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GENETIC ALGORITHM-BASED OPTIMIZATION OF INTER-MACHINE DELAYS IN AUTOMATIVE MANUFACTURING

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ABSTRACT

Considering the many situations in which the industrial sector is involved, it is known that industrial innovations should be emphasized especially for the obstacles in front of product development. In every situation where production is involved, undesirable situations may occur due to human-induced errors and errors in the operation of machines and automation systems. There are many products that are lacking in terms of both time wastage and quality in the product to be produced. Various artificial intelligence programs have been used to prevent this situation. In this study, a permutation order was created between the machines by including the automotive sector, which has delays in actual production and takes into account the inter-machine times. In this study, the automotive sector, which has delays in actual production, is included in the process. In addition, permutation ordering between the machines is provided based on the inter-machine times. Used R program makes the comparison of selected models has used. In the program, some machines in the genetic algorithm structure are kept constant during the permutation order. This study is an example of what kind of way should be followed for the sequence to be applied in cases where a production process is dominant in the industrial sector and what conditions should be created for effective optimization. Furthermore, the importance of time-based strategic planning in production sectors is stressed.

Key Words: Genetic Algorithm, Tardiness, Manufacturing

INTRODUCTION

During the existence of the enterprises, it is likely that different processes and stages will operate for the management process to function efficiently. Examining these stages from a broad perspective at the point of diversification of business activities is a prominent issue in this case. One of these subjects and activities is known as production. There are issues of efficiency, effectiveness, capacity, and flexibility, which have an important place in the production process. It is foreseeable to increase the speed capacity in production by creating value and ensuring coordination between units. The fact that full-time production has not to be carried to the point where it should be among the production activities in the enterprises is possible due to insufficient work in this field or the lack of coordination of the production process. However, by showing the necessary sensitivity, this problem will eliminate.

Efficiency, which is the ratio of the value output to the amount of input, has expressed as the combination of effectiveness and efficiency with the explanation of the Asian Productivity Organization. Efficiency is an output of the potential situation of enterprises in their resources. Effectiveness is a method used when evaluating resources in companies. High efficiency and effectiveness will contribute positively to the situation in achieving their goals while realizing the targets that the businesses have previously determined (Parastoo Roghaniana, Amran Raslia, & Gheysaria, 2012). It is not only productivity, effectiveness, and efficiency but also quality, cost, and conditions that lead to competition. Along with a holistic perspective, control activities should be together in the process. In terms of quality control in enterprises, many issues can be used to evaluate the conditions that cause delays in production areas. It is possible to distinguish two types of delays in the production area. These are the delays that will occur due to errors that may occur in the machines involved in the production and human involvement.

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In this study, while making decisions for the delays that occur through machines, along with the explanation of the model proposed for the analysis process to be applied, while evaluating these delays as time, algorithm, and so on. However, in the production phase, where there is a time constraint for production delays, the appropriate model will be selected in the analyzes made using genetic algorithms, and the analysis steps will be implemented.

LITERATURE REVIEW

After revealing the errors in production due to the human factor, what kind of measures will be taken for the determination and analysis of priority situations is an important issue. The products that are qualified for the products formed after the production process indicate the quality issue. In addition, the steps to be taken for the process in the prevention of product defects are critical (Özdemir, 2004). There are many methods used in actual production, and process management has been expressed as fully effective by creating infrastructures for their development and trying to add an appropriate decision structure. Different algorithm structures are possible for application trials. Much research has been done in the literature on the tardiness due to errors in production. Bierwirth and Kuhpfahl, focusing on scheduling problems in production, explained that the algorithm structure in production and the weighted total delay, which is referred to as TWT (Total Weighted Tardiness), improves the service-based aspects to be made in the field of logistics and is also effective in planning. (Bierwirth & Kuhpfahl, 2017). Many algorithms are used for delays in machines in production. These provide many advantages as well as reducing the processing time. Used methods, mathematical programming, branch and bound, metaheuristic, and genetic algorithms for this sortings. Chiang and Fu explained that the processing time should minimize to minimize tardiness. (T. C. Chiang & Fu, 2007).

There are many studies on the job shop (order type production) system in work planning to prevent production delays. Kutanoglu and Sabuncuoglu focused on weighted delay criteria in dynamic job shop scheduling and researched W (CR+ SPT) (weighted CR and SPT), COVERT (cost over time), and BD (bottleneck dynamics) methods. They stated that these methods play a major role in minimizing production delays (Kutanoglu E. & Sabuncuoglu I., 1999). Veronique et al. reported that the combined use of the CR and SPT methods resulted in less time to complete Maximum tardiness in terms of performance compared to SPT and CR (Veronique S., Mario V., & G., 2012). SPT (Shortest Process Time), which is among the job shop scheduling methods minimizes the average delay While LPT (Longest Process Time) operation process time decreases the processing time for semi-online scheduling, they have stated that it has a significant difference and superiority compared to algorithms such as SOSDP (Sum over Subsets Dynamic Programming) (Cheng, 2012). Veronique et al. stated that the SPT method gave better results than the LPT method in terms of makespan minimization and maximum tardiness (Veronique S. et al., 2012).

Asep et al. researched minimizing makespan by using LPT and SPT methods together. These methods, which are among the parallel machine scheduling methods, are based on an algorithm. When compared to LPT and SPT methods, they explained that the FCFS(First Come First Served) method did not produce a dominant result (Asep Anwar, Didit Damur Rochman, & Ferdian, 2021). Horng et al. have made some suggestions by including and adjusting the random process time in the ESOO(Evolutionary strategy, ordinal optimization) method in 8 jobs and 8 machines (Horng, Lin, & Yang, 2012). Bekker et al. used the LCFS method for the cases where the waiting times are included in the heavy traffic sections to obtain an average value in the waiting time. İncluded this method is in the multi-queue single-server system. Gamma distribution did not cause a change in the scheduling result expression, which is one of the distributions used in the model (Bekker, Dorsman, van der Mei, Vis, & M., 2013). El-Bouri et al. used time values in a dynamic flowshop. Their work is based on the reduction of the mean flow time. In addition, they explained that the Least Work Remaining method does not produce a good result in terms of performance compared to the SPT (Shortest Process Time) method, which reduces the maximum waiting time and average delay (El-Bouri, 2008). Veronique et al. stated that the LWKR method is more inefficient than the SPT method for Maximum tardiness and that the use of only the SPT method produces better results than the combined use of the LWKR and SPT method (Veronique S. et al., 2012).

