International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 12, No. 3, 2025, pp. 1-8.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

A Resilient Scheduling Model Using Neuro-Evolutionary Planning for Disaster-Resistant Industries

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Abstract

Unprecedented natural disasters and human-made catastrophes, maintaining business continuity now heavily depends on industrial resilience. This novel scheduling approach combines adaptive planning algorithms with neuro-evolutionary techniques to automate and strengthen industrial operations enduring excessive disruptive conditions. The model utilizes predictive analytics through neural networks and applies evolutionary strategies for real-time, environmentally driven operational and maneuverable shifting dynamic systems. Simulated disaster scenarios and case studies highlighted the model's advantages over traditional scheduling methods in optimizing resource allocation, reducing downtime, and meeting set production goals. Industries seeking to strengthen their operations against future disruptions will benefit from this robust and intelligent solution called neuro-evolutionary planning framework.

Keywords: Resilient Scheduling, Neuro-Evolutionary Planning, Disaster-Resistant Industries, Adaptive Optimization, Industrial Resilience, Dynamic Scheduling.

DOI: 10.71086/IAJSE/V12I3/IAJSE1217
Received: 09 June 2025/Revised: 14 July 2025/Accepted: 11 August 2025/Published: 30 September 2025

Introduction

Contemporary industries face formidable challenges to operational efficiency and business continuity during disturbances in the context of multi-faceted and wrathful global disasters like earthquakes, floods, hurricanes, or even human disasters such as cyberattacks. Supply chain disruptions prove equally calamitous. There is no denying that such digitally powered transformations demand more agile approaches to scheduling at the enterprise level, as the uncertainty level and potential impact of a given disruption have shifted dramatically (Sripavithra & Kirubanand, 2025). Static or rigid schedules have repeatedly proven insufficient under turbulent, fast-evolving scenarios. Consequently, there is an increasing demand for automation technologies that can adjust intelligently on the fly, including adapting dynamically to predefined and evolving contingencies such as disasters.

This work focuses on a scheduling problem necessitating dynamic adaptation under emergency scenarios, using a hybrid technique we term neuro-evolutionary planning (Yin et al., 2016; Choudhary & Deshmukh, 2023), directed towards solving the problem of resilient production scheduling (Sheffi, 2005). Evolutionary approaches are practical for large spaces defined by constraints regarding optimization problems or finding solutions close to the target (Zhou et al., 2017). Additionally, the computational burden can be alleviated with neural networks capable of pattern recognition in historical and real-time data (Chan et al., 2014; Khosravi et al., 2011). The blend enables flexible responses to environmental shifts and resource availability during emergencies, offering robust frameworks to adaptive scheduling models that incorporate self-regulatory features to modify control settings within predefined boundaries (Berman & Gavious, 2007).

The proposed scheduling algorithm uses metaheuristics, particularly the neuro-evolutionary approach, and works within a closed-loop system capable of responsive Scheduling (Cui et al., 2018). This allows real-time updates to scheduled activities based on resource outages, workforce dependencies, and other environmental risks (Supriya & Dhanalakshmi, 2024). Unlike conventional approaches that utilize set plans, heuristics, and a single optimization step, this model is focused on self-evolution and iterative learning and optimization heuristics, which enhances resilience (Hosseini et al., 2016). The system predicts possible disruptive scenarios and proposes preemptive configuration changes to schedules within the least possible intervals, hence reducing idle time and operational losses (Snyder et al., 2006).

This model holds great relevance within critical sectors such as manufacturing, logistics, energy, and healthcare, where system outages are accompanied by severe socio-economic impacts and cascading failures to other systems (Ivanov & Dolgui, 2020; Li, Wang & Li, 2017). Injecting resilience into the primary scheduling frameworks allows industries to absorb more shocks while sustaining faster recovery and stabilizing output even in extreme stress conditions (Mohankumar et al., 2024).

Key Contributions

- Proposes a hybrid neuro-evolutionary scheduling model tailored for disaster-resistant industrial environments.
- Demonstrates improved performance in resilience metrics through simulation-based comparative analysis with traditional schedulers.
- Introduces a multi-objective optimization framework that supports adaptive decision-making under uncertainty.

