

Single Machine Scheduling Problem with Learning and Deterioration Effects and Sequence-Dependent Setup Times

Mügenur Ünal, Gamze Ağan and Derya Deliktas

Kütahya Dumlupınar University Engineering Faculty

Industrial Engineering Department, Kütahya, Türkiye

mmugeunall@icloud.com, gamzeagann@gmail.com, derya.deliktas@dpu.edu.tr,
derya.deliktas@outlook.com

Abstract

In modern manufacturing environments, maintaining production continuity and cost efficiency critically depends on the seamless coordination of interconnected processes. However, bottlenecks disrupt this coordination, leading to capacity losses, workflow interruptions, and increased operational costs. This study addresses a critical bottleneck observed in the slitting stage of a paper bag manufacturing system, where sequence-dependent setup times significantly affect operational efficiency. The problem is formulated as a single-machine scheduling problem with sequence-dependent setup times, explicitly incorporating both learning and deterioration effects to capture human and system dynamics. While the learning effect reflects performance improvements due to operator experience, the deterioration effect represents performance degradation caused by fatigue and interruptions. The integration of these opposing dynamics results in a more realistic yet computationally challenging NP-hard problem structure. To effectively solve this problem, a Genetic Algorithm (GA)-based solution framework is developed. Given the sensitivity of GA performance to parameter settings, a full factorial experimental design is conducted to systematically analyze parameter interactions and identify the most effective configuration. The proposed approach is validated using real-world production data consisting of 66 jobs derived from Pareto analysis. The results demonstrate that the proposed model not only captures the complexity of real production environments but also provides a robust and practical decision-support tool capable of significantly improving production flow efficiency.

Keywords

Single machine scheduling, Sequence-dependent setup times, Learning and deterioration effects, Genetic Algorithm.

1. Introduction

In today's competitive production environment, efficiency and time management are fundamental factors that directly affect the sustainability of enterprises. In order to ensure this critical time management, scheduling is a decision-making process that is regularly utilized in many manufacturing and service industries (Biskup 1999). From a more technical perspective, scheduling can be defined as the process of assigning resources to jobs over specified time periods in manufacturing and service systems, with the objective of optimizing one or more performance criteria (Pinedo 2008).

This theoretically defined process encounters various dynamic factors in real-world applications. For instance, in the slitting machine of a paper bag production facility, long setup times and their dependency on job sequence create a significant bottleneck in the production line. In such a dynamic environment, operators' ability to reduce setup times through experience also becomes a critical factor directly influencing the problem. In the scheduling literature, Biskup (1999) is recognized as one of the pioneers in studies addressing learning effects. Mosheiov (2001) later standardized the terminology by referring to this phenomenon as the "learning effect." On the other hand, the deterioration effect in scheduling was first introduced by Gupta and Gupta (1988), who proposed heuristic algorithms for a nonlinear

processing time function. Browne and Yechiali (1990) developed a stochastic single-machine model incorporating job deterioration with the objective of minimizing the expected makespan and derived several optimal scheduling policies. The authors suggested that the processing time of a job depends on the cumulative number of jobs previously completed on the same machine.

The presence of dynamic factors such as changes in processing times due to operator experience and machine deterioration transforms the problem into a highly complex (NP-hard) structure that cannot be effectively solved by traditional deterministic methods. Therefore, heuristic approaches that can provide optimal or near-optimal solutions are commonly preferred for solving such problems (Pinedo 2008). In this study, a Genetic Algorithm is employed to determine the optimal job sequence that minimizes the total flow time, while incorporating both learning and deterioration effects observed in the slitting process of a paper bag production system.

The remainder of this paper is structured as follows. Section 2 provides a critical review of the relevant literature, highlighting key gaps addressed in this study. Section 3 presents the materials and methodological framework in a detailed and systematic manner. Section 4 describes the implementation of the proposed approach and discusses the results with an emphasis on their practical implications. Finally, Section 5 concludes the study by summarizing the main findings and outlining potential directions for future research.

2. Literature Review

Various studies in single-machine scheduling problems have considered setup and transportation times together with learning and deterioration effects. These studies generally aim to improve performance measures such as makespan and total flow time by employing mathematical models, branch-and-bound algorithms, and metaheuristic approaches. A summary of the approaches in the literature is presented in Table 1 to illustrate how different solution methodologies address the problem.

Table 1. An overview of previous solution approaches applied to scheduling problems.

Sources	Year	Type of Scheduling		Solution Methods	Descriptions
		Single Machine	Parallel Machines		
Saraç and Özçelik (2025)	2025	✓		Harmony search	Stochastic
Atalay and Toksarı (2025)	2025	✓	✓	Heuristic algorithms	Learning and deterioration effects
Arık (2022)	2022	✓		Heuristic algorithms	Learning and deterioration effects
Mustu (2020)	2020	✓		Genetic algorithm, Variable neighborhood search	Learning-forgetting effects
Ceylan et al. (2019)	2019	✓		Priority rules (SPT, LPT, EDD, FCFS)	Sequence-dependent setup times
Dawd and Ayvaz (2017)	2017	✓		Branch-and-Bound	Total weighted tardiness
Eren and Güner (2016)	2016	✓		Dispatching rules (SPT, EDD, MST, MTSR)	Learning effect
Yazgan et al. (2014)	2014	✓		Fuzzy axiomatic design	Fuzzy parameters
Eren and Güner (2013)	2013		✓	Integer programming	Learning effect
Eren (2011)	2011	✓		Time complexity analysis	Learning effect

As can be clearly observed from Table 1, existing studies in the literature have predominantly focused either on testing learning and deterioration effects within theoretical models or on minimizing due dates and tardiness under specific constraints. However, the simultaneous integration of sequence-dependent setup times—one of the most inevitable

dynamics in industrial production environments—together with human-based learning effects and machine-based deterioration effects within a single model has remained quite limited.

The primary contribution that distinguishes this study from similar research in the literature is its direct focus on a real critical bottleneck encountered in the slitting stage of paper bag manufacturing, supported by actual shop-floor data. Furthermore, the study proposes a modeling framework aimed at minimizing total flow time. Another significant aspect of this work is the application of a Genetic Algorithm (GA) to solve this NP-hard problem using large-scale real-world data consisting of 66 jobs.

Unlike the majority of existing studies that address learning and deterioration effects or sequence-dependent setup times in isolation, this study integrates all these critical factors within a unified optimization framework. Moreover, the proposed model is directly grounded in real industrial data obtained from a paper bag manufacturing system, thereby enhancing both its practical relevance and applicability. This distinguishes the study not only in terms of modeling complexity but also in its contribution to bridging the gap between theoretical scheduling models and real-world industrial applications.

3. Problem Definition

This study addresses the problem of optimizing the job sequencing of a slitting machine that constitutes a critical bottleneck in a paper bag production line. The production system under consideration consists of 25 parallel bag-making machines, whose continuous operation directly depends on the supply of semi-finished materials (slit reels) provided by the slitting machine.

The products manufactured on the bag machines comprise a wide range of size combinations that vary according to customer demands (e.g., 80×50, 100×140, 90×102, 65×93, etc.). In this study, each distinct bag size is treated as an independent job. The high level of product variety represents one of the main factors that increases the complexity of production planning.

During the operations performed on the slitting machine, reel widths and cutting blades must be reconfigured for each job transition. This leads to the emergence of sequence-dependent setup times that are independent of processing times. The differences in dimensions between consecutive jobs directly affect the magnitude of setup times. In addition, while operators' accumulated experience over time generates a learning effect that reduces processing times, factors such as shift changes, interruptions, or fatigue weaken this effect and result in a deterioration effect. The coexistence of these two effects renders the system dynamic and non-deterministic in nature.

In this study, as shown in Figure 1, a Pareto analysis conducted on real production data identified the top 66 bag sizes that account for a large portion of total production volume, and the optimization study was focused on this product group. This approach reduces the solution space and enables a more efficient handling of the problem.

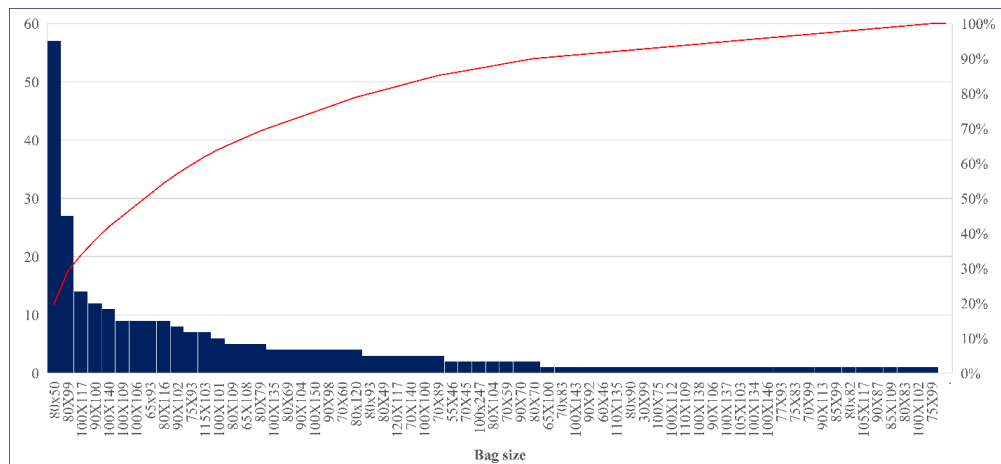


Figure 1. Pareto analysis

The problem aims to determine the sequence of jobs on the slitting machine in order to minimize the total flow time. The main objective is to reduce the waiting times of bag machines for raw materials and eliminate the bottleneck effect in the production line. Considering sequence-dependent setup times together with learning and deterioration effects makes the problem more complex than classical scheduling approaches and results in an NP-hard structure. Therefore, a genetic algorithm, which is a heuristic method capable of efficiently exploring large solution spaces, is employed as the solution approach. In the model, processing times that vary depending on the position of jobs in the sequence and setup times arising from transitions between jobs are evaluated jointly. In this way, an optimization framework that reflects the real production environment is established. Visuals of the production line under consideration and the slitting machine where the bottleneck occurs are presented in Figure 2.



Figure 2. Slicing machine where the workpieces are processed in the problem under consideration.

4. Material and Methods

This study focuses on determining the optimal job sequence that minimizes total flow time in a single-machine scheduling problem with sequence-dependent setup times, where learning and deterioration effects are integrated. Within this scope, the theoretical background of the problem is first presented, followed by a detailed explanation of the genetic algorithm used as the solution method, and finally the experimental design and implementation process are described.

Production scheduling is defined as the process of allocating jobs to limited resources under certain constraints in line with a specific objective (Büyüksünetçi 2006). In the scheduling literature, problems are generally addressed under the assumption that processing times are constant. However, in real production environments, processing times are not fixed and may vary depending on the position of the job or its starting time. This situation renders classical deterministic models inadequate (Tanyaş and Baskak 2017).

Studies on variable processing times began with the independent works of Gupta and Gupta (1988) and Browne and Yechiali (1990), and a substantial body of literature has since been developed (Badiru 1992; Alidaee and Womer 1999; Cheng et al. 2004; Gawiejnowicz 2008). These studies proposed models in which processing times vary depending on time or position.

In this study, two fundamental factors affecting processing times—learning effect and deterioration effect—are considered simultaneously. The learning effect refers to the reduction in processing times as a result of job repetition, whereas the deterioration effect refers to the increase in processing times due to the decline in system performance over time. By incorporating both effects, a more realistic production model is established. The model used in this context is expressed as in Eq. (1):

$$P_{j,r}(t) = p_j(\alpha \cdot a^{(r-1)} + \beta) \cdot (b \cdot t + c) \quad (1)$$

Here, $P_{j,r}(t)$, denotes the updated processing time of job j starting at time t in position r . The parameters in the model are defined as follows:

- r : position of the job in the schedule
- t : starting time of the job
- a : learning rate
- b, c : deterioration coefficients
- α, β : weighting coefficients of learning and deterioration effects

Under this structure, processing times are not constant but are recalculated for each job sequence, which makes the problem more complex compared to classical scheduling approaches.

The problem addressed belongs to the class of NP-hard problems due to the exponential growth of the solution space (Cheng et al. 2005; Wang and Yuan 2013; Deliktaş 2022). Therefore, obtaining optimal solutions using classical methods becomes impractical for large-scale instances. In such cases, metaheuristic approaches are preferred to obtain acceptable solutions within reasonable computational times.

In this study, a Genetic Algorithm (GA) is employed as the solution method. Genetic algorithms are population-based optimization techniques inspired by the principle of natural selection, developed by Holland (1975), De Jong (1975), and Goldberg (1989). Due to their effectiveness in solving complex and nonlinear problems, they are widely used in scheduling applications (Coley 1999).

Within the scope of the genetic algorithm implementation, a suitable chromosome structure is first defined and an initial population is generated. In this study, each chromosome is modeled as a permutation representing the sequence of jobs, such that each individual corresponds to a feasible schedule. The initial population is generated randomly in order to explore a wide portion of the solution space and to reduce the risk of premature convergence.

In the subsequent stages of the algorithm, the fundamental operators of genetic algorithms—selection, crossover, and mutation—are applied. Tournament selection is adopted as the selection operator, where individuals with better (i.e., lower) fitness values have a higher probability of being selected for the next generation, thereby mimicking the principle of natural selection. This ensures that better solutions are preserved and improved over successive generations. In the selection phase, tournament selection with a tournament size of 2 is employed.

For the crossover operator, offspring chromosomes are generated from two parent chromosomes. In this study, the Partially Matched Crossover (PMX) method is used, where two random cut points are selected to define a crossover region. However, due to randomness, this process may lead to duplicate or missing genes in the offspring. To address these inconsistencies, a gene mapping procedure is applied between parent chromosomes, ensuring that missing or repeated genes are corrected and a valid solution is obtained (Duan et al. 2025). The PMX operator used in the proposed algorithm is illustrated in Figure 3, where the procedure is demonstrated for a representative case with 10 jobs.

The mutation operator is applied to preserve diversity within the population and to prevent the algorithm from getting trapped in local optima. Common mutation methods for permutation problems include swap, insertion, and inversion (Oğuz and Ercan 2005; Deb 2011). In this study, the insertion mutation operator is employed.

To evaluate the performance of the algorithm, total flow time is used as the fitness function. The objective is to minimize the total time spent by all jobs in the system, thereby achieving a more balanced and efficient production flow.

The performance of the genetic algorithm is highly dependent on the selected parameter values (e.g., population size, crossover rate, mutation rate). Therefore, determining appropriate parameter combinations is considered a critical step. In this context, a full factorial experimental design approach is adopted to obtain systematic and statistically significant results. Experimental design is a powerful method that enables the analysis of factors affecting system output as well as their interactions (Montgomery 2017). In a full factorial design, all combinations of factor levels are tested, allowing

both main effects and interaction effects to be examined in detail. This approach provides a significant advantage in revealing the individual and interactive effects of genetic algorithm parameters on performance.

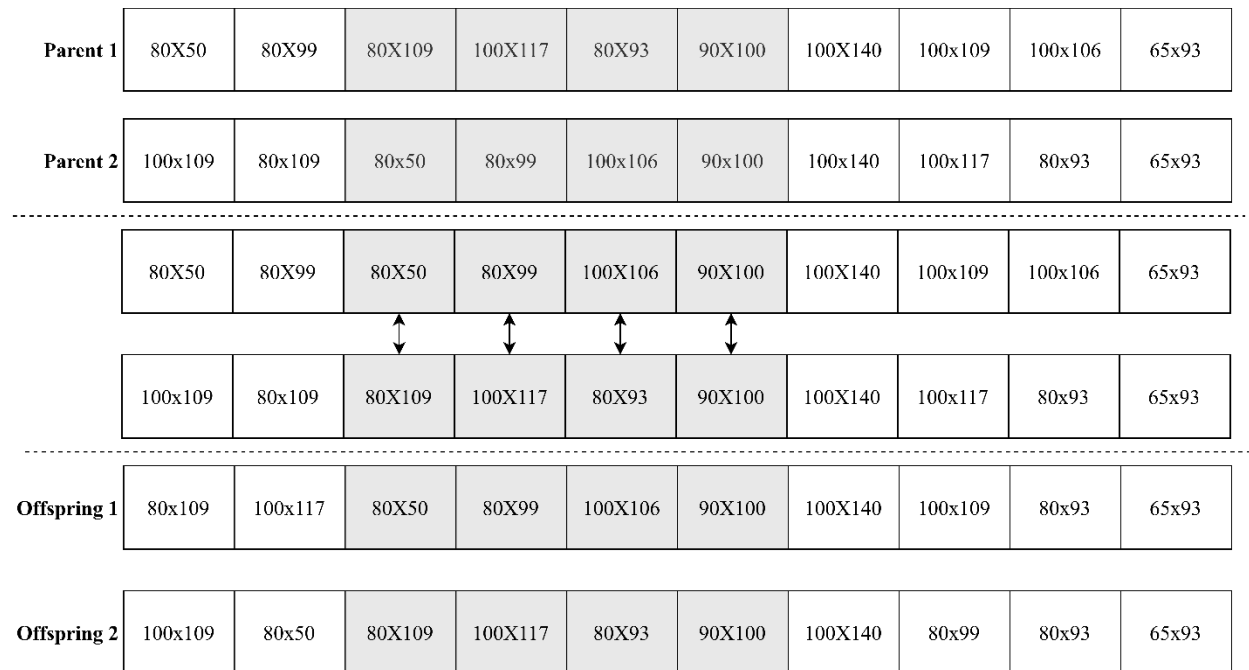


Figure 3. The proposed crossover operator adapted from Duan et al. (2025).