Takakuwa has done some research on flexible manufacturing systems. Research using the MWKR method has shown that the maximum flow time result gives more effective results than other methods (Takakuwa, 1997). Veronique et al. emphasized that the MWKR method is more suitable for Makespan minimization than other methods and found the lowest time. (Veronique S. et al., 2012). Gordon et al.

have proposed to improve the delivery date for the TWK method, along with the dispatching rule and simulation results, with the definition of multiple process times. In addition, Gordon et al. explained that it has a field of use in the dynamic TWK method in deterministic scheduling problems (Gordon, Proth, & Chu, 2002). Dyachuk and Deters explained that the FOPNR (Fewest Operation Remaining) method, which is used when the job size is not defined and the minimum number of activities is reached, is worse in terms of performance than the FIFO (First in First Out) method in terms of workflow (Dyachuk & Deters, 2007). Roychowdhury et al. stated that although the EDD (Earliest Due Date) method, which stands out in terms of delay, is useful in ordinary use, the low inventory level does not have an effective performance in the method (Roychowdhury, Allen, & Allen, 2017). Chen and Matis stated that Slack (Slack Time), which is important in terms of delays, is effective in reducing the waiting time in queuing problems, but if this time value is negative, it will increase the waiting time for the planned job and cause disruption of the work. However, they determined that this value mostly took a positive value (Chen & Matis, 2013). The WINQ (Work in Next Queue) method has the feature of having the priority of the situation where the workload is the lowest in job scheduling. Rajendran and Ziegler used the 2PT+WINQ+NPT Dispatching Rule in this method and stated that Ho is superior to the heuristic in terms of performance. They also explained that the SPT and PT+WINQ rules caused an increase in the operation percentage, but they also explained that they were effective in reducing the makespan and total flow time (Rajendran & Ziegler, 2001). Veronique et al. reported that while the 2PT+WINQ+NPT method outperformed FIFO, LIFO, LPT, LWKR, and Slack in terms of makespan, it did not outperform SPT (Veronique S. et al., 2012).

Zegordı et al. added the Priority index used in the expression of priority degrees to the SA (simulated annealing) algorithm and explained the measurement values in the scheduling. Then, they expressed it as an early or delayed flow shop for the sorting process in the Backward-Forward Exchange Priority table (Zegordi, Itoh, & Enkawa, 1995). TÜRKER et al., focusing on EDD, SLACK PR, and SEWT in production, explained that they affect the number of delayed orders and delivery dates, although they use the Weka program in data mining. While they stated that the method they used produced good values in terms of results, they informed that the assignment types affect the delay (Türker et al., 2020). Demirci and Gökce designed an interface to speed up the production process and shorten the production time and created a design that works as a single module. They have shown that this design also provides an advantage in terms of cost. Since different stages are used during the process, the possibility of making mistakes is also eliminated (Demirci & Gökçe, 2010). Koca stated that during the design phase of manufacturing, performing the optimization process in the power copy feature of the computer program named Catia V5 reduces the planned time. This period is reduced from 2 weeks to 3 days. While a 24-hour period prevails in laser cutting technology, where processes such as welding, cutting, and drilling are used intensively in engineering, production errors are minimized in the automation system, thus saving time (Koca, 2006). Aydoğdu explained that programmable flexible automation systems increase production speed in minimizing human errors. In addition, delays in production has brought to a minimum (Aydoğdu, 2006). Loshin explained that data management should be at the forefront of preventing production delays. For this reason, errors will be reduced as much as possible (Loshin, 2009).

As a result, based on literature research, any contribution to be made to improve industrial efficiency at the point of improvement of production delays will also contribute to the production process. This contribution will provide an advantage both in accelerating the production process and in reducing the cost. Moreover, the contribution provided is extremely useful for business planning in production.

THEORETICAL BACKGROUND

Production management is a form of management that includes some expressions such as machinery, materials, and labor force among the departments that produce in enterprises. It also points to the minimization of the products formed as a result of the interaction of these situations in terms of finances. Production management approaches; flexible production, total quality management, lean production, process-oriented management, supply chain management, just-in-time production, six sigma, and computer-integrated production.

Systems such as flexible production systems, group technology, NC, computer-aided process planning, just-in-time production, and MRPII production resource planning, which are production management approaches, are also used with CAD/CAM systems (Storey, 1994). When it comes to meeting the needs of customers in total quality management, the service to be received primarily focuses on eliminating areas that cause waste at the target point. Overproduction, waste of time, and inventory issues are considered as outputs to determine the causes of waste. There is a systematic approach to this production management (García-Alcaraz, Oropesa-Vento, Maldonado-Macías, & SpringerLink (Online service), 2017).

Lean manufacturing; is a production management approach created and developed based on just-in-time production. Lean manufacturing; It is effective in reducing costs with the name of lean operation by giving more weight to issues such as cost efficiency, low inventory, and production process (Wu, 2019). The main key point in this operation is to identify and try to reduce the waste of time or the reasons that cause it. There is a map called Value Stream Map (VSM) in lean manufacturing. This map has some fields such as lead time, number of operators, value added time, cycle time. It also refers to the schema in a certain time period (Ledbetter, 2018).

Required minimum capital is necessary for process-oriented production management. Taken decisions aim at increasing the diversity in products (Omar, 2011). It is the issue of providing certain integration processes in supply chain management, which is in the process until the products produced are delivered to the customer. However, there are some disadvantages during implementation. These are the fact that the human resources team is not at the desired level on a qualitative basis, the effect of competitive conditions in the market, the dominance of uncertainty, and the involuntariness of the supplier against innovation (Sandeep, Attri, & Panwar, 2016). (Sandeep, Attri, & Panwar, 2016). Risk management and early detection of risks are very important for the sustainability of supply chain management (Subic, Wellnitz, Leary, & Koopmans, 2012).

Just in time (JIT); is a type of production in which the management approach is dominant in a synchronized way, in which production is determined by how much production amount and how long it must be configured (Ledbetter, 2018) (Ledbetter, 2018).

4 principles dominate just-in-time production (Gobetto, 2014):

-Continuous one-piece flow: Adjustments should be made so that there is only one flow direction in the interprocess flow.

-Takt time: The time requested by the customer should be determined.

-Pull (favor): It is the realization of production by considering the product types belonging to the product requested by the customers, starting from the assembly.

-0 error: conditions must be created in the preliminary stage for zero error to construct. In addition, it is known that an error that will occur in the production system if people are involved in the production system will disrupt the flow and cause a defective product. Considering this situation, errors that may occur in transactions after activities should be prevented by the quality control team.

Six sigma aims to improve the system with management strategies as well as the use of statistical tools to the point of creating perfect transactions in operations. For this design, measurement, analysis, improvement, and control processes are available. In this development, it is necessary to determine the problem that will occur at the lowest level and to establish a holistic production management approach after its solution (Tjahjono et al., 2010). In computer-integrated production, CAD and CAM technologies have the advantage of being used in 2 different situations. In a business, CAM systems are used for situations where users tend to control or are controlled by a computer, and CAD systems are used to assist design in design and manufacturing (Storey, 1994). The make-to-order (MTO) order system is used to solve the reasons that cause delays in production within production systems. This production system provides information on the average delay (Altendorfer, 2014). MTS (make-to-stock) production system, unlike MTO, focuses on customer waiting time and demand forecasting, not on delay. Customer satisfaction is a priority (Danica Lečić-Cvetković, Nikola Atanasov, & Babarogic, 2010). It is a fast response system as customer satisfaction and service are at the forefront (Rabbani & Dolatkhah, 2017).

Empirical Studies and Gaps

- Many algorithms are used for delays in machines in production. These provide many advantages as well as reducing the processing time. Used methods include: mathematical programming, branch and bound, metaheuristic, and genetic algorithms.

- **Job Shop Scheduling Methods:** Kutanoglu and Sabuncuoglu focused on weighted delay criteria in dynamic job shop scheduling (Kutanoglu E. & Sabuncuoglu I., 1999). **SPT (Shortest Process Time)** minimizes the average delay (Cheng, 2012). **EDD (Earliest Due Date)** stands out in terms of delay (Roychowdhury et al., 2017). **Slack (Slack Time)** is effective in reducing the waiting time in queuing problems (Chen & Matis, 2013).
- **Genetic Algorithms:** Chiang and Fu explained that the processing time should minimize to minimize tardiness (T. C. Chiang & Fu, 2007). Bierwirth and Kuhpfahl showed that the algorithm structure improves service-based aspects in logistics (Bierwirth & Kuhpfahl, 2017).
- This study addresses a gap by applying genetic algorithms, including **fixed points** and **multi-objective optimization**, to actual production data in an industrial setting.

Development of Hypotheses / Conceptual Model

- Genetic Algorithms (GA): These algorithms contain the logic of Darwin’s theory of evolution and are stochastic (Mirjalili, 2018; Lambora et al., 2019). They consist of:
- **Gene:** The smallest part in the solution process.
- **Chromosome:** Occurs from the fusion of genes, showing the steps to reach the solution.
- **Population:** The structure formed by combining chromosomes.
- **Selection Operator:** Guides the behavior of iterations within the population (e.g., Roulette Wheel, Tournament Selection).
- **Crossover:** The process where new individuals are formed by the replacement of two individuals on the chromosome (e.g., PMX, Cycle Crossover).
- **Mutation:** Operations carried out to reduce the effect of local solutions (e.g., Swap, Insert, Inversion Mutation).
- **Fitness Function:** The building block that maintains the genetic algorithm structure while reaching the optimal result.
- This study proposes a GA model that includes **fixed machine points** when creating the permutation order to minimize delays.

METHODOLOGY

This research uses three different machine data for 21,28 and 35 machines with the criteria. Machines are used to estimate actual production tardiness. In such a way, both tardiness and fixed points for machines about genetic algorithm optimization are to produce solutions. We used the proposed algorithm by applying it in R programming.

Research Design

The research design is a computerized **simulation/experimental modeling** approach to optimize delays in an industrial process. A Genetic Algorithm (GA) model is applied to create a permutation order that minimizes inter-machine times in the context of automative sector.

Sample and Data Collection

The study uses a data set from the automative sector with actual production delays and considering inter-machine times. The data includes three different n times 7n matrices for 21, 28, and 35 machines.

Table 1 summarizes inter machines' times as seconds.

Table 1: Inter-machine times

	Mak_1	Mak_2	Mak_3	Mak_4	...	...	...	Mak_34	Mak_35
Mak_1	0	3313	2963	3175	...	...	...	818	944
Mak_2	3313	0	1318	1326	...	...	...	643	556
Mak_3	2963	1318	0	204	...	...	...	549	395
Mak_4	3175	1326	204	0	...	...	...	991	468
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
Mak_34	818	643	549	991	...	...	...	0	858
Mak_35	944	556	395	468	...	...	...	858	0

Resource: https://github.com/Burcu2708/Production/blob/main/Machine%20Table.docx

Measures / Variables

The study uses three multi-objective functions from Liao et al. (2007) for safety vehicles in the automotive sector. The objective functions are vehicle mass, full frontal crash, and 40% offset-frontal crash:

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$\mathrm{Mass}($, A_{in}(f2), Intrusion(f3)

(x), (x),…, (x): are the m objective functions

x: design space.