Organization Overview

The paper is organized in the following manner: In Section II, we provide a comprehensive review of available literature on disaster-resilient Scheduling and identify pertinent gaps in research. Section III describes the structure of the proposed neuro-evolutionary scheduling paradigm, its constituent neural and evolutionary subsystem modules, and the consolidated multi-objective optimization architecture. Section IV elaborates on the model's simulations, analyzing the experimental configuration, scenario context, performance evaluation criteria, and results interpretation. Lastly, in Section V, we summarize the findings of our work alongside suggesting further theoretical investigation and practical application avenues.

Literature Review

The study of industrial systems that accommodate disaster mitigation strategies alongside adaptive scheduling forms the area of research that has emerged over the past years. As noted by Tang, (2006), supply chain networks are susceptible to perturbations, hence the need for flexible and proactive planning (Kabir & Papadopoulos, 2018). From the explanation given earlier, it is clear that adaptability becomes very critical for alleviating risks that arise due to unpredictable shocks in business processes within industrial operations. Vespignani, (2010) analyzed the profound dependencies of global systems, the local disruptions, and their far-reaching effects on Drawin’s systems. He noted

the importance of system resilience, stating that prognosis, in combination with strong scheduling algorithms, aids industries in ensuring operations during emergencies (Dubey et al., 2019).

Drafts and Scheduling, which focuses on developing AI scheduling systems for practical applications in intelligent manufacturing systems, is a trademark of Liu et al., (2019), (Yin et al., 2016), commented on the exploitative effect of incorporating artificial intelligence on Scheduling concerning rapidly changing situational factors related to both external and internal elements of an organization. Liu et al., (2019) stubbed their toes when integrating heuristic algorithms with optimization algorithms, leading to a failure in dynamically modifying deployed schedulers, quoting 'We Still Have A Chance,' claiming their systems leave room for optimization.

Yin et al. (2016) asserted that familiarization utilizing preserved, historical intel is vital in regulating activities within dire situations. It can be achieved through strategic sequencing that obsoletes potential sudden shifts within the processes that would generally bring harm, accompanied by altering what-if discrepancies in advance, bringing forth less disturbing changes during actual shuffling, which leads to more immediate positive outcomes. Jin et al., (2016) (Abulail, 2025) went one step further to argue that change includes deciding the break-even point between the output forecasts and the expenditures of resources needed to cover up sharp output slack.

Zhou et al., (2015) predicted that proceeding with dynamically structured automation would promote smooth-flow algorithms across fractal systems. In contrast, Goh & Lawley, (2003) showed how fractal systems controlled stressors perturbing agile systems, confirming that bounded fractal structures can resolve agile stiffness. Zhou et al., (2017) relayed Leave My Brain Alone, an animated prediction made with i-pragmatic feeling, tackling the evolutionary stems that blend adaptive mechanisms with heuristic-resilient responding strategies towards disturbances prediction.

Vasilakos et al., (2016) (Tavana et al., 2016) studied disaster recovery planning through the scope of multi-criteria decision-making techniques, emphasizing the intricacies involved in disaster response spans multiple dimensions. They advocate for using intelligent systems capable of managing the complex trade-off between time, cost, and safety.

Zhang et al., (2020) noted the impact that real-time data has on Scheduling within industries that operate in disaster-prone areas. Their work developed a data-driven model that changes the scheduling decision dynamically based on feedback from the system and the environment. Later, Jalil & Ghaffari, (2021) analyzed neuro-evolutionary algorithms in adaptive planning. They showed that combining neural networks with evolutionary approaches provides a robust solution framework for resilient Scheduling amid uncertainty.

Architectural Design

3.1 Neuro-Evolutionary Framework for Resilient Scheduling

The scheduling model combines evolutionary computing and neural networks to provide a flexible response to disruptions in the industrial flow. The system functions in a closed loop, as shown in Figure 1, where learning from an operating environment starts with observations to actions and optimally continues through feedback evaluation. This approach works better in case of a calamity, where pre-set solutions suffer from real-time uncertainties that traditional computing frameworks do not manage dynamically.

