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Multi-objective Job Shop Scheduling under Risk Using GA

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Abstract In this study, a multi-objective job-shop scheduling model is developed to optimize makespan, maximum job tardiness and maximum tardiness and maximum idle time of machines under risk. The model considers multi-jobs and multi-machines. Each task has a specific due date and random processing times of specific probability distribution. The model is solved using @RiskOptimizer.

Keywords: *job-shop scheduling, optimization, uncertainty, @RiskOptimizer, genetic algorithm*

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1. Introduction

The aim of Job Shop Scheduling (JSS) problem may be defined as a main of the planning functions of production that comprises a set of hard optimization problems [1].

Ant Colony Optimization [2,3], Mathematical Programming [4,5], Tabu Search [6,7], Simulated Annealing [8,9], Particle Swarm Optimization [10,11], Memetic Algorithm [12], Genetic Algorithms [13,14], Goal Programming [15], and differential evolution algorithm [16] have been used in optimization of JSSP.

Most researches tackled the scheduling problems as a single objective optimization problem [5,13,14,17,18,19] like tardiness [5] and makespan [17,18] optimization. The multi-objective treatment is required in scheduling process to consider conflicting objectives [19]. So, researchers often deal with problems that involve multiple usually conflicting criteria [20].

Regarding Multi-Objective Job Shop Scheduling (MOJSS) optimization, R. T. Marler and J. S. Arora [21] presented a comprehensive study about the methods of multi-objective optimization. Some researches have been performed using different methods like Pareto front [22,23,24,25], the □-constraint method [26,27,28], and the preemptive objectives procedure M. S. Al-Ashhab [29]. Genetic Algorithms (GA) [30-33], Ant Colony System (ACS) [34,35,36,37], Particle Swarm Optimization (PSO) [38,39,40,41,42], A Non-Dominated Algorithm [43] and Distribution Estimation Algorithm [44,45,46,47].

In realistic job shops, the working environment bears some uncertainties, such as job release time delay that may stem from late deliveries of subcontractors [48], or late arrivals of raw materials from a supplier [49]. When facing uncertainties, the optimum schedule performance may deteriorate.

In the existing literature, although Multi-Objective Scheduling has been used to solve flow shop scheduling [50,51], it has not yet been investigated to make robust schedules in job shops with uncertainties, where the environment is much more complex than the deterministic permutation flow shop.

In this paper, an MOJSS model using Pre-emptive goal programming procedure has been formulated to minimize the makespan, maximum job tardiness and maximum tardiness and maximum idle time of machines under risk. The model has been formulated using Excel spreadsheets and solved using @RiskOptimizer to consider the uncertain processing time. This work is an extension of the work done by Jaber S. Alzahrani [52]

2. Problem Description and Assumptions

The processing sequences of three jobs on four machines are shown in Table 1. The durations and the due date of each job are shown in Table 2.

Table 1. Job Sequences

J1	M 1 »»»	M 3 »»»	M 4	
J2	M 1 »»»	M 2 »»»	M 3 »»»	M 4
J3	M 4 »»»	M 3 »»»	M 2	
J4	M 2 »»»	M 3 »»»	M 4 »»»	M 1
J5	M 1 »»»	M 3		

Table 2. Durations and the due dates

M/J	J1	J2	J3	J4	J5
M1	19	10		19	15
M2		30	31	14	
M3	10	18	18	10	16
M4	19	11	15	20	
Due date	**100**	**115**	**90**	**85**	**31**

The optimization process starts with accurate problem modelling. For any given set of decision values, called adjustable cell values, the model evaluates an objective function, which required to be optimized. @RiskOptimizer searches for the solution, the objective function provides feedback about the solution quality. @RiskOptimizer continues to search for better solutions until no considerable improvements can be obtained in a predefined number of trials.

In the beginning, the problem is solved considering deterministic processing times after that the durations are assumed to follow different well-known distributions. The following assumptions have been considered in the model:

- Jobs are mutually independent,
- Jobs have equal processing priorities,
- The due date of each job is known and constant,
- The processing times of some tasks are uncertain,
- Each job will be processed by the same machine only one time,
- Any operation is not allowed to be processed until its preceding operations are completed,
- All jobs and machines are ready at time zero,
- Only one job can be processed on each machine at a time,
- No circulation is allowed.

3. Model Formulation

3.1. Sets

M: Set of machines
J: Set of jobs

3.2. Parameters

D_j: Due date of job j, (j = 1, …, n) of J
SEQ: Processing sequence array
P_{ji}: Processing time for job j on m/c i (i=1, …, m) of M

3.3. Decision Variables

S_{ji}: Starting time of job j on machine i,
F_{ji}: Finishing time of job j on machine i,
C_j: Completion time of job j,
E_j: Earliness of job j = (D_j - C_j) if $D_j > C_j$, and 0 otherwise,
T_j: Tardiness of job j = (C_j - D_j) if $C_j > D_j$, and 0 otherwise,
MITi: Idle time of machine i = $MAX(Fji) - \sum_{j\in N} Pji$

The formula of each objective is given in Equations (1- 3).

$$\text{minimize makespan } f1 = \max(Cj) - \min(Sj) \forall j \in N \quad (1)$$

$$\text{minimize maximum tardiness } f2 = \max(Tj) \forall j \in N \quad (2)$$

$$\text{minimize maximum machine Idle time } f3 = \max(MITi) \forall j \in N \quad (3)$$

$$f4 = f1 + f2 + f3 \quad (4)$$

$$f5 = 2*f1 + f2 + f3 \quad (5)$$

$$f6 = f1 + 2*f2 + f3 \quad (6)$$

$$f7 = f1 + f2 + 2*f3. \quad (7)$$

The make-span measure in (1) is calculated as the difference between the maximum completion time and the minimal starting time of all jobs. The maximum tardiness in (2) is defined as the maximum of differences between the due date of each job and completion time in which its due date is larger than the completion time. The maximum machine idle time in (3) is defined as the maximum difference between the maximum completion time on a machine and summation of all processing times on the same machine.

Subject to conjunctive (Equation 8) and disjunction (Equation 9, 10) constraints

Disjunction constraints:

$$(S_{hi} - S_{hj}) \geq P_{hj} - M\, Y_{hij}, \forall i, j \in N, \forall h \in M \quad (8)$$

$$(S_{hj} - S_{hi}) \geq P_{hi} - M\,(1 - Y_{hij}), \forall i, j \in N, \forall h \in M \quad (9)$$

Conjunction constraints:

$$\sum_{i\in M}\left(S_{SEQ(j,i),j} + P_{SEQ(j,l),j}\right) \geq \sum_{i\in M} S_{SEQ(j,i+1),j}, \forall j \in N, \forall i \in M-1. \quad (10)$$

4. Computational Results and Analysis

In this section, the results of applying the proposed model are introduced and analyzed. The model has been solved using @RiskOptimizer solver. In consequence, the model has been solved using @RiskOptimizer which operated in an Intel® Core™ i3-2310M CPU @2.10 GHz.

The accuracy of the model is verified through solving and analysing a 5J*4M problem ot ten precent variation for all tasks, which was solved seven times to optimise the following objectives:

1) makespan
2) Maximum job tardiness
3) Maximum machine idle time
4) Multi-objectives (Equal weights)
5) Multi-objectives (double weighted makespan)
6) Multi-objectives (double weighted maximum job tardiness)
7) Multi-objectives (double weighted maximum machine idle time)

The Total or maximum earliness will not be optimized since its optimization gives no practical schedules [52].

The model has been solved using Evolver assuming constant processing times and the results are presented in Table 3. These results verified the accuracy of the model since the optimized objective has gotten its best value all over the seven cases. The Gantt chart of minimizing the makespan is depicted in Figure 1.

Table 3. Optimization results of the seven cases

	1	2	3	4	5	6	7
Make Span	92	108	93	104	104	104	104
Max. Tard.	61	4	62	15	15	15	15
Max Idle time	36	39	11	24	24	24	24
Multi-objectives (Equal weights)	189	151	166	143	143	143	143
Multi-objectives (double weighted makespan)	281	259	259	247	247	247	247
Multi-objectives (double weighted maximum job tardiness)	250	155	228	158	158	158	158
Multi-objectives (double weighted maximum machine idle time)	225	190	177	167	167	167	167

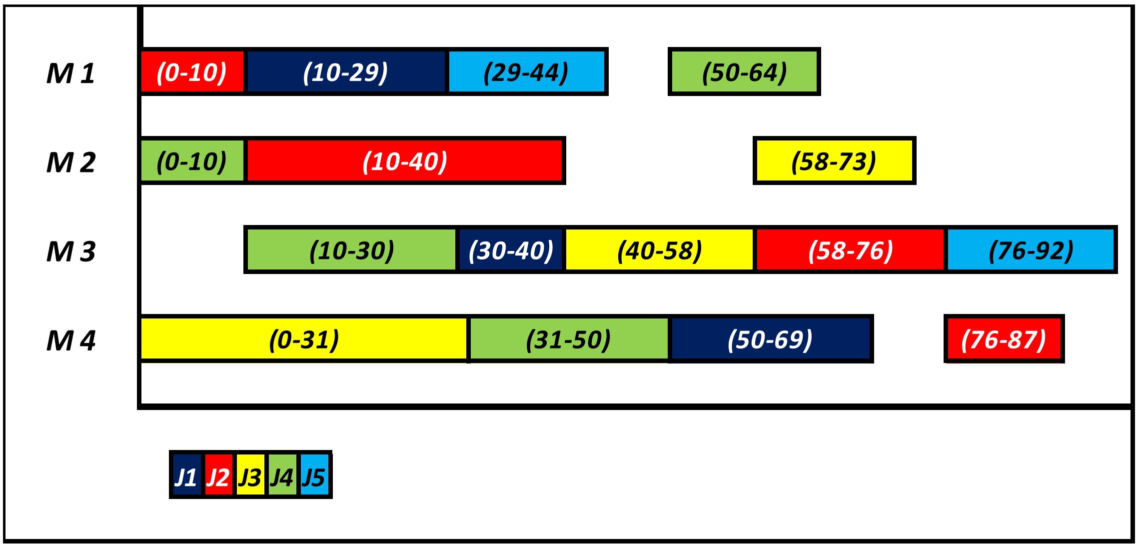

Figure 1. Gantt chart of makespan objective [[52]]

4.1. Makespan

In this case, the problem has been solved to optimize the makespan. The resultant optimal distribution of the makespan is presented in Figure 2 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 3 from which it is noticed that the duration of the second task of job 5 on machine 3 has the greatest effect on the resultant optimal mean of the makespan which is logic according to the Gantt chart shown in Figure 1.

The resultant distributions of the other objectives while optimizing the makespan are presented in Figure 4 to Figure 9.

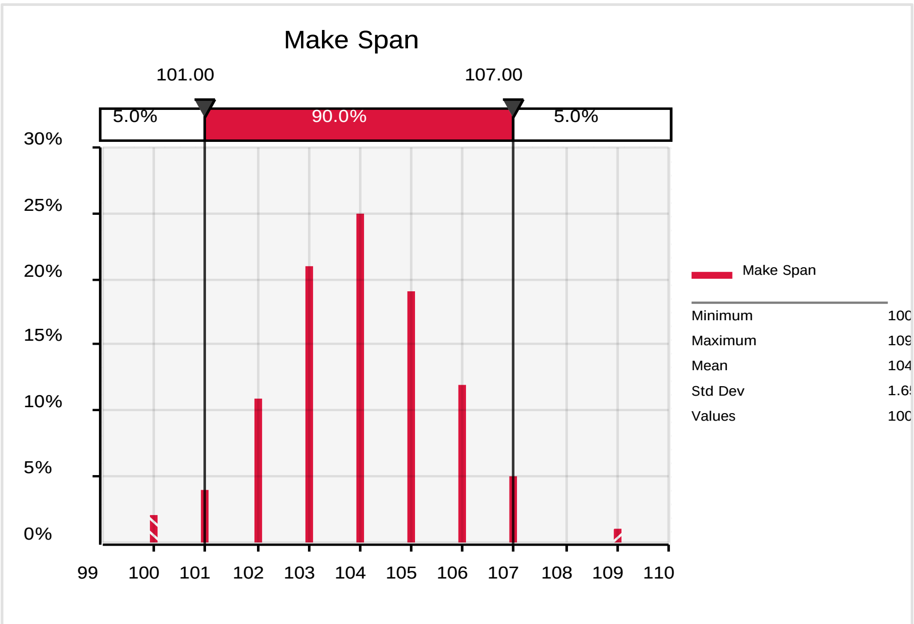

Figure 2. Optimal makespan distribution

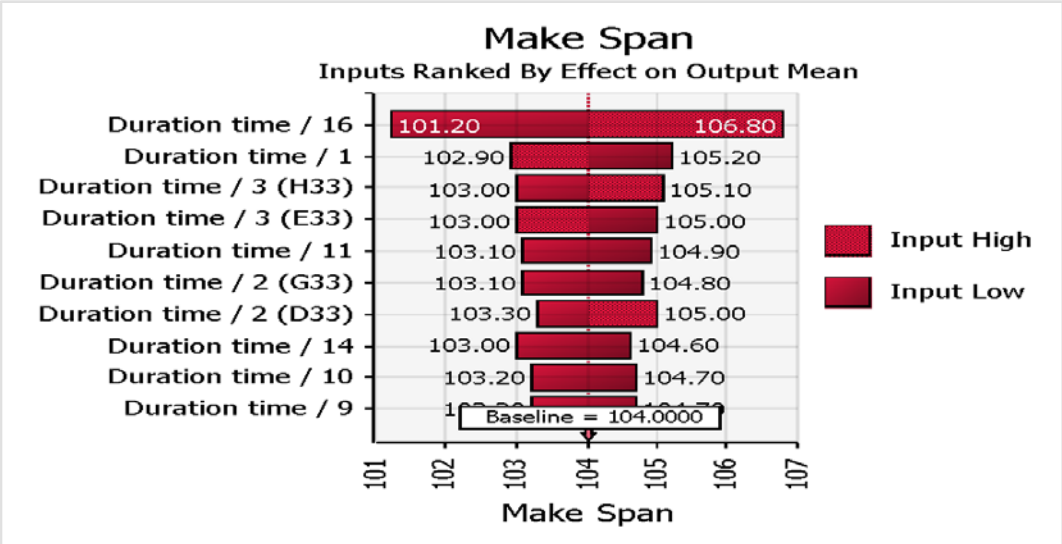

Figure 3. Inputs ranked by the effect on makespan mean

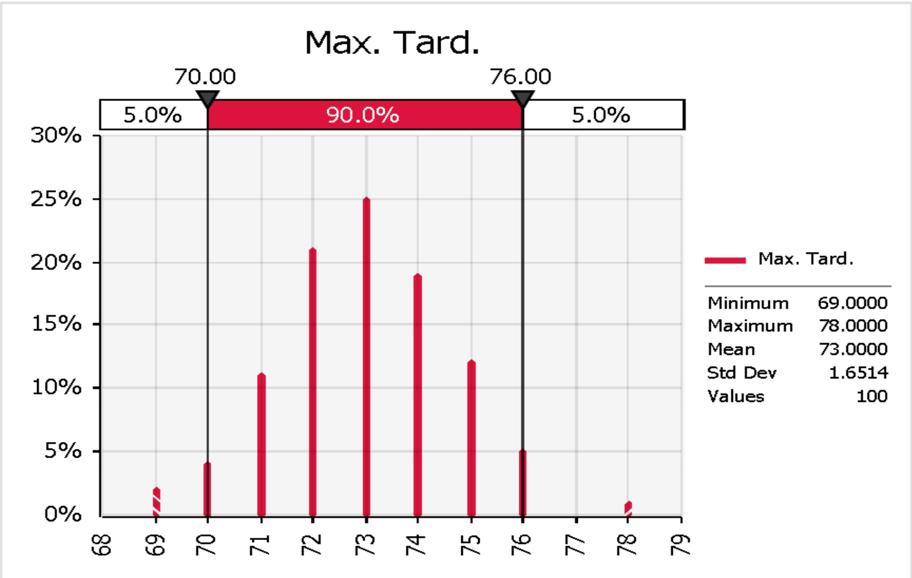

Figure 4. The resulted in maximum tardiness while optimizing the makespan

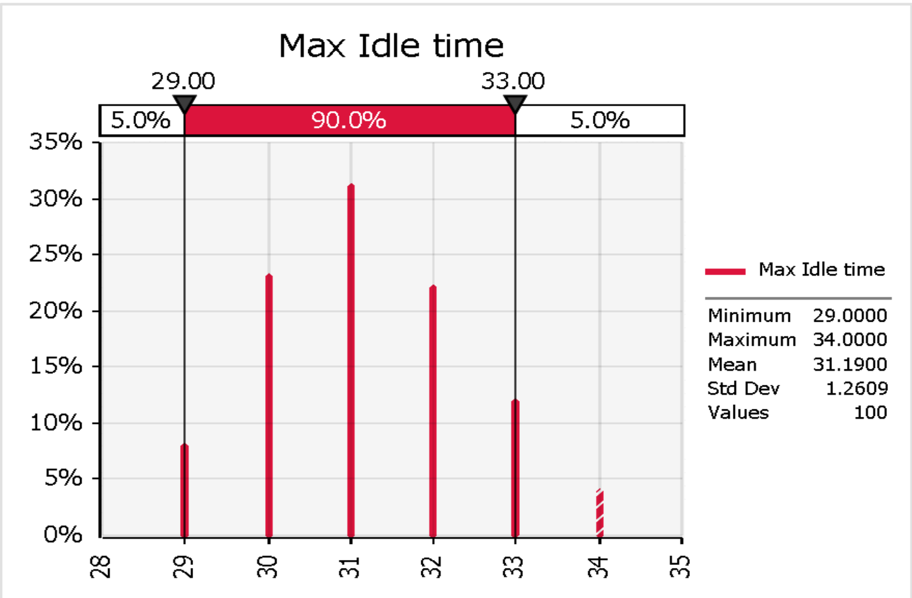

Figure 5. The resulted in maximum machine idle time while optimizing the makespan

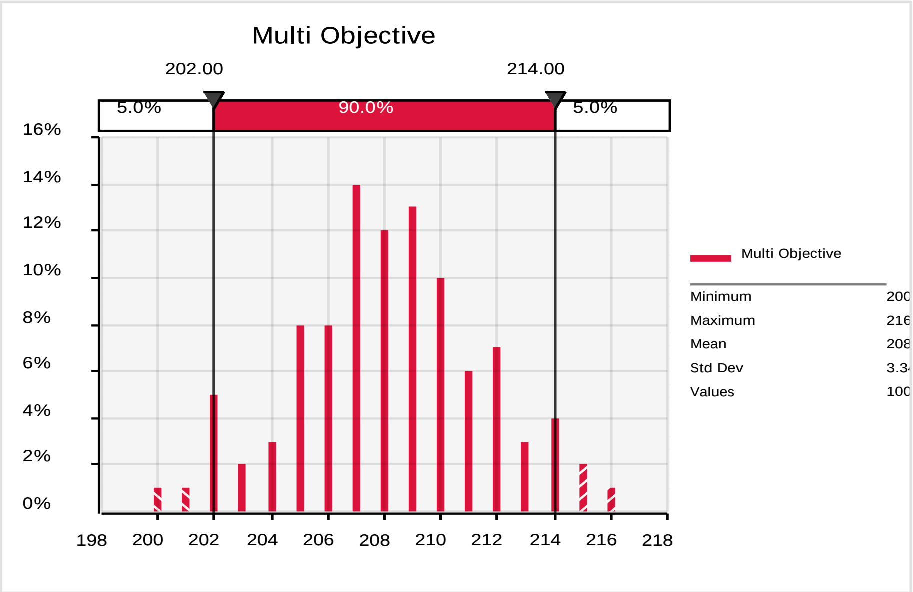

Figure 6. The resulted in multi-objectives (Equal weights) while optimizing the makespan

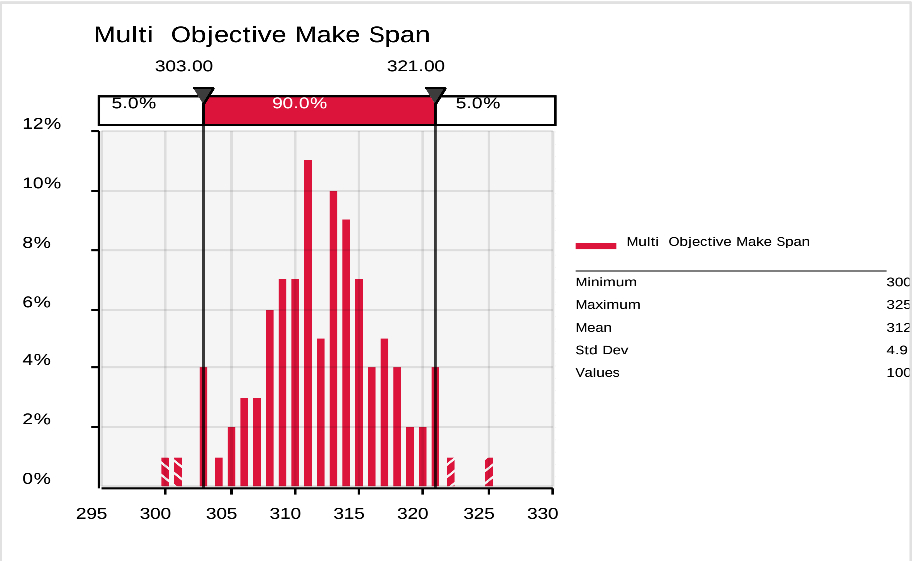

Figure 7. The resulted in Multi-objectives (double weighted makespan) while optimizing the makespan

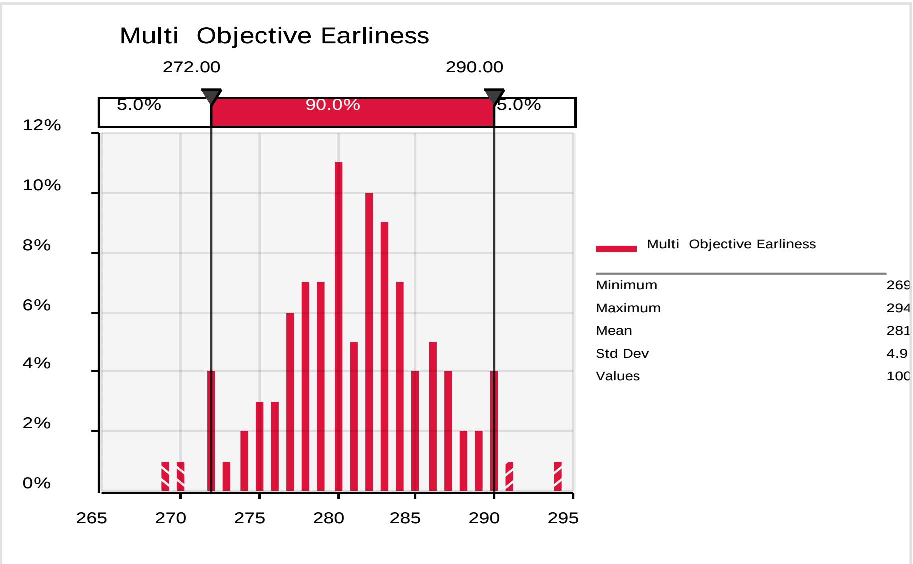

Figure 8. The resulted in Multi-objectives (double weighted maximum job tardiness) while optimizing the makespan

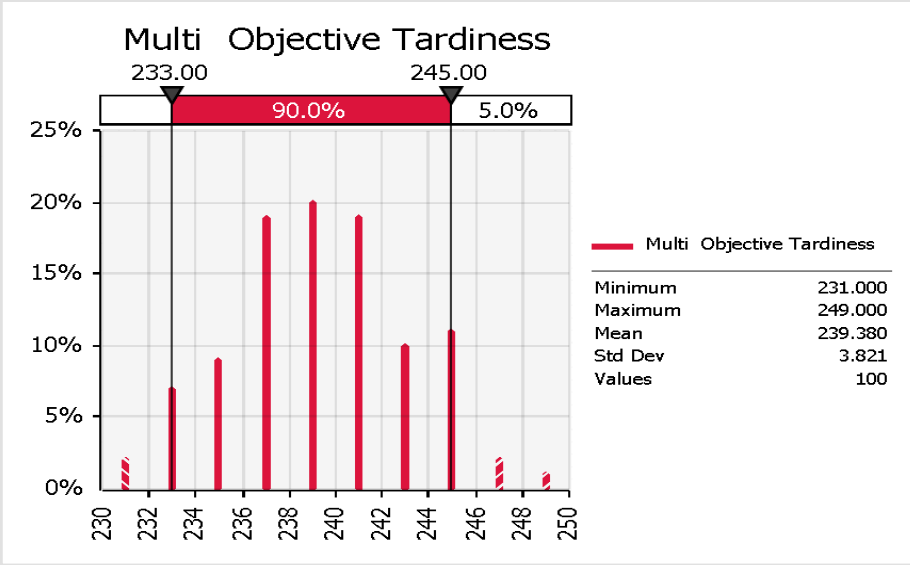

Figure 9. The resulted in Multi-objectives (double weighted maximum machine idle time) while optimizing the makespan

4.2. Maximum Job Tardiness

In the second case, the maximum job tardiness has been minimized. The resultant optimal distribution of the maximum job tardiness is presented in Figure 10 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 11 from which it is also noticed that the duration of the second task of job 5 on machine 3 has the greatest effect on the resultant optimal mean of the maximum job tardiness which is logic according to the Gantt chart shown in Figure 1.

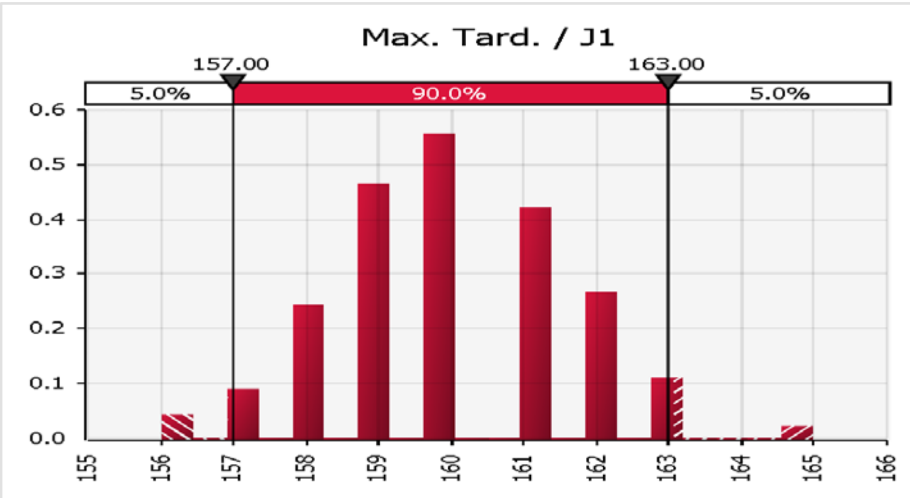

Figure 10. Optimal maximum job tardiness distribution

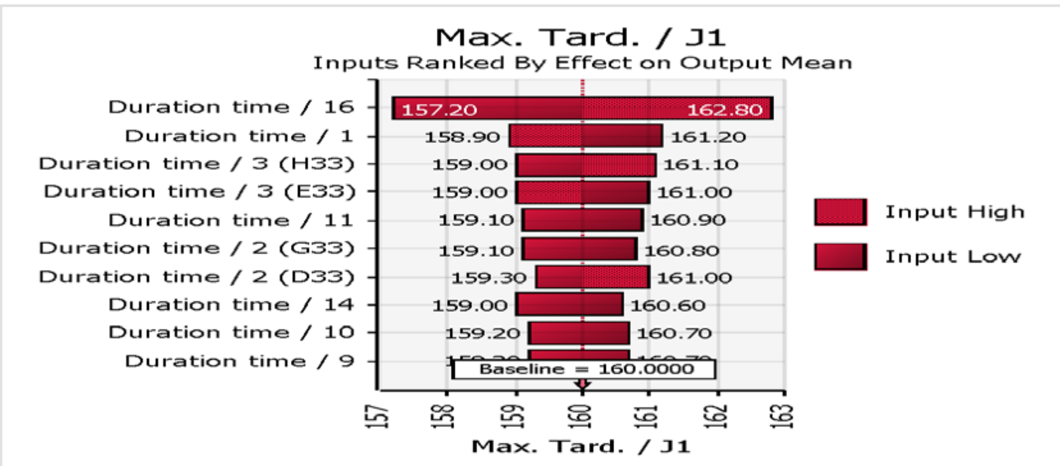

Figure 11. Inputs ranked by the effect on maximum job tardiness

4.3. Maximum Machine Idle Time

In the third case, the problem is solved to minimize the maximