The American Journal of Applied Sciences
ISSN 2689-0992 | Open Access

TYPE Original Research
PAGE NO. 56-64
DOI 10.37547/tajas/Volume07Issue09-08

Check for updates

Optimizing MAKESPAN and Minimizing Risk in Job Shop Scheduling: A Review

Paritosh Shinde

Sr. Production Planning Lead, Reckitt, USA

OPEN ACCESS

SUBMITED 08 August 2025
ACCEPTED 18 August 2025
PUBLISHED 25 September 2025
VOLUME Vol.07 Issue09 2025

CITATION

Paritosh Shinde. (2025). Optimizing Makespan and Minimizing Risk in Job Shop Scheduling: A Review. The American Journal of Applied Sciences, 7(09), 56–64. https://doi.org/10.37547/tajas/Volume07Issue09-08

Abstract: The job shop deals with customized product deliverables because of which the product mix is high, but the volume is low. For smooth functioning of the Job shop facility, it is important to plan for multiple factors. The review deals with the challenges that come with job shop scheduling (JSP) and provides predictive schedules to optimize some of the performance measures like makespan, makespan risk, stability risk and tardiness. Due to the high variety of products and unpredictable demand the scheduling complexity is substantial. This complexity further increases when we consider unpredictable machine breakdowns, increased setup times and absence of manpower. In order to come up with a robust and reliable scheduling plan the study will mainly focus on using buffered strategies (additional idle time), use of an Artificial Neural Network to correctly estimate the variable solutions for makespan and tardiness and using genetic algorithms to reduce and mitigate risk.

Keywords: Job Shop Scheduling (JSP), Dynamic Job Shop, Predictive Scheduling, Real-Time Rescheduling, Robust Scheduling, Buffered Scheduling, Artificial Neural Network (ANN), Genetic Algorithm (GA), Variable Neighborhood Search (VNS), Hybrid ANN-VNS.