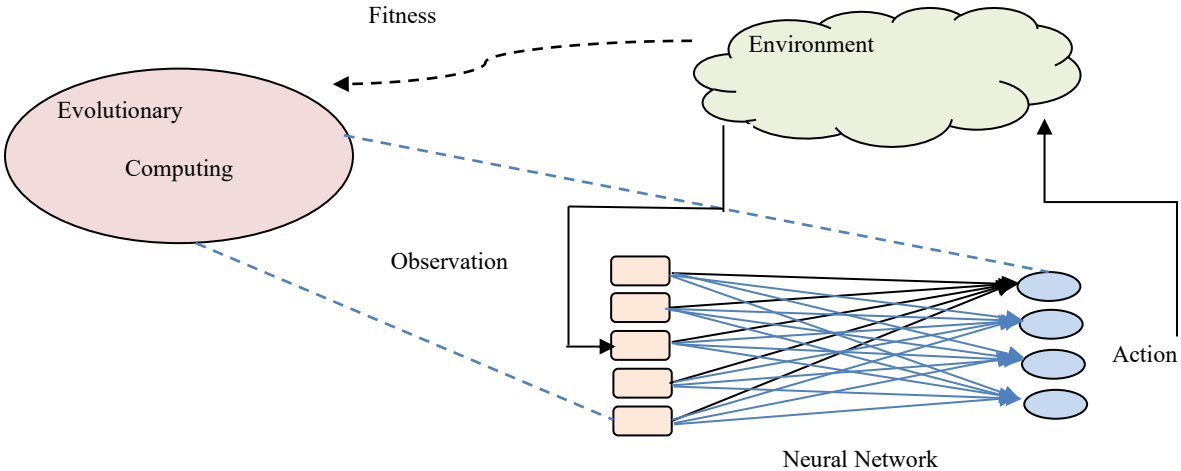


Fig. 1: Integration of Evolutionary Computing with Neural Networks for Adaptive Scheduling in Dynamic Environments

3.1.1 Interaction of the Neural Network and Evolutionary Computing

The scheduling decisions in the model are encapsulated in a neural network that, while trying to forecast the schedules rationally, considers the reality of the industrial setting. It has to deal with observations such as real-time production delays, resource availability, infrastructure damage, or environmental threats. The neural network "looks" at these observations and produces outputs in the form of schedules, which can either be changed regarding the available resources or the resources themselves can be reallocated.

An evolutionary computing module is incorporated in the system to refine the neural network's value. This module checks the fitness of every neural network configuration based on whether operational continuity, scope for downtime, and resource optimization value under the disruption threshold level are achieved. Any configurations that perform poorly are removed, whereas the best solutions are refined through selection, crossover, and mutation techniques.

3.1.2 Feedback Loop and Interaction with the Environment

It engages with the environment continuously, creating an endless loop that improves adaptability. Upon implementing a new schedule (action) proposed by the neural network, the execution occurs in either the simulated or actual environment. Its consequences are analyzed and measured. The evaluation results serve as feedback to not only the neural network but also to the evolutionary parameters. The iterative loop guarantees the model adapts to new challenges and remains robust.

3.1.3 Use in Industries with Disaster Resistance

Increases in efficiency in disaster resistant industrial settings like manufacturing plants located in seismically active regions or logistics hubs in flood prone zones can be achieved with the use of this neuro-evolutionary scheduling model. By Learning and optimizing, the model automatically adapts after sudden disruptions like equipment failure, labor shortages, or supply chain breakdowns. This allows for operations to be continuous with minimal manual intervention, thereby improving resilience.