$(x_1, x_2$ ^{T}: are n design variables.

t_1, t_2, t_3, t_4, t_5: design variables of the vehicle model

The design variables are x= t_1, t_2, t_3, t_4, t_5, defined in the range $1\,mm \le x \le 3$

x= $(t_1, t_2, t_3, t_4, t$

Objective functions are three by using optimization problems. These are the mass of the vehicle, full frontal crash, and 40% offset-frontal crash, respectively. Described model by using stepwise regression analysis, mentioned by Liao et al. as follows (Liao, Li, Yang, Zhang, & Li, 2007):

Regression Models Used:

Mass = 1640.2823 + 2.3573285 + 2.3220035 +4.5688768 + 7.7213633 + 4.4559504

A_{in} = 6.5856 + 1.15 -1.0427 + 0.9738 +0.8364 - 0.3695 + 0.0861 + 0.3628 - 0.1106 - 0.3437 + 0.1764

Intrusion = -0.0551 + 0.0181 + 0.1024 +0.0421 – 0.0073 + 0.024 – 0.0118 -0.0204 – 0.008 – 0.0241 +0.0109

$\min F(x) = [\mathrm{M}$, A_{in}, Intrusion)]

$1\,mm \le x \le 3$

To perform analysis for the proposed model, we conducted the fixed points. These are 2, 3, and 4, respectively.

Number of machines: 7n

Fixed Point: n-1

Mass(, A_{in}( ), Intrusion( )

Fixed Points: Fixed machines are determined according to number of machines n corresponding to 7n (e.g., 21 machines, 3 for machines, 4 for 35 machines).

Data Analysis

Data analysis was performed using the R programming language.

Steps:

1. Write down the time values of the machines.
2. Consider these times as distance, create a distance matrix, and find the time interval between the machines.
3. Determine the population size (100), crossover rate (0.8), and mutation rate (0.2).
4. Ensure certain machines remain stable during the machine permutation process (e.g., "Mak_4" and "Mak_5" for 21 Machines).
5. Identify a suitable starting population.
6. Create mutations by including fixed points.
7. Determine the appropriate model for crossover (gaperm_pmxCrossover, gaperm_cxCrossover, gareal_blxCrossover).
8. Determine the fitness function.
9. Perform the optimization process.
10. Obtain the result of the permutation order.
11. Compare the models by determining how much delay each model causes.

RESULTS

The findings present the results of genetic algorithm variations applied to three different machine numbers (21, 28, 35).

Descriptive Statistics

Descriptive statistics summarize the GA parameters and fixed points used for each machine set.

Machine Number	Population Size	Crossover Rate	Mutation Rate	Elitism	Fixed Points
21	100	0.8	0.2	5	"Mak_4"=1, "Mak_5"=6
28	100	0.8	0.2	5	"Mak_4"=1, "Mak_5"=6, "Mak_6"=11
35	100	0.8	0.2	5	"Mak_4"=1, "Mak_5"=6, "Mak_6"=11, "Mak_7"=16

Hypothesis Testing (Model Comparison)

The tables below show the solution distances and fitness function values obtained using different objective functions and crossover methods. A lower fitness function value represents better optimization.

Table 2: 21 Machine Results

Name	Functions	Crossover	Fitness Function value
A1	f1, f2, f3	gaperm_pmxCrossover	2022.625
A2	f1, f2, f3	gaperm_cxCrossover	2022.625
A5	f1, f2, f3	gareal_blxCrossover	1975.541
A1.1	f1	gaperm_pmxCrossover	2022.625
A2.1	f1	gaperm_cxCrossover	2022.625
A5.1	f1	gareal_blxCrossover	1990.624

Table 3: 28 Machine Results

Name	Functions	Crossover	Fitness Function value
B1	f1, f2, f3	gaperm_pmxCrossover	2156.102
B2	f1, f2, f3	gaperm_cxCrossover	2156.102
B5	f1, f2, f3	gareal_blxCrossover	2098.955
B1.1	f1	gaperm_pmxCrossover	2156.102
B2.1	f1	gaperm_cxCrossover	2156.102
B5.1	f1	gareal_blxCrossover	2098.955

Table 4: 35 Machine Results

Name	Functions	Crossover	Fitness Function value
C1	f1, f2, f3	gaperm_pmxCrossover	2289.58
C2	f1, f2, f3	gaperm_cxCrossover	2289.58
C5	f1, f2, f3	gareal_blxCrossover	2222.176
C1.1	f1	gaperm_pmxCrossover	2289.58
C2.1	f1	gaperm_cxCrossover	2289.58
C5.1	f1	gareal_blxCrossover	2193.352

Key Findings:

- In all three machine sets (**A5, B5, C5**), the **gareal_blxCrossover** model yielded better (lower) fitness function values compared to the other models when using three functions.
- The best solution for inter-machine tardiness based on row criteria is the **C5.1** model (2193.352), obtained using **n=35** machines and **a single function (f_1)**.
- When the machine number is odd (21 and 35), the number of functions used does not make a significant difference in the solution.

Additional Analyses

Table 5, 6, and 7: Genetic Algorithm permutation orders show the most suitable machine sequence for each model (A1, A2, A5, B1, B2, B5, C1, C2, C5, etc.). These sequences represent the tardiness-minimizing routes, considering the fixed points.

Table 8: Graphs showing the change of best, mean, and median fitness values by generations (Graphs cannot be represented in text here, please refer to the graphs in your original document. These graphs show that the **gareal_blxCrossover** model (A5, B5, and C5 variations) converges quickly and shows a more stable distribution.

Table 5: Genetic Algorithm Permutation Order for 21 Machines with Table 2 İnformation