Within the scope of this study, the selected parameter levels are systematically combined, and each combination is evaluated through independent experiments. To reduce the variability arising from the stochastic nature of the algorithm and to obtain more reliable results, each parameter combination is executed with 31 independent runs.

To ensure both robustness and statistical reliability, each parameter configuration was evaluated through 31 independent runs. This experimental design mitigates the stochastic variability inherent in metaheuristic algorithms and enables a more reliable assessment of algorithmic performance. Such a rigorous evaluation framework strengthens the validity of the obtained results and enhances the credibility of the proposed approach.

In this study, the population size {60, 80, 100}, crossover rate {0.8, 0.9, 1.0}, and mutation rate {0.05, 0.1, 0.15} were determined, and a full factorial experimental design was implemented. Based on the analysis conducted using the Minitab software, the main effects and interaction plots presented in Figure 4 were obtained. According to these results, the optimal parameter configuration was identified as a population size of 100, a crossover rate of 0.8, and a mutation rate of 0.05. The tournament size was set to 2.

In this study, the maximum iteration number was taken as 500 as shown in Figure 5. All approaches are coded in C# 2022 programming language, and the experiments are executed on a laptop equipped with a 2.1 GHz Core i7 CPU and 8.00 GB RAM. The performance measures obtained from the experiments are analyzed, and the most suitable parameter combinations are identified. Due to data confidentiality considerations, the datasets used in this study are not publicly shared. However, all experimental procedures, algorithmic structures, and parameter configurations are described in sufficient detail to ensure the reproducibility and transparency of the proposed approach.

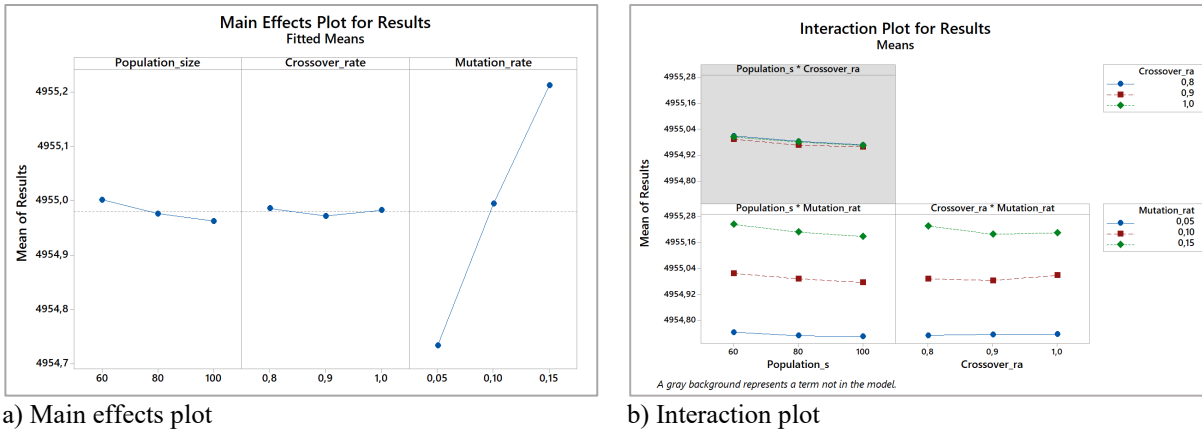


Figure 4. Main effects plot (a) and Interaction plot (b) obtained from the full factorial experimental design for parameter calibration of the proposed genetic algorithm