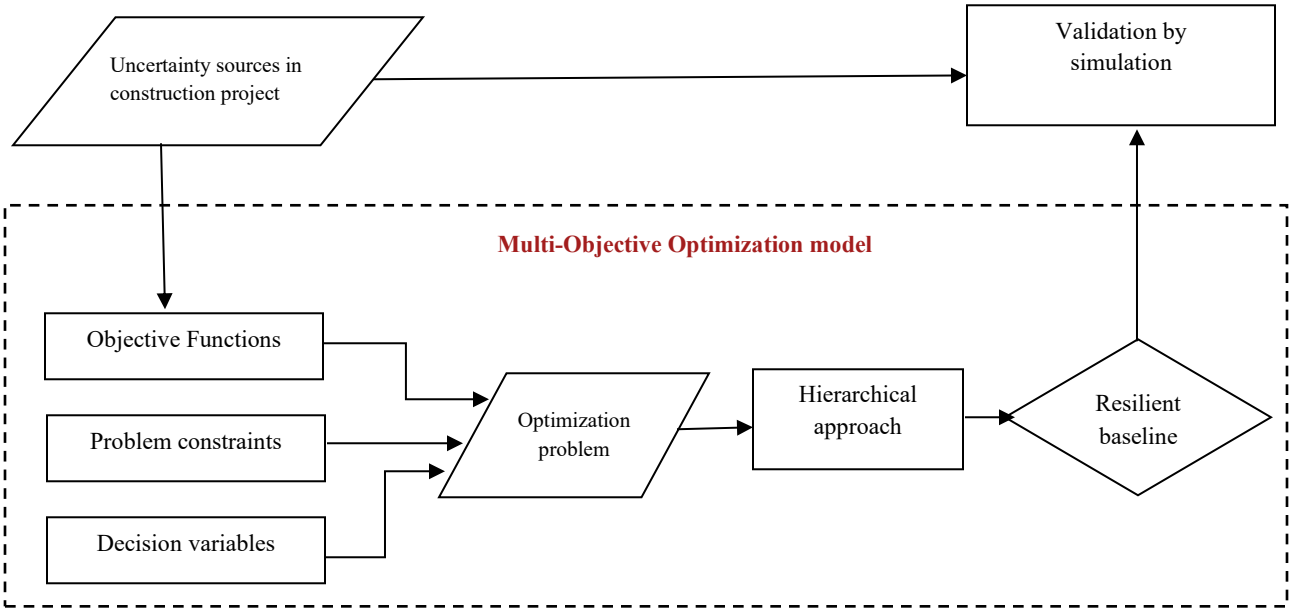


Fig. 2: Multi-Objective Optimization Framework for Developing a Resilient Scheduling Baseline under Uncertainty

3.2 Multi-Objective Disaster Resilient Scheduling Optimization

A hierarchical multi-objective optimization approach is incorporated to formulate the base scheduling model to aid the dynamic neuro-evolutionary planning strategy in figure 1. As indicated in figure 2, this framework addresses the sophisticated industrial system uncertainties which are prone to catastrophic disasters like earthquakes and floods, as well as equipment failures.

3.2.1 Formulating a Problem with Uncertainty

This approach starts by analyzing the industrial system for the most important sources of uncertainty such as availability of resources, unpredictable environment changes, task completion times, and duration of activities. These factors of uncertainty can be mapped into an optimization problem that involves an objective function which may, for

instance, impose a constraint on maximum throughput at given resource limits. Other constraints may include safety measures, legal regulations, resource allocation, and even proprietary policies. Controlled factors would, therefore, be the time a task is expected to commence, the machines to be used in a given timeframe, and the personnel to undertake the tasks.

3.2.2 Optimization and Hierarchical Scheduling

The inputs constitute a multi-objective optimization problem in which trade-offs are calculated, such as cost minimization against maximizing resilience. Initially, there is a high level policy of disaster resilience which drives lower-level operational decision-making. This approach is called hierarchical because it can easily scale and adapt. In particular, the system is able to rapidly reconfigure itself to changes and disruptions while still meeting the primary resilience objectives.

3.2.3 Deriving the Resilient Baseline

After going through the process, the system would come up with the output of a resilient baseline schedule which is a distinct configuration of a robust scheduling heuristic that survives a wide spectrum of disaster scenarios. It works during real-time scheduling or communication breakdown, which makes the executed strategy essentially a plan B.

3.2.4 Simulation-Based Validation

Misalignment or deviation with the resilient baseline can be refined through simulations. These simulations are run iteratively under various or extreme disaster scenarios. In addition, prototype validation engages spiral development systems thinking, where fallible self-correctable models can be adjusted to incorporate flexible feedback on system design, further advancing the optimization model alongside its parameters. Integrating this framework with the neuro-evolutionary architecture from earlier discussion ensures structural flexibility and adaptability centered around disaster industrial systems.