Properties	Order
A1	"Mak_4" "Mak_3" "Mak_9" "Mak_1" "Mak_17" "Mak_5" "Mak_11" "Mak_21" "Mak_13" "Mak_16" "Mak_19" "Mak_10" "Mak_18" "Mak_14" "Mak_12" "Mak_6" "Mak_7" "Mak_8" "Mak_20" "Mak_2" "Mak_15
A2	"Mak_4" "Mak_21" "Mak_6" "Mak_15" "Mak_16" "Mak_5" "Mak_14" "Mak_13" "Mak_19" "Mak_2" "Mak_18" "Mak_11" "Mak_7" "Mak_12" "Mak_8" "Mak_17" "Mak_9" "Mak_10" "Mak_20" "Mak_1" "Mak_3
A5	"Mak_4" "Mak_1" "Mak_12" "Mak_8" "Mak_11" "Mak_5" "Mak_15" "Mak_6" "Mak_13" “Mak_2” "Mak_21" "Mak_10" "Mak_9" "Mak_20" "Mak_19" "Mak_16" "Mak_18" "Mak_7" "Mak_17" "Mak_14"
A1.1	"Mak_4" "Mak_11" "Mak_21" "Mak_15" "Mak_12" "Mak_5" "Mak_6" "Mak_8" "Mak_7" "Mak_3" "Mak_18" "Mak_19" "Mak_1" "Mak_14" "Mak_16" "Mak_13" "Mak_20" "Mak_17" "Mak_2" "Mak_10" "Mak_9"
A2.1	"Mak_4" "Mak_1" "Mak_20" "Mak_13" "Mak_18" "Mak_5" "Mak_9" "Mak_16" "Mak_11" "Mak_3" "Mak_6" "Mak_17" "Mak_12" "Mak_2" "Mak_14" "Mak_7" "Mak_8" "Mak_15" "Mak_19" "Mak_10" "Mak_21”
A5.1	"Mak_4" "Mak_7" "Mak_11" "Mak_20" "Mak_1" "Mak_5" "Mak_9" "Mak_8" "Mak_17" "Mak_19" "Mak_10" "Mak_2" "Mak_14" "Mak_15" "Mak_13" "Mak_16" "Mak_21" "Mak_18" "Mak_6" "Mak_12" "Mak_3"
A1.2	"Mak_4" "Mak_1" "Mak_10" "Mak_12" "Mak_8" "Mak_5" "Mak_13" "Mak_17" "Mak_15" "Mak_6" "Mak_16" "Mak_14" "Mak_3" "Mak_11""Mak_7" "Mak_2" "Mak_20" "Mak_18" "Mak_9" "Mak_19" "Mak_21"
A2.2	"Mak_4" "Mak_21" "Mak_6" "Mak_15" "Mak_16" "Mak_5" "Mak_14" "Mak_13" "Mak_19" "Mak_2" "Mak_18" "Mak_11" "Mak_7" "Mak_12" "Mak_8" "Mak_17" "Mak_9" "Mak_10" "Mak_20" "Mak_1" "Mak_3"
A5.2	"Mak_4" "Mak_1" "Mak_12" "Mak_8" "Mak_11" "Mak_5" "Mak_15" "Mak_6" "Mak_13" "Mak_3" "Mak_2" "Mak_21" "Mak_10" "Mak_9" "Mak_20" "Mak_19" "Mak_16" "Mak_18" "Mak_7" "Mak_17" "Mak_14"

Table 6: Genetic Algorithm Permutation Order for 28 Machines with Table 3 İnformation

Properties	Order
B1	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_20" "Mak_8" "Mak_1" "Mak_25" "Mak_6" "Mak_24" "Mak_22" "Mak_7" "Mak_19" "Mak_21" "Mak_9" "Mak_26" "Mak_28" "Mak_13" "Mak_18" "Mak_27" "Mak_10" "Mak_3" "Mak_14" "Mak_15" "Mak_2" "Mak_17"
B2	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_1" "Mak_19" "Mak_15" "Mak_26" "Mak_6" "Mak_24" "Mak_20" "Mak_25" "Mak_21" "Mak_13" "Mak_28" "Mak_18" "Mak_27" "Mak_10" "Mak_17" "Mak_3" "Mak_2" "Mak_8" "Mak_7" "Mak_14" "Mak_22" "Mak_9"
B5	"Mak_4" "Mak_7" "Mak_12" "Mak_11" "Mak_27" "Mak_5" "Mak_23" "Mak_13" "Mak_28" "Mak_2" "Mak_6" "Mak_14" "Mak_25" "Mak_15" "Mak_18" "Mak_1" "Mak_19" "Mak_10" "Mak_20" "Mak_24" "Mak_3" "Mak_22" "Mak_8" "Mak_21" "Mak_17" "Mak_9" "Mak_26" "Mak_16"
B1.1	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_20" "Mak_8" "Mak_1" "Mak_25" "Mak_6" "Mak_24" "Mak_22" "Mak_7" "Mak_19" "Mak_21""Mak_9" "Mak_26" "Mak_28" "Mak_13" "Mak_18" Mak_27" "Mak_10" "Mak_3" "Mak_14" "Mak_15" "Mak_2" "Mak_17"
B2.1	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_1" "Mak_19" "Mak_15" "Mak_26" "Mak_6" "Mak_24" Mak_20" "Mak_25" "Mak_21" "Mak_13" "Mak_28" "Mak_18" Mak_27" "Mak_10" "Mak_17" "Mak_3" "Mak_2" "Mak_8" “Mak_7" "Mak_14" "Mak_22" "Mak_9"
B5.1	"Mak_4" "Mak_7" "Mak_12" "Mak_11" "Mak_27" "Mak_5" "Mak_23" "Mak_13" "Mak_28" "Mak_2" "Mak_6" "Mak_14" "Mak_25""Mak_15" "Mak_18" "Mak_1" "Mak_19" "Mak_10" "Mak_20" "Mak_24" "Mak_3" "Mak_22" "Mak_8" "Mak_21" "Mak_17" "Mak_9" "Mak_26" "Mak_16"
B1.2	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_20" "Mak_8" "Mak_1" "Mak_25" "Mak_6" "Mak_24" "Mak_22" "Mak_7" "Mak_19" "Mak_21" "Mak_9" "Mak_26" "Mak_28" "Mak_13" "Mak_18" "Mak_27" "Mak_10" "Mak_3" "Mak_14" "Mak_15" "Mak_2" "Mak_17"
B2.2	"Mak_4" "Mak_12" "Mak_23" "Mak_11" "Mak_16" "Mak_5" "Mak_1" "Mak_19" "Mak_15" "Mak_26" "Mak_6" "Mak_24" "Mak_20" "Mak_25" "Mak_21" "Mak_13" "Mak_28" "Mak_18" "Mak_27" "Mak_10" "Mak_17" "Mak_3" "Mak_2" "Mak_8" "Mak_7" "Mak_14" "Mak_22" "Mak_9"
B5.2	"Mak_4" "Mak_7" "Mak_12" "Mak_11" "Mak_27" "Mak_5" "Mak_23""Mak_13" "Mak_28" "Mak_2" "Mak_6" "Mak_14" "Mak_25" "Mak_15" "Mak_18" "Mak_1" "Mak_19" "Mak_10" "Mak_20" "Mak_24" "Mak_3" "Mak_22" "Mak_8" "Mak_21" "Mak_17" "Mak_9" "Mak_26" "Mak_16"

Table 7: Genetic Algorithm Permutation Order for 35 Machines with Table 4 İnformation

Properties	Order
C1	"Mak_4" "Mak_25" "Mak_19" "Mak_30" "Mak_9" "Mak_5" "Mak_17" "Mak_2" "Mak_15" "Mak_18" "Mak_6" "Mak_21" "Mak_8" "Mak_13" "Mak_12" "Mak_7" "Mak_35" "Mak_32" "Mak_14" "Mak_26" "Mak_10" "Mak_33""Mak_28" "Mak_23" "Mak_29" "Mak_22" "Mak_20" "Mak_24" "Mak_16" "Mak_27" "Mak_31" "Mak_34" "Mak_3" "Mak_1" "Mak_11"
C2	"Mak_4" "Mak_25" "Mak_19" "Mak_30" "Mak_9" "Mak_5" "Mak_17" "Mak_22" "Mak_16" "Mak_15" "Mak_6" "Mak_10" "Mak_33""Mak_32" "Mak_26" "Mak_7" "Mak_35" "Mak_2" "Mak_14" "Mak_21" "Mak_8" "Mak_28" "Mak_18" "Mak_20" "Mak_13" "Mak_27" "Mak_11" "Mak_34" "Mak_23" "Mak_24" "Mak_29" "Mak_1" "Mak_31" "Mak_12" "Mak_3"
C5	"Mak_4" "Mak_15" "Mak_14" "Mak_3" "Mak_35" "Mak_5" "Mak_20" "Mak_25" "Mak_18" "Mak_33" "Mak_6" "Mak_10" "Mak_11" "Mak_34" "Mak_29" "Mak_7" "Mak_27" "Mak_30" "Mak_2" "Mak_32" "Mak_8" "Mak_19" "Mak_12" "Mak_13" "Mak_9" "Mak_28" "Mak_1" "Mak_17" "Mak_24" "Mak_22" "Mak_31" "Mak_26" "Mak_16" "Mak_21" "Mak_23"
C1.1	"Mak_4" "Mak_10" "Mak_35" "Mak_27" "Mak_16" "Mak_5" "Mak_30" "Mak_2" Mak_25" "Mak_26" "Mak_6" "Mak_33" "Mak_13" "Mak_34" "Mak_1" "Mak_7" "Mak_20" "Mak_23" "Mak_32" "Mak_17" "Mak_24" "Mak_3" "Mak_9" "Mak_11" "Mak_14" "Mak_31" "Mak_28" "Mak_19" "Mak_29" "Mak_8" "Mak_15" "Mak_22" "Mak_21" "Mak_12" "Mak_18"
C2.1	"Mak_4" "Mak_10" "Mak_35" "Mak_27" "Mak_16" "Mak_5" "Mak_3" "Mak_21" "Mak_28" "Mak_30" "Mak_6" "Mak_22" "Mak_31" "Mak_29" "Mak_9" "Mak_7" "Mak_19" "Mak_15" "Mak_1" "Mak_33" "Mak_8" "Mak_25" "Mak_34" "Mak_17" "Mak_18" "Mak_13" "Mak_32" "Mak_26" "Mak_24" "Mak_11" "Mak_14" "Mak_20" "Mak_2" "Mak_23" "Mak_12"
C5.1	"Mak_4" "Mak_25" "Mak_20" "Mak_10" "Mak_24" "Mak_5" "Mak_14" "Mak_13" "Mak_23" "Mak_21" "Mak_6" "Mak_11" "Mak_26" "Mak_33" "Mak_12" "Mak_7" "Mak_1" "Mak_30" "Mak_28" "Mak_34" "Mak_2" "Mak_17" "Mak_3" "Mak_29" "Mak_35" "Mak_15" "Mak_19" "Mak_18" "Mak_8" "Mak_27" "Mak_31" "Mak_16" "Mak_22" "Mak_32" "Mak_9"
C1.2	"Mak_4" "Mak_25" "Mak_26" "Mak_34" "Mak_10" "Mak_5" "Mak_35" "Mak_21" "Mak_2" "Mak_14" "Mak_6" "Mak_13" "Mak_32" "Mak_18" "Mak_24" "Mak_7" "Mak_17" "Mak_11""Mak_20" "Mak_3" "Mak_12" "Mak_29" "Mak_30" "Mak_19" "Mak_8" "Mak_15" "Mak_16" "Mak_9" "Mak_22" "Mak_28" "Mak_23" "Mak_31" "Mak_27" "Mak_33" "Mak_1"
C2.2	"Mak_4" "Mak_25" "Mak_26" "Mak_34" "Mak_10" "Mak_5" "Mak_24" "Mak_17" "Mak_33" "Mak_12" "Mak_6" "Mak_8" "Mak_28" "Mak_13" "Mak_14" "Mak_7" "Mak_29" "Mak_23" "Mak_30" "Mak_2" "Mak_35""Mak_15"

	"Mak_1" "Mak_21" "Mak_19" "Mak_22" "Mak_18" "Mak_3" "Mak_16" "Mak_9" "Mak_31" "Mak_20" "Mak_27" "Mak_32" "Mak_11"
C5.2	"Mak_4" "Mak_16" "Mak_26" "Mak_34" "Mak_35" "Mak_5" "Mak_29" "Mak_25" "Mak_14" "Mak_13" "Mak_6" "Mak_9" "Mak_3" "Mak_31" "Mak_12" "Mak_7" "Mak_27" "Mak_21" "Mak_10" "Mak_23" "Mak_8" "Mak_32" "Mak_17" "Mak_2" "Mak_18" "Mak_22" "Mak_30" "Mak_20" "Mak_11" "Mak_19" "Mak_15" "Mak_24" "Mak_1" "Mak_28" "Mak_33"

Table 8: Conclusion Graphs of Genetic Algorithm for All Machines

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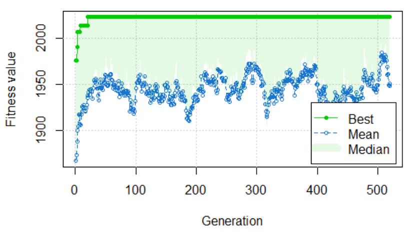

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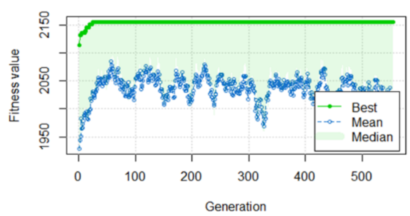

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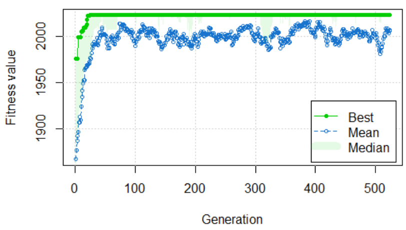

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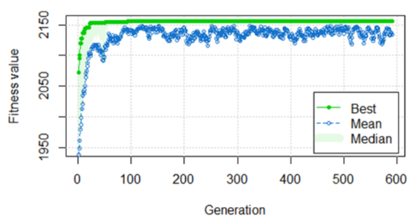

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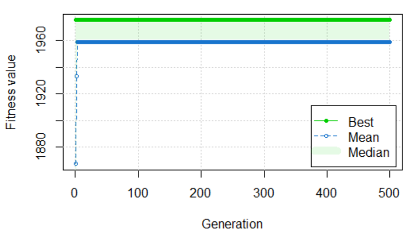

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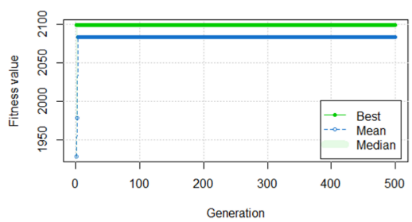

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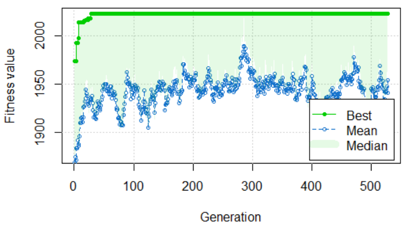

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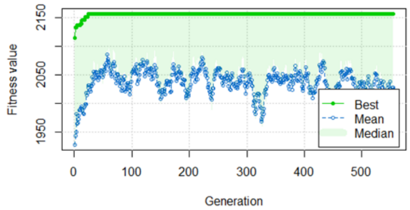

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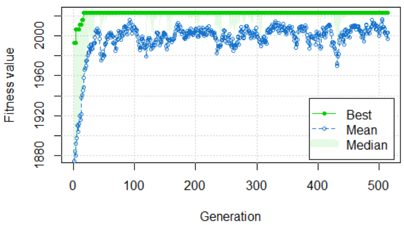

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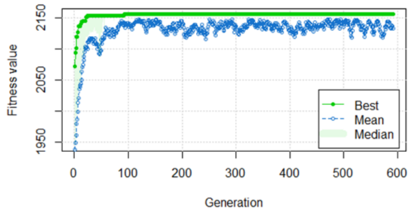

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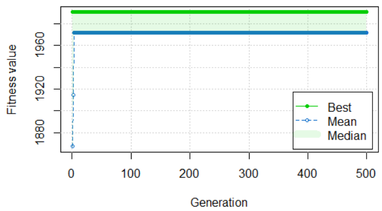

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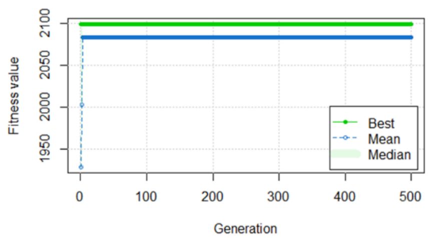

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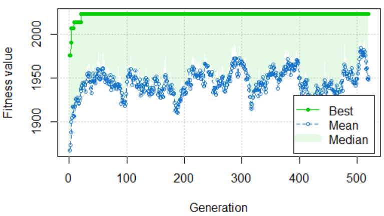

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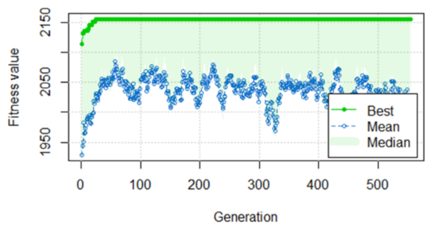

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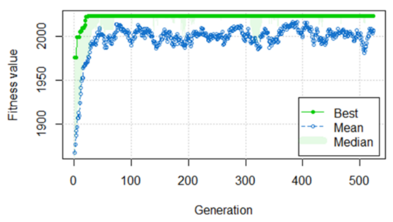

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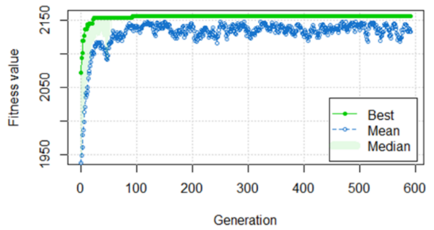

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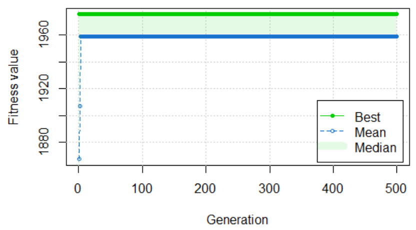

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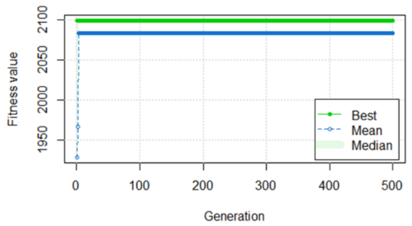

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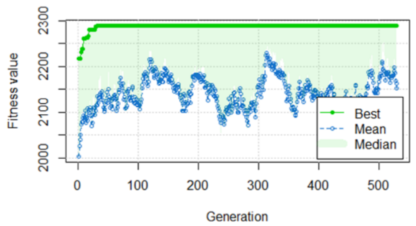

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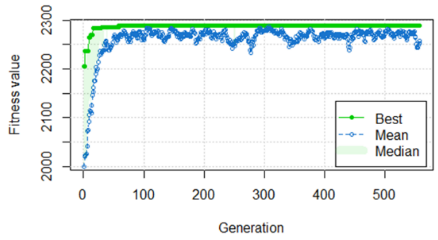

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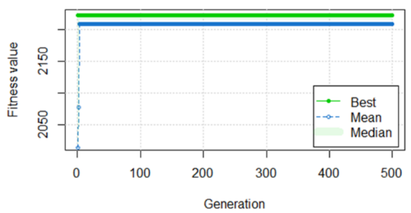

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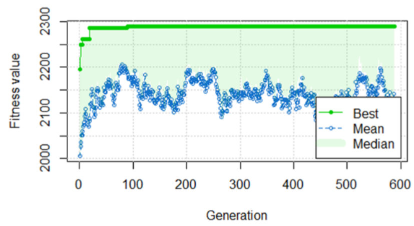

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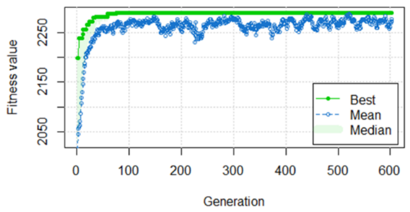

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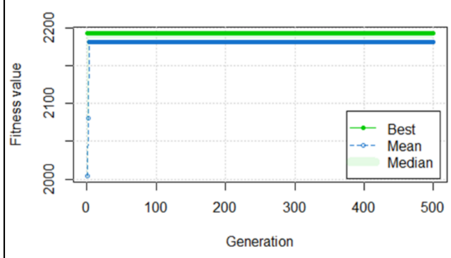

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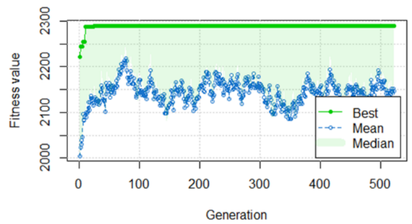

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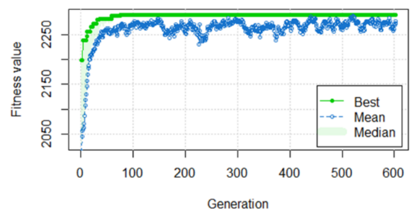

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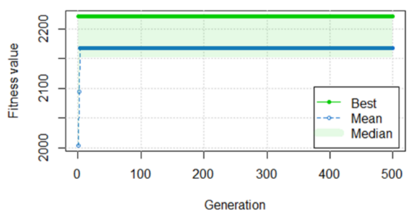

DISCUSSION

The findings confirm the effectiveness of the Genetic Algorithm-based multi-objective optimization model for solving machine delays in actual production processes.

Summary of Findings

The study showed that the **gareal_blxCrossover** crossover method provides lower tardiness (better fitness value) compared to other methods (gaperm_pmxCrossover and gaperm_cxCrossover), whether using a single or multi-objective function. In cases of an odd number of machines (21 and 35), using a single function (f_1 - Mass) can yield very good results. The best overall solution (C5.1) was obtained in the 35-machine scenario with a single function.

Theoretical Implications

This work demonstrates that genetic algorithms are a powerful tool in permutation-based scheduling problems, especially when incorporating real-world constraints such as **fixed points**. The inclusion of fixed points increases the model's adaptability to industrial scenarios and offers a new application scenario to the genetic algorithms literature. The performance of the **gareal_blxCrossover** model suggests its superiority over traditional permutation-based crossover methods for this type of optimization problem.

Practical Implications

The proposed optimization model offers directly applicable practical results for solving the tardiness problem in complex production environments such as the automotive sector. Production managers can use this GA model to determine the best machine sequence to:

1. **Reduce Delays:** Shorten production time by implementing the optimal permutation sequence.
2. **Increase Cost-Effectiveness:** Gain a cost advantage by reducing delays and errors.
3. **Enhance Planning Flexibility:** Optimization can be performed without sacrificing operational requirements by preserving fixed points (e.g., critical quality control stations).

Limitations and Future Research

This study addressed the tardiness problem through machine sequencing and fixed points. However, the results are limited to the used data set and determined GA parameters. Future research may include:

- Examining different models, crossover, and mutation types in the Genetic Algorithm.
- Combining data with others using different approaches.
- Extending the approach for this n times n data.
- Developing another concept for this data.
- Changing the fixed points using data.
- Broadening variations number of rows.
- Extending adaptation with new approaches for other industrial sectors.

CONCLUSION

This paper presents a Genetic Algorithm optimization process, including fixed machine points, to solve the tardiness problem in the industrial sector. Based on GA model created in R programming, three models were created for the mathematical concept. The results showed that the **gareal_blxCrossover** crossover method is particularly effective, yielding the most efficient solutions. The best solution was obtained in the scenario involving an odd number of machines (n=35) with a single function, demonstrating that the number of functions does not differentiate the solution when the machine number is odd. This study serves as an example for researchers on how to deal with the tardiness problem by selecting different machine numbers and fixed points, providing a rich basis for future research.

Researchers may include these topics:

- Taking the different models, crossover, and mutation types in the Genetic Algorithm.
- Combining data with others by using different approaches.
- Extending the approach for this n*n data.
- Enhancing another concept for this data.
- Changing the fixed points by using data.
- Broadening variations number of rows.
- Extending adapt with new approaches for other industrial sectors.

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