sparrow Search Algorithm," *Symmetry ,* vol. 14, no. 1. 2022, doi: 10.3390/sym14010168.
[18] M. Dell'Amico and M. Trubian, "Applying tabu search to the job-shop scheduling problem," *Annals of Operations research,* vol. 41, no. 3, pp. 231–252, 1993.
[19] M. Saidi-Mehrabad and P. Fattahi, "Flexible job shop scheduling with tabu search algorithms," *The international journal of Advanced Manufacturing technology,* vol. 32, pp. 563–570, 2007.

[20] T. K. Dao, T. S. Pan, T. T. Nguyen, and J. S. Pan, "Parallel bat algorithm for optimizing makespan in job shop scheduling problems," *Journal of Intelligent Manufacturing,* vol. 29, no. 2, pp. 451–462, 2018, doi: 10.1007/s10845-015-1121-x.

[21] T. T. Nguyen, M. J. Wang, J. S. Pan, T. kien Dao, and T. G. Ngo, "A Load Economic Dispatch Based on Ion Motion Optimization Algorithm," *in Smart Innovation, Systems and Technologies,* 2020, vol. 157, pp. 115–125, doi: 10.1007/978-981-13-9710-3_12.

[22] J.-F. Camacho-Vallejo, L. López-Vera, A. E. Smith, and J.-L. González-Velarde, "A tabu search algorithm to solve a green logistics bi-objective bi-level problem," *Annals of Operations Research,* vol. 316, no. 2, pp. 927–953, 2022.

[23] K. Musiał, J. Kotowska, D. Górnicka, and A. Burduk, "Tabu search and greedy algorithm adaptation to logistic task," *in Computer Information Systems and Industrial Management: 16th IFIP TC8 International Conference, CISIM 2017*, Bialystok, Poland, June 16-18, 2017, Proceedings 16, 2017, pp. 39–49.

[24] T.-T. Nguyen, H.-J. Wang, T.-K. Dao, J.-S. Pan, J.-H. Liu, and S.-W. Weng, "An Improved Slime Mold Algorithm and Its Application for Optimal Operation of Cascade Hydropower Stations," *IEEE Access,* vol. 8, p. 1, 2020, doi: 10.1109/ACCESS.2020.3045975.

[25] G. Waligora, "Tabu search for discrete–continuous scheduling problems with heuristic continuous resource allocation," *European Journal of Operational Research,* vol. 193, no. 3, pp. 849–856, 2009.

[26] Y. Yu, M. Pan, X. Li, and H. Jiang, "Tabu search heuristics for workflow resource allocation simulation optimization," *Concurrency and Computation: Practice and Experience,* vol. 23, no. 16, pp. 2020–2033, 2011.

[27] T. Dao, T. Nguyen, J. Pan, Y. Qiao, and Q. Lai, "Identification Failure Data for Cluster Heads Aggregation in WSN Based on Improving Classification of SVM," *IEEE Access,* vol. 8, pp. 61070–61084, 2020, doi: 10.1109/ACCESS.2020.2983219.

[28] T.-T. Nguyen, J.-S. Pan, T.-Y. Wu, T.-K. Dao, and T.-D. Nguyen, "Node Coverage Optimization Strategy Based on Ions Motion Optimization," *Journal of Network Intelligence,* vol. 4, no. 1, pp. 1–9, 2019.

[29] M. da Conceicao Cunha and L. Ribeiro, "Tabu search algorithms for water network optimization," *European Journal of Operational Research,* vol. 157, no. 3, pp. 746–758, 2004.

[30] E. L. Da Silva, J. M. A. Ortiz, G. C. De Oliveira, and S. Binato, "Transmission network expansion planning under a tabu search approach," *IEEE Transactions on Power Systems,* vol. 16, no. 1, pp. 62–68, 2001.

[31] J. Renaud, G. Laporte, and F. F. Boctor, "A tabu search heuristic for the multi-depot vehicle routing problem," *Computers & Operations Research,* vol. 23, no. 3, pp. 229–235, 1996.

[32] O. Exler, L. T. Antelo, J. A. Egea, A. A. Alonso, and J. R. Banga, "A tabu search-based algorithm for mixed-integer nonlinear problems and its application to integrated process and control system design," *Computers & Chemical Engineering,* vol. 32, no. 8, pp. 1877–1891, 2008.

[33] B. Lin, S. Chavali, K. Camarda, and D. C. Miller, "Computer-aided molecular design using Tabu search," *Computers & Chemical Engineering,* vol. 29, no. 2, pp. 337–347, 2005.

[34] F. Glover, "Artificial intelligence, heuristic frameworks and tabu search," *Managerial and Decision Economics,* vol. 11, no. 5, pp. 365–375, 1990.

[35] O. Lambrechts, E. Demeulemeester, and W. Herroelen, "A tabu search procedure for developing robust predictive project schedules," *International Journal of Production Economics,* vol. 111, no. 2, pp. 493–508, 2008.

[36] M. A. Abido, "A novel approach to conventional power system stabilizer design using tabu search," *International Journal of Electrical Power & Energy Systems,* vol. 21, no. 6, pp. 443–454, 1999.

[37] M. A. Abido, "Optimal power flow using tabu search algorithm," *Electric power components and systems,* vol. 30, no. 5, pp. 469–483, 2002.

[38] A. Lamghari and R. Dimitrakopoulos, "A diversified Tabu search approach for the open-pit mine production scheduling problem with metal uncertainty," *European Journal of Operational Research,* vol. 222, no. 3, pp. 642–652, 2012.

[39] H. Zhang, K. Zhang, Y. Chen, and L. Ma, "Multi-objective two-level medical facility location problem and tabu search algorithm," *Information Sciences,* vol. 608, pp. 734–756, 2022.

[40] H. Gao, S. Kwong, B. Fan, and R. Wang, "A hybrid particle-swarm tabu search algorithm for solving job shop scheduling problems," *IEEE Transactions on Industrial Informatics,* vol. 10, no. 4, pp. 2044–2054, 2014.

[41] T. G. Crainic, J.-Y. Potvin, and M. Gendreau, *Parallel tabu search.* Université de Montréal, Centre de recherche sur les transports, 2005.

[42] H. Pirim, B. Eksioglu, and E. Bayraktar, "Tabu Search: a comparative study," *Optimization* 2008.
[43] A. M. Mohammed and S. O. Duffuaa, "A tabu search based algorithm for the optimal design of multi-objective multi-product supply chain networks," *Expert Systems with Applications,* vol. 140, p. 112808, 2020.
[44] M. Gendreau, M. Iori, G. Laporte, and S. Martello, "A Tabu search heuristic for the vehicle routing problem with two-dimensional loading constraints," *Networks: An International Journal,* vol. 51, no. 1, pp. 4–18, 2008.
[45] D. Pham and D. Karaboga, "Intelligent optimisation techniques: genetic algorithms, tabu search, ", *simulated annealing and neural networks.* Springer Science & Business Media, 2012.