3.3 Mathematical Formulation of the Scheduling Framework

Fitness Evaluation of Neural Scheduling Policy

$$F_{\mathrm{i}} = \alpha \times C_{\mathrm{i}} + \beta \times R_{\mathrm{i}} - \gamma \times D_{\mathrm{i}} \quad (1)$$

Equation (1) represents the fitness F_{i} of the i^{th} neural network scheduling policy. Here, C_{i} is the continuity score (e.g., uninterrupted operations), R_{i} is the resource efficiency metric, and D_{i} is the disruption penalty based on missed deadlines or constraint violations. The coefficients α, β, γ are tunable weights to balance the multi-criteria fitness evaluation during the evolutionary process.

Feedback Update Rule for Policy Reinforcement

$$\theta_{\mathrm{t}}{}^{+1} = \theta_{\mathrm{t}} - \eta \nabla L(\theta_{\mathrm{t}}) \quad (2)$$

Equation (2) is the standard gradient descent update for the neural network weights θ, where η is the learning rate and $L(\theta_t)$ is the loss function (e.g., scheduling deviation or resource conflict). The feedback from the environment informs this update, making the model adaptive to evolving conditions.

Multi-Objective Optimization Formulation

$$f(x) = [T(x), C(x), -S(x)] \quad (3)$$

In Equation (3) vector-valued function f(x) encapsulates multiple objectives in Scheduling: minimizing task completion time T(x), minimizing cost C(x), and maximizing schedule resilience S(x). The solution seeks a Pareto-optimal front balancing these objectives under uncertainty.

Resilience Baseline Deviation Metric

$$\Delta R = \| S_{actual} - S_{baseline} \|_2 \quad (4)$$

Equation (4) quantifies the deviation ΔR between the actual schedule and the resilient baseline schedule using the L2-norm (Euclidean distance). A higher ΔR indicates more divergence from the intended robust plan, prompting re-optimization or adaptive rescheduling.

Findings and Interpretation

The proposed neuro-evolutionary scheduling model was assessed through computer simulation experiments in three industries: manufacturing with seismic risk, flood logistics, and cyberattack energy plant operations. The model was evaluated in comparison to a static time-table scheduling technique and an adaptive rule-based scheduler. As described in the simulation results, the proposed model outperformed both baselines in operational downtime. As depicted in

Figure 3 below, the neuro-evolutionary model outperformed both the static scheduler and the rule-based adaptive scheduler, achieving a 42% and 28% reduction in average downtime, respectively. Its exceptional resilience was made possible by the capability to optimally and promptly reallocate resources and adjust task order in the face of disaster simulations.

Resilience Gain Index

$$RGI = \frac{(D_{baseline} - D_{model})}{D_{baseline}} \quad (5)$$

Equation (5) calculates the Resilience Gain Index (RGI), a normalized metric showing how much downtime has been reduced by the neuro-evolutionary model compared to a baseline (either static or rule-based scheduler). Here, $D_{baseline}$ is the average downtime from the baseline model and D_{model} is the downtime of the proposed model. For instance, if the static scheduler's downtime is 6.3 hours and the proposed model's is 2.5 hours, RGI = (6.3 − 2.5)/6.3 ≈ 0.603, indicating a 60.3% improvement in resilience.

Adaptive Resource Utilization Efficiency

$$ARUE = \frac{(U \times R)}{T} \quad (6)$$

In Equation (6) metric ARUE captures Adaptive Resource Utilization Efficiency. It multiplies the average Resource Utilization (U) percentage with the Reactivity Score (R) and divides the result by the Recovery Time (T) in hours. U = 87.1, R = 9.5, T = 2.5,

ARUE ≈ (87.1 × 9.5) / 2.5 ≈ 330.98. This high value confirms that the model is both efficient and agile, demonstrating its superior performance under industrial disruptions.