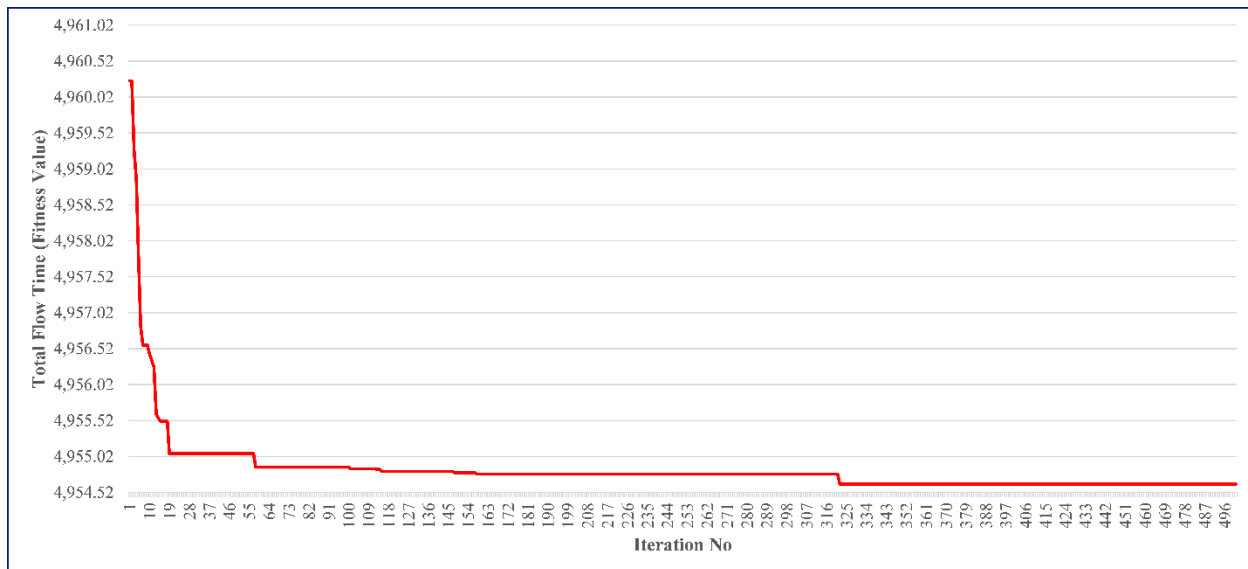


Figure 5. Convergence graph for the maximum number of iterations

Based on the determined parameter settings, the algorithm was executed independently 31 times, and the best job sequence yielded a total flow time of 4964.669 minutes.

5. Conclusions

This study presents a comprehensive and practically grounded solution framework for a complex single-machine scheduling problem characterized by sequence-dependent setup times, as well as learning and deterioration effects. By simultaneously incorporating these dynamic and often conflicting factors, the proposed model provides a significantly more realistic representation of production environments compared to conventional scheduling approaches.

The developed Genetic Algorithm, supported by a rigorously designed full factorial experimental framework, demonstrates strong performance in navigating the large and complex solution space. The identification of optimal parameter settings and the consistent results obtained from multiple independent runs confirm the robustness and stability of the proposed approach. The best-obtained solution, yielding a total flow time of 4964.669 minutes, clearly indicates the algorithm's effectiveness in reducing bottlenecks and improving operational efficiency in real-world production systems.

From a practical perspective, this study offers a decision-support tool that can be directly utilized in manufacturing environments where setup times, human factors, and system dynamics play a critical role. The integration of real production data further enhances the industrial applicability and reliability of the findings.

Nevertheless, several promising research directions emerge from this work. First, the proposed algorithm can be benchmarked against other state-of-the-art metaheuristic and hybrid approaches, such as Particle Swarm Optimization, Simulated Annealing, Tabu Search, and memetic algorithms, to provide a more comprehensive performance evaluation. Second, the problem can be extended into a multi-objective optimization framework by incorporating additional performance criteria such as total tardiness, makespan, machine idle time, and energy consumption. This would enable decision-makers to analyze trade-offs and achieve more balanced production strategies.

Furthermore, future studies may explore adaptive and self-tuning parameter control mechanisms to enhance algorithmic performance under varying problem conditions. Hybridization with problem-specific heuristics or machine learning-based prediction models also presents a promising avenue for improving solution quality. Finally, applying the proposed framework to different industrial settings and larger-scale problem instances would further validate its generalizability and scalability.

In conclusion, this study not only contributes to the scheduling literature by integrating multiple complex factors into a unified model but also provides a scalable and effective optimization approach with strong practical relevance. It establishes a solid foundation for future research on advanced, data-driven, and multi-objective scheduling methodologies.

Acknowledgments

This study was supported by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) under the 2209-A - Research Project Support Programme for Undergraduate Students project number [1919B012416202].

References

- Alidaee, B. and Womer, N.K., Scheduling with time dependent processing times: Review and extensions, *J. Oper. Res. Soc.*, 50 (7): 711–720, 1999. <https://doi.org/10.1057/palgrave.jors.2600740>
- Arık, O. A. Öğrenme ve Bozulma Etkileri Altındaki Ortak Teslim Tarihli Tek Makine Erken/Geç Tamamlanma Çizelgeleme Probleminin Optimal Çizelgesinin V Şeklindeki Özelliği. *Endüstri Mühendisliği*, 33(1), 115:129, 2022. <https://doi.org/10.46465/endustrimuhendisligi.963831>
- Atalay, B., and Toksarı, M. D. Job rejection scheduling problems with deterioration and learning effects. *Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi*, 14(2), 607:614, 2025. <https://doi.org/10.28948/ngumuh.1381334>
- Badiru, A.B., Computational Survey of Univariate and Multivariate Learning Curve Models, *IEEE Trans. Eng. Manag.*, 39 (2): 176–188, 1992. <https://doi.org/10.1109/17.141275>
- Biskup, D., Single-machine scheduling with learning considerations, *European Journal of Operational Research*, 115(1), 173-178, 1999. [https://doi.org/10.1016/S0377-2217\(98\)00246-X](https://doi.org/10.1016/S0377-2217(98)00246-X)
- Browne, S. and Yechiali, U., Scheduling Deteriorating Jobs on a Single Processor, *Operations Research*, 38(3), 495–498, 1990. <https://doi.org/10.1287/opre.38.3.495>
- Büyüksünetçi, A. Tepkin Çizelgeleme Yaklaşımının Akış Tipi Atölye Ortamında Etkinliğinin Analizi, *Yüksek Lisans Tezi, Osmangazi Üniversitesi, Eskişehir*, 2006.
- Ceylan, Z., Karan, R. E., Bakırcı, Ç., and Sabuncu, S., Sıra Bağımlı Hazırlık Süreli Tek Makine Çizelgeleme Problemi: Beyaz Eşya Sektöründe Bir Uygulama. *International Journal of Multidisciplinary Studies and Innovative Technologies*, 3(1), 14-21, 2019. <https://izlik.org/JA33KL48RE>
- Cheng, T.C.E., Ding, Q. and Lin, B.M.T., A concise survey of scheduling with time-dependent processing times, *Eur. J. Oper. Res.*, 152 (1): 1–13, 2004. [https://doi.org/10.1016/S0377-2217\(02\)00909-8](https://doi.org/10.1016/S0377-2217(02)00909-8)
- Cheng, T. E., Ng, C. T., Yuan, J. J. and Liu, Z. H. Single machine scheduling to minimize total weighted tardiness. *European Journal of Operational Research*, 165(2), 423-443, 2005. <https://doi.org/10.1016/j.ejor.2004.04.013>
- Coley, D. A., An Introduction to Genetic Algorithms for Scientists and Engineers, *World Scientific, Singapore*, 1999. <https://doi.org/10.1142/3904>

- Dawd, S. T. and Ayvaz, B. A Branch And Bound Approach For Single Machine Scheduling Problem. *İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi*, 16(31), 43-55, 2017. <https://izlik.org/JA23DT99PD>
- Deliktaş, D. Self-adaptive memetic algorithms for multi-objective single machine learning-effect scheduling problems with release times. *Flexible Services and Manufacturing Journal*, 34(3), 748-784, 2022. <https://doi.org/10.1007/s10696-021-09434-7>
- De Jong, K. A., An Analysis of the Behavior of a Class of Genetic Adaptive Systems, *Ph. D Thesis, University of Michigan*, 1975.
- Deb, K. Multi-objective optimisation using evolutionary algorithms: an introduction. In *Multi-objective evolutionary optimisation for product design and manufacturing* pp. 3-34, 2011. https://doi.org/10.1007/978-0-85729-652-8_1
- Duan, J., Liu, Z., Wang, M., Du, Y. and Yang, M. A problem-specific knowledge-based multi-objective algorithm for sustainable scheduling of distributed heterogeneous welding permutation flow shop. *Engineering Applications of Artificial Intelligence*, 156, 111197, 2025. <https://doi.org/10.1016/j.engappai.2025.111197>
- Eren, T. Hazırlık ve taşıma zamanlarının öğrenme etkili olduğu tek makineli çizelgeleme problemi: Geciken iş sayısı minimizasyonu. *International Journal of Engineering Research and Development*, 3(2), 34:36, 2011. <https://izlik.org/JA36LX65TY>
- Eren, T. and Güner, E. Öğrenme Etkili Akış Tipi Çizelgelemede Ortalama Akış Zamanının Enküçüklenmesi. *Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi*, 19(2), 2013. <https://izlik.org/JA23LL35YY>
- Eren, T., Güner, E. Hazırlık ve Taşıma Zamanlarının Öğrenme Etkili Olduğu Tek Makineli Çizelgeleme Problemleri. *Trakya Üniversitesi Fen Bilimleri Dergisi*, 8(1), 7:13, 2016. <https://izlik.org/JA66SH73TN>
- Gawiejnowicz, S., Time-dependent scheduling, *Springer Science & Business Media, Berlin, Heidelberg*, 2008.
- Goldberg, D., Genetic Algorithms in Search, Optimization, and Machine Learning, *Addison-Wesley, Reading, MA*, 1989.
- Gupta, J.N.D. and Gupta, S.K., Single Facility Scheduling with Nonlinear Processing Times, *Computers and Industrial Engineering*, 14(4), 387–393, 1988. [https://doi.org/10.1016/0360-8352\(88\)90041-1](https://doi.org/10.1016/0360-8352(88)90041-1)
- Holland, J. H., Adaptation in Natural and Artificial Systems, *Ann Arbor: MI: The University of Michigan Press*, 1975.
- Montgomery, D. C. Design and analysis of experiments. *John Wiley & sons*, 2017.
- Mosheiov G., Scheduling problems with a learning effect, *European Journal of Operational Research*, 132(3), 687-693, 2001. [https://doi.org/10.1016/S0377-2217\(00\)00154-1](https://doi.org/10.1016/S0377-2217(00)00154-1)
- Muştu, S., Öğrenme-unutma etkili ve ayar süreli tek makine çizelgeleme problemleri için yeni çözüm yaklaşımları, *Kırıkkale Üniversitesi Fen Bilimleri Enstitüsü Doktora Tezi*, 2020.
- Oğuz, C. and Ercan, M. F. A genetic algorithm for hybrid flow-shop scheduling with multiprocessor tasks. *Journal of Scheduling*, 8(4), 323-351, 2005.
- Pinedo, M. L., Scheduling: theory, algorithms, and systems, *Springer*, 2008. <https://doi.org/10.1007/978-0-387-78935-4>
- Saraç, T., and Özçelik F. Stokastik Teslim Zamanlı Tek Makine Çizelgeleme Problemi İçin Bir Harmoni Arama Algoritması. *Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi*, 27(80), 247:256, 2025. <https://doi.org/10.21205/deufmd.2025278011>
- Tanyaş, M. and Baskak M., Üretim planlama ve Kontrol, (7. Baskı), *İstanbul: İrfan Yayıncılık*, 2017.
- Wan, L. and Yuan, J. (2013). Single-machine scheduling to minimize the total earliness and tardiness is strongly NP-hard. *Operations Research Letters*, 41(4), 363-365. <https://doi.org/10.1016/j.orl.2013.04.007>
- Yazgan, H. R., Kır, S., Özbakır, S. and Sezik, E. Sıra Bağımlı Tek Makineli Çizelgeleme Probleminde Erkenlik ve Geçlik Katsayılarının Bulanık Aksiyomatik Tasarım Yöntemi ile Belirlenmesi. *Endüstri Mühendisliği*, 25(3), 20-32, 2014. <https://izlik.org/JA54HE22CE>

Biographies

Mügener Ünal is a graduating senior in the Department of Industrial Engineering in the Faculty of Engineering at Kütahya Dumlupınar University, Turkey. She has gained comprehensive practical experience in manufacturing environments through engineering internships across different sectors, including paper and ceramics production. During her professional tenure, she actively engaged in production planning, time and motion studies, process visualization using Power BI, and continuous improvement methodologies. Her research and technical focus center around industrial engineering applications, operational efficiency, and data analytics. Additionally, she serves as a core researcher in a TÜBİTAK 2209-A student research project targeting manufacturing systems optimization.

Gamze Ağan is a graduate of the Department of Industrial Engineering in the Faculty of Engineering at Kütahya Dumlupınar University, Turkey. During her undergraduate studies, she focused on manufacturing systems,

scheduling, optimization, and AI-driven decision-making methodologies. Professionally, she pursues her career in the transformer sector, serving as a Planning Engineer at a transformer manufacturing facility. Her operational responsibilities encompass production planning, capacity planning, scheduling, process improvement, inventory management, and operational efficiency. Her research interests include production scheduling problems, optimization techniques, meta-heuristic algorithms, artificial intelligence applications, and Industry 4.0.

Derya Deliktaş is an associate professor at Department of Industrial Engineering in Faculty of Engineering, Kütahya Dumlupınar University, Turkey. She received the B.S. degree in industrial engineering and Ph.D. degree in industrial engineering from Erciyes University and Sakarya University, respectively. She did her post-doctoral research as a researcher supported by Scientific and Technological Research Council of Turkey (TÜBİTAK) in Computer Science and Operational Research with the Computational Optimisation and Learning (COL) Lab in the School of Computer Science at the University of Nottingham (UoN) in UK. Her research interests and activities are scheduling problems, assembly line balancing problems, portfolio optimization, artificial intelligence methods, multi-criteria decision-making methods, and data mining.