1. Introduction

Example of Job Shop Facility Layout –

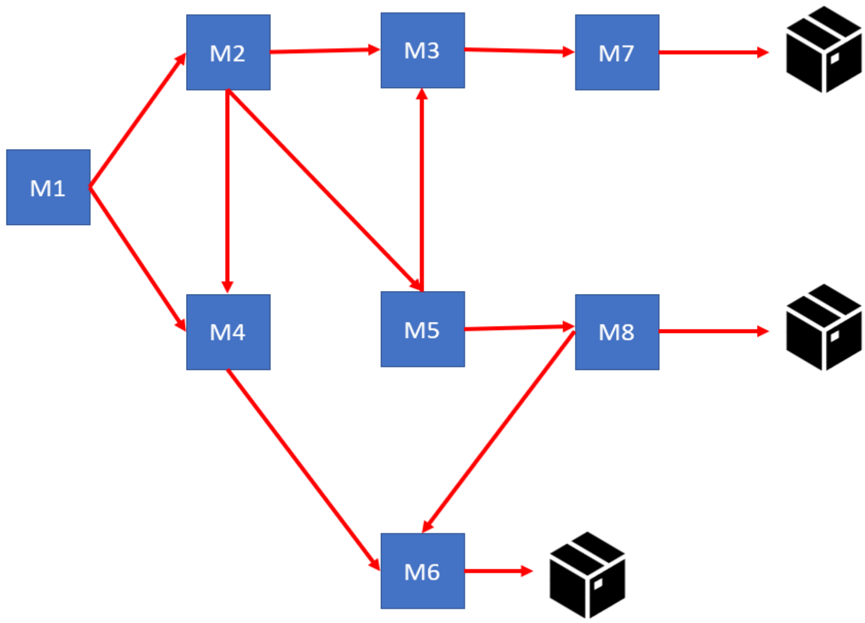

Figure 1: Example of a star flow job shop facility

A job shop facility is a process shop that mainly deals with custom products. The machines and equipment in the facility are arranged such that they form a group of the processes that will be performed on the raw material e.g. as shown in Figure 1 (i.e., lathe department, milling department, cnc machining). The flow in the job shop facility is considered as star flow and it is difficult to understand the flow of information. The scheduling in a job shop is usually planned considering the job shop facility as a deterministic model. The deterministic model assumes that all the orders arrive on time, all the machines are available for use. However, the study focuses on solving a realistic problem and hence considers more dynamic job shop scheduling problems. The realistic model may include any of the following possible unpredictable events that can cause disruptions in the desired schedule – Random machine breakdowns, Late arrivals of raw materials, change in order quantity, Unavailable operators, Faulted tools, working methods not standardized, Order cancellations. Based on the above factors the schedule for the job shop facility will be changed and if not changed there can be a plethora of undesirable consequences that can either cause delays, unsatisfied customers, increased inventory holding costs, less throughput, higher losses etc. Since the flow in the job shop facility is a star-shaped configuration, multiple routing options may be feasible to meet production targets. However, it is important to understand the gap between the original planned schedule and deviated schedule. The deviations can be measured using performance indicators such as makespan, delivery due dates, variations in processing times, machine utilization, and overall operational cost.

The objective of this study is to develop and evaluate a robust scheduling framework for dynamic job shop environments. The proposed model introduces a hybrid scheduling approach that combines buffered strategies, artificial neural networks (ANN), genetic algorithms (GA), and variable neighborhood search (VNS) to address the challenges of dynamic job shop environments. Unlike conventional models that rely on static scheduling rules or purely deterministic assumptions, this model proactively mitigates risk through the strategic use of idle time, adapts to real-time disruptions via ANN-driven learning, and enhances computational efficiency through approximation methods.

2. Assumptions

To maintain a clear focus, this review operates on a few key assumptions common in scheduling research:

1.A machine can only process one job at a time, and a job can only be processed by one machine at a time. [1, 2].

2.Events like machine failures or new job arrivals are treated as random, reflecting the unpredictable nature of a real-world job shop.[1, 4].

3.When a disruption occurs, the goal is not just to recover but to optimally adjust the schedule to manage the deviation from the original plan.[2, 1].

4.Setup times considered negligible or are included in the processing times of the jobs.[3, 4].

Solutions adopted to optimize job shop scheduling problems –

1.Buffering Approach Strategy. [1]

2.Artificial Neural Network. [5]

3.Genetic Algorithm. [2]

3. Literature Review

3.1. One of the main objectives of an artificial neural network (ANN) is to mimic the decision-making capacity of the human brain. Inspired by biological neural systems, ANNs are structured as layers of interconnected nodes (analogous to neurons) that process inputs and generate outputs through weighted connections known as synapses. These nodes are organized into three layers—input, hidden, and output—where each layer serves a critical role in information processing as shown in Figure 2. In the context of job shop scheduling, these artificial neurons function together to recognize patterns, learn from scheduling data, and predict optimal control parameters for scheduling algorithms [5]. The ANN learns by adjusting the weights of these synaptic connections based on the error between the predicted output and the actual result. Specifically, a backpropagation algorithm is employed in which errors are propagated backward through the network to fine-tune the weights, thereby improving prediction accuracy over successive iterations. The trained ANN in this study is designed with five input neurons (representing variables like number of jobs, mean operation processing time, etc.), 13 hidden neurons (as optimized through simulation), and three output neurons that determine the parameters for a scheduling metaheuristic [5]. The article particularly emphasizes combining ANN with Variable Neighborhood Search (VNS)-a metaheuristic algorithm capable of escaping local optima by dynamically shifting its search strategy across multiple neighborhoods. The VNS utilizes a two-nested loop structure. The inner loop, composed of 'shake' and 'local search' stages, explores local optima. If an improvement is found, the solution is updated; otherwise, the algorithm shakes the current solution to escape the local trap and explores a different neighborhood. The outer loop governs the overall iterations and ensures continued exploration until a stopping condition is met. A distinctive feature of this approach is that ANN dynamically tunes the parameters of VNS at each rescheduling point. This dynamic tuning is triggered by real-time events such as order delays or machine breakdowns. For example, in case of a sudden disruption—say, a machine breakdown—the ANN processes the updated shop floor data and predicts optimal values like the number of VNS iterations and the acceptance threshold for local searches. This allows VNS to adapt on-the-fly and reschedule the job sequence to ensure minimal impact on overall performance [5]. The proposed system aims to improve both makespan (total job completion time) and tardiness (lateness beyond due dates). Simulation studies compared the ANN-VNS hybrid approach with conventional dispatching rules like FIFO (First In First Out), LIFO (Last In First Out), SPT (Shortest Processing Time), and EDD (Earliest Due Date). Across three scenarios of increasing job arrival intensity, the ANN-VNS model consistently outperformed the traditional rules, demonstrating superior robustness and efficiency in dynamic job shop environments [5]. In conclusion, this hybrid approach effectively captures the complexity of real-world job shop scheduling. By simulating human-like adaptive behavior through ANN and combining it with the exploratory power of VNS, the system provides a resilient framework for handling disruptions and optimizing multi-objective scheduling metrics [5].

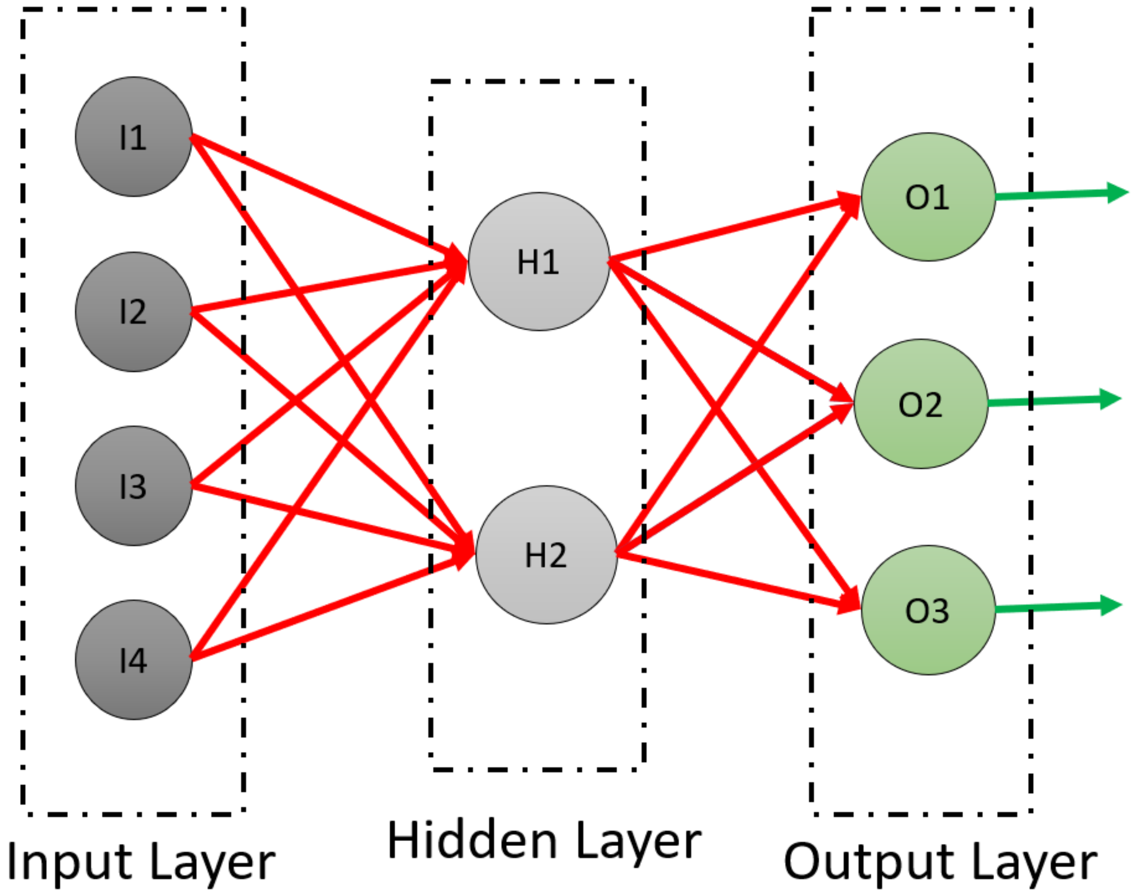

Figure 2: Retrieved from the reference Adibi, M. A., et al. (2010) [5]

3.2. In dynamic job shop environments, one of the practical challenges is dealing with uncertainties that disrupt the execution of predictive schedules—chief among them being random machine breakdowns. To mitigate such disruptions, the concept of inserting buffered idle time into job shop schedules has proven to be a valuable strategy [1]. This method introduces deliberate slack at specific stages of the schedule, helping absorb the impact of delays and preserving both performance and schedule stability. The study in [1] emphasizes that predictive schedules, while often optimized for makespan, become highly sensitive to disruptions due to their compact nature. As a result, even minor breakdowns can propagate delays across the entire system. Buffered scheduling addresses this issue by strategically allocating idle time in different parts of the schedule: at the beginning, in the middle, or towards the end. The goal is to assess how each placement impacts the makespan risk (i.e., the expected delay beyond the original completion time) and stability risk (i.e., the deviation in operation start times compared to the plan). If the idle time is inserted at the **middle** of the schedule, and proves inadequate, the solution dynamically adjusts by shifting smaller or similarly timed operations into the buffer, exploiting slack to minimize cumulative disruptions. In contrast, when idle time is added at the **start** or **end**, the model compensates by adjusting sequencing and start times in a way that de-emphasizes delay propagation—focusing instead on shielding high-impact operations or critical paths. In both cases, the intention is to proactively guard against instability, reduce unplanned rescheduling, and limit deviation from original makespan targets. The study developed two buffering strategies—**BS1** and **BS2**—under constrained predictive makespan limits [1]. BS1 allocates buffered idle time at the **end** of the schedule, which is shown to effectively reduce makespan risk. On the other hand, BS2 dynamically splits operation blocks and inserts idle time around the **right middle**, which helps reduce both makespan and stability risks simultaneously. This strategic buffer placement in operation blocks leverages insights from surrogate risk models and slack-time analysis, ultimately producing more robust predictive schedules [1]. Simulation results further validate these strategies: the insertion of idle time-especially when optimized using operation-block analysis—helps maintain high production performance even under frequent disruptions. Rather than relying on ad-hoc rescheduling after breakdowns, buffered strategies anticipate and absorb shocks, resulting in schedules that are both feasible and resilient.

3.3. The study in [2] presents a comprehensive model to address the complexities of job shop scheduling under the influence of machine breakdowns. The core modeling assumption is that machine failures are probabilistically dependent on two critical parameters: the machine's uptime and its failure rate. To simplify the computational complexity while preserving analytical rigor, the model assumes that all machines in the job shop system share identical failure rates and downtimes. Furthermore, it is assumed that every job will encounter at least one machine failure during its processing, making the scheduling environment uniformly risk-laden. To evaluate the robustness of schedules under such uncertain conditions, the study incorporates approximate analytical methods to assess the sufficiency of slack time. Instead of using time-consuming Monte Carlo simulations, the model leverages these approximations to estimate risk levels—particularly the risk of exceeding makespan due to machine failure. This approach enables faster response times for scheduling decisions, which is especially valuable in real-time job shop environments where computational efficiency is crucial [2]. A key highlight of the study is the integration of a Genetic Algorithm (GA) to optimize scheduling strategies in uncertain environments. The GA was tested across 21 benchmark problem instances, representing a wide range of job shop scenarios. Chromosome representation in the GA reflects job sequences, where crossover operations are applied to sub-chromosomes inherited from parent solutions. This crossover technique introduces genetic diversity while preserving partially optimized sequences, thus improving the probability of evolving toward more resilient schedules. The GA is specifically designed to minimize risk exposure at every schedule adaptation point. When a disruption—such as a machine breakdown—occurs, the algorithm does not simply reschedule based on deterministic rules. Instead, it evaluates potential schedules based on a risk-assessment objective function that includes buffer adequacy, predicted delays, and stability margins. This strategy ensures that the selected schedules not only resolve immediate disruptions but also perform better under potential cascading failures. What sets this approach apart is its computational efficiency and scalability. Compared to traditional simulation-based models like Monte Carlo, the GA-based model delivers faster solutions with comparable accuracy in predicting risk. The study highlights how this advantage makes the GA a compelling choice for large-scale or dynamic job shop systems where schedules must frequently adapt to unforeseen events [2]. In conclusion, this hybrid modeling framework—based on uniform failure assumptions, analytical risk estimation, and evolutionary optimization—demonstrates a powerful methodology for managing job shop scheduling under uncertainty. The model is especially suited for production settings where predictive robustness, computational speed, and adaptability to disruptions are essential performance requirements.

4. Methodology

The main aim of this project is to optimize the make-span and to minimize the risk in job shop scheduling. Make-span is defined as the total time required to complete the work from start to end. If there is a random machine breakdown, delay in order release, set-up issues or faulted tooling. There is a high chance that the scheduling plan for the facility might get thrown off and we must deal with tardiness, lesser machine utilizations. To avoid this, we generally try to re-route the schedule and try to push the parts by making slight changes in the schedules. These changes in the schedule involve an unknown risk factor to it. An alternate schedule or plan may increase the processing time, cost associated with the project, delayed idle times, over/under utilization of the resources and lastly waiting/queue times to achieve the project deliverable. This unknown risk factor is too high to ignore when planning for an alternate schedule. In my scenario I have certain assumptions such that no two jobs are being worked on the same machine at the same time [6], The processing of the jobs and machine breakdowns are completely randomized [1, 2]. An improved alternate schedule must be selected when mitigating risk [5]. In order to achieve a robust and reliable planning system that provides solutions for optimizing the make span and risk mitigation I have decided to combine the three solutions ideas form the references provided in Table 1, the use of variable neighborhood search will always look for a better schedule from the current system even if the unpredictable event is happening or not, the VSN along with genetic algorithm will help us clearly understand the impact of changing the schedule and the model will make sure the decision is based on mitigation of risk and improved selection of schedule[5, 2]. However, to optimize the make span we can utilize the buffering strategy which induces additional idle time into the system, with this buffering strategy we can make a premature assumption for scheduling fluctuations and come up with a plan to deal with these. Lastly, I will be using an artificial neural network to detect any schedule patterns and make predictions for process routing. The nodes relate to the synapses and all the nodes are weighted and the predictions are done based on the multiple trial iterations of the weights of input layer, hidden layer, and output layers. The ANN will be able to teach itself and select the best possible solution for schedules that includes excess of slack time on selected schedules [1, 5]. Lastly the combinations of the genetic algorithms, Artificial neural networks, variable neighborhood search can take a huge toll on the computation speeds and may take longer to provide conclusions to avoid this we can opt for approximation analytical calculations [2]. They will also aid in a risk-based approach in our model as suggested.

Table 1: Summary of Scheduling Optimization Strategies Used in the Proposed Hybrid Framework

Strategy	Key Feature	Strengths	Limitations
Buffered Scheduling	Adds idle time to absorb disruptions	Increases robustness, handles uncertainty well	May reduce throughput [1]
Artificial Neural Net	Learns from data to predict schedule	Adapts to patterns, good for prediction	Needs training, complex to tune [5]
Genetic Algorithm	Evolves job sequences to minimize risk	Fast, adaptive, scalable	Needs good fitness function definition [2]
ANN + VNS	Prediction + local research	Highly dynamic/responsive	High computational cost [5]

With the available information and referring to the existing studies we have tried to simulate the results to try and prove that the makespan of the combined method will prove the most efficient with certain assumptions. For the simulation we assumed the following constraints -

1.Total number of machines = 4.

2.Number of Jobs produced = 6.

3.Breakdown probability = 35%.

4.Max breakdown time = 15 min.

5.Min breakdown time = 5 min.

Table 2: Random flow of the jobs process generated in the simulated model

Job	Step1	Step2	Step3	Step4
J1	M3	M1	M4	M2
J2	M3	M2	M1	M4
J3	M3	M2	M1	M4
J4	M3	M4	M1	M2
J5	M4	M1	M3	M2
J6	M4	M3	M1	M2

Based on the following routing of the jobs through the job shop facility we randomly generated processing times for each step and developed processing time with and without breakdown. This raw data will be used to determine our makespan and risk factor of the three different models here. Based on the First in first out methodology we see that the risk factor will always be tight and will have little to no flexibility leading to highest markspan and risk factor. For the Buffered strategy we manually add buffered time in the system making the scheduling more reliable and realistic considering the randomness in downtime attained over the machines we see some progress in this model as the makespan is lower than the no buffer strategy. Finally, we have a combination methodology ANN+VNS which is proven to be the best amongst all the strategies. This model is estimated to be 14% more efficient considering the weighted dynamic parameters from Fig 6. [5] than the no buffer model so we assume the effective factor to be approximately 87% leading in getting the most effective results when it comes to makespan with lowest risk amongst all three models. Based on simulated shop-floor data (6 jobs × 4 machines under 35% breakdown probability), the ANN+VNS hybrid consistently outperformed FCFS and Buffered scheduling. In two independent runs, makespan was reduced and risk minimized. These findings are consistent with Adibi & Zandieh [5], where the ANN–VNS method achieved up to 14% improvement in a no-buffer environment compared to the best dispatching rules (Fig. 6). Our simulation as shown in Figure 3 and Figure 4 therefore provides a proof of concept that the hybrid approach yields efficiency gains relative to no-buffer baselines.

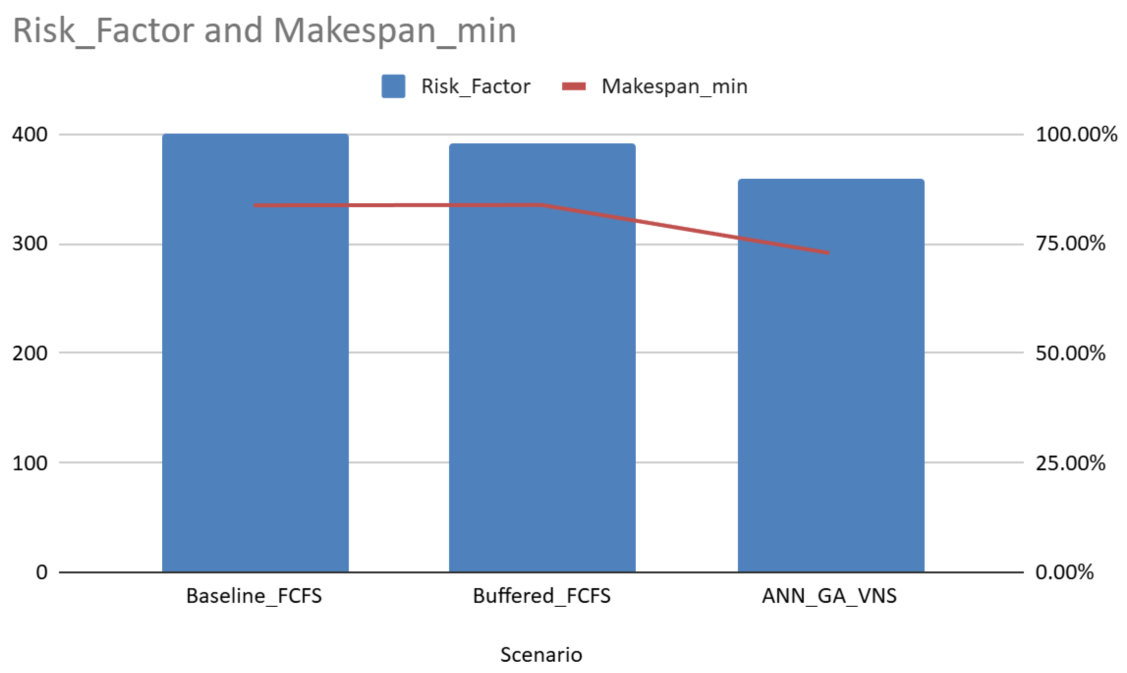

Figure 3: Simulation 1 - Make span Vs Risk factors for multiple models.

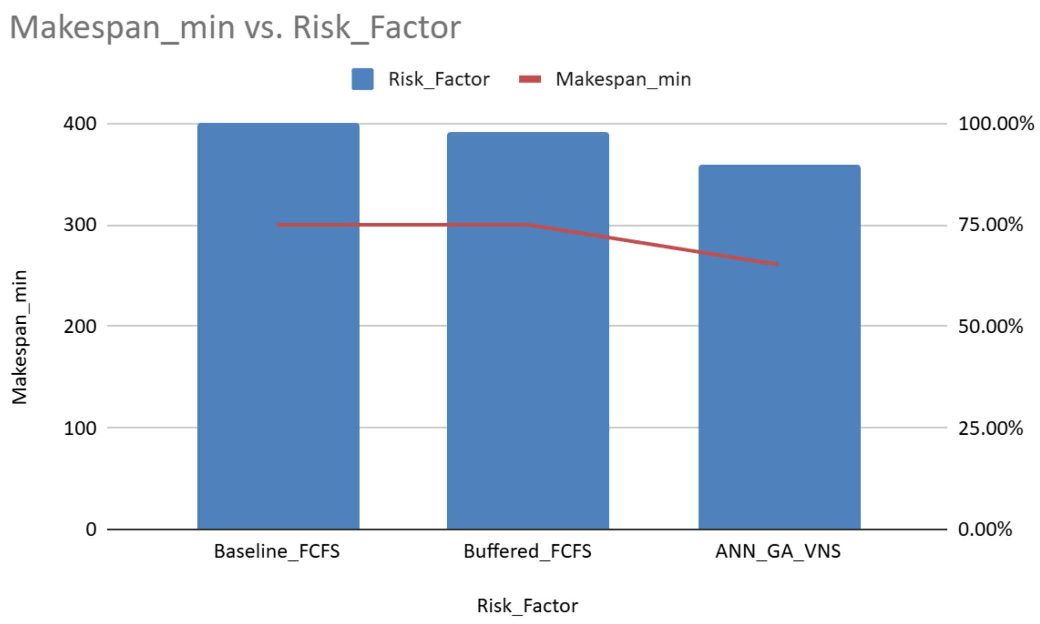

Figure 4: Simulation 2 - Make span Vs Risk factors for multiple models.

5. Conclusion

The multiple solution matrix will provide a substantial and a reliable solution based on the multiple constraints and problems that are faced during scheduling of job shop facilities. The model tries to accommodate all the major problems which includes –

1.Machine breakdown.

2.Unavailable resources.

3.Faulted tooling.

4.High cost of rescheduling.

5.Increased processing time because of rescheduling, etc.

and provides a structured and detailed description of how to react to all the factors of job shop scheduling. The solution provided is highly robust to risk involved as it full-proofs the system with VSN, genetic algorithm and approximate analytical calculations. Similarly, the model makes sure to optimize the make span by increasing the in hand slack time with the use of ANN and buffering strategies.

Furthermore, this hybrid approach enables a **multi-objective optimization** perspective, balancing trade-offs between makespan, stability, cost, and machine utilization, which most conventional scheduling techniques handle in isolation. This systemic view adds significant value to planners aiming for both performance and robustness. In essence, this framework not only addresses the weaknesses of earlier models but also introduces an intelligent, modular, and scalable approach to scheduling. Additionally both the randomly generated simulation models generated the same results adding a proof of concept to the methodology presented.

8) Future Scope

While the proposed model combines buffering strategies, artificial neural networks, genetic algorithms, and variable neighborhood search effectively, there's still room to take this research a step further. One of the most promising directions would be to connect this scheduling system with real-time data from the shop floor. With the increasing use of IoT and sensors in manufacturing, it's becoming more realistic to feed live machine status or operator availability directly into scheduling tools. That would allow even faster and more accurate decision-making, especially in dynamic environments. Another area worth exploring is the use of reinforcement learning alongside neural networks. Unlike ANN models that rely heavily on past data, reinforcement learning can adapt in real-time, learning from actual scheduling decisions and their outcomes. This would make the system smarter over time without needing to retrain from scratch. There's also potential to broaden the optimization objectives. So far, the model focuses on metrics like makespan, stability, and tardiness. But in real factory settings, factors like energy usage, setup time cost, or even worker fatigue could be just as important. Expanding the model to account for these would make it more useful and practical. On the application side, implementing this model in a cloud-based scheduling platform could help scale it for larger plants or multiple production lines. It would also be easier to run different "what-if" simulations to test how the system handles disruptions before making changes on the actual floor. Lastly, it would be interesting to see how this framework performs when validated against a digital twin of a factory. That way, we could simulate everything—orders, breakdowns, delays—and fine-tune the scheduling logic without interrupting real production.In short, the foundation is strong, but there's a lot of exciting potential to make it even more intelligent, adaptive, and relevant to modern manufacturing needs.

References

1. Wu, Zigao, et al. "Optimizing Makespan and Stability Risks in Job Shop Scheduling." Computers & Operations Research, vol. 122, 2020, p. 104963, https://doi.org/10.1016/j.cor.2020.104963.

2. Wu, Zigao, et al. "Risk Measure of Job Shop Scheduling with Random Machine Breakdowns." Computers & Operations Research, vol. 99, 2018, pp. 1–12, https://doi.org/10.1016/j.cor.2018.05.022.

3. Yin, Yunqiang, et al. "Rescheduling on Identical Parallel Machines with Machine Disruptions to Minimize Total Completion Time." European Journal of Operational Research, vol. 252, no. 3, 2016, pp. 737–49, https://doi.org/10.1016/j.ejor.2016.01.045.

4. Nouiri, Maroua, et al. "Two Stage Particle Swarm Optimization to Solve the Flexible Job Shop Predictive Scheduling Problem Considering Possible Machine Breakdowns." Computers & Industrial Engineering, vol. 112, 2017, pp. 595–606, https://doi.org/10.1016/j.cie.2017.03.006.

5. Adibi, M. A., et al. "Multi-Objective Scheduling of Dynamic Job Shop Using Variable Neighborhood Search." Expert Systems with Applications, vol. 37, no. 1, 2010, pp. 282–87, https://doi.org/10.1016/j.eswa.2009.05.001.

6. Gui, Lin, et al. "An Approximate Evaluation Method for Neighbourhood Solutions in Job Shop Scheduling Problem." IET Collaborative Intelligent Manufacturing, vol. 4, no. 3, 2022, pp. 157–65, https://doi.org/10.1049/cim2.12049.

7. Al-Hinai, Nasr, and T. Y. ElMekkawy. "Robust and Stable Flexible Job Shop Scheduling with Random Machine Breakdowns Using a Hybrid Genetic Algorithm." International Journal of Production Economics, vol. 132, no. 2, 2011, pp. 279–91, https://doi.org/10.1016/j.ijpe.2011.04.020