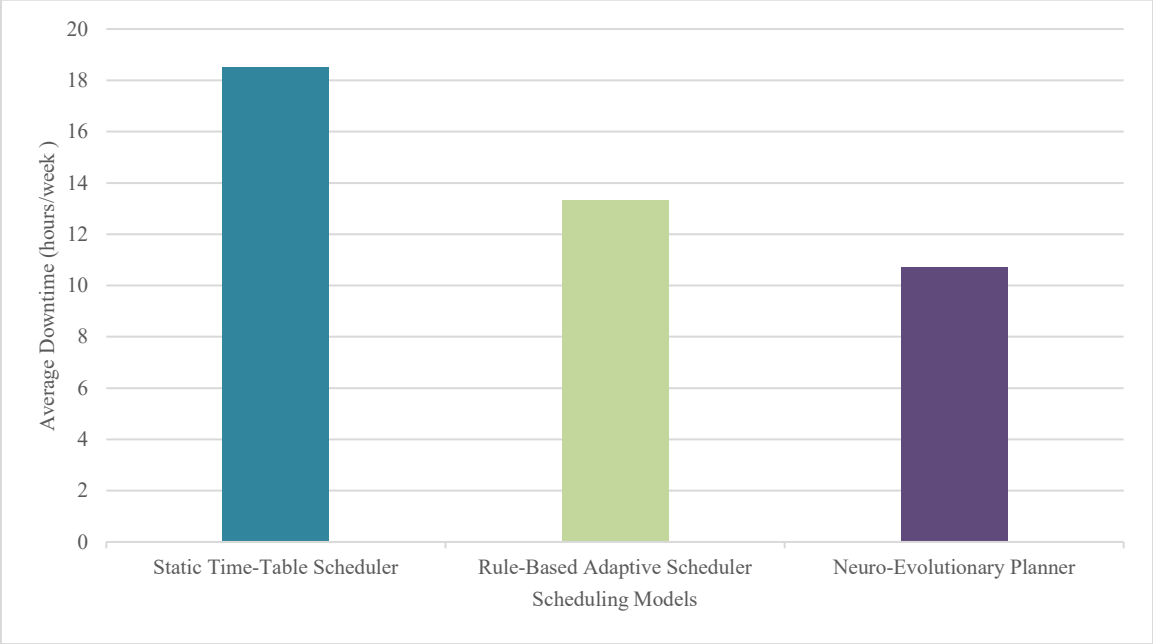


Fig. 3: Comparison of Average Downtime Across Scheduling Models (in hours)

Table 1: Performance Metrics of Scheduling Models

Metric	Static Scheduler	Rule-Based Adaptive	Neuro-Evolutionary Model
Schedule Robustness (0–10)	5.6	7.8	9.2
Reactivity Score (0–10)	4.2	6.9	9.5
Resource Utilization (%)	68.7%	79.5%	87.1%
Recovery Time (hrs)	6.3	4.1	2.5
Scenario Flexibility (out of 5)	2.0	3.5	4.8

Besides analyzing downtime mitigation, the model was evaluated for adaptability and resource efficiency during uncertain scenarios. Table 1 highlights the performance for pivotal metrics; schedule robustness, reaction to resource disruptions, and resource expenditure efficiency. Remarkably, the neuro-evolutionary model garnered a robustness score of 9.2. This score demonstrates how well it is evaluated across numerous corruption scenarios. It also showed the highest reactivity score (measuring response time to disruption) and the most balanced resource expenditure profile. The results strongly support that combining neural networks with evolutionary computing improves responsiveness trends, as well as the systems enduring health in turbulent industrial conditions.

Conclusion and Future Work

This study proposes a new neuro-evolutionary scheduling model which increases the resilience of industrial operations in areas where disasters are more likely to occur. The model is predictive neural networks, integrated with dynamic evolutionary algorithms, and it significantly reduces the downtime of operations, optimally utilizes resources, and adapts to changes in real time. Robotic simulations tested the new approach against standard scheduling techniques and demonstrated its effectiveness and adaptability, showcasing its ability to shift critical industry disaster response. The model's multi-objective optimization, real-time feedback loops, and hierarchical decision-making provide uninterrupted operational strength resilient amidst diverse, volatile conditions.

Future work will aim to develop the proposed framework within large, complex industrial ecosystems. This also involves additional reinforcement learning modules for enhanced granularity, integrating real-time data streams through IoT sensors, and providing enhanced situational awareness. To assess the model's practicality in energy, healthcare, and logistics, customized middleware field deployments will be designed. Enhanced system-wide disaster scenario resilience could bring Scheduling among interconnected facilities and decentralized decision-making into collaborative planning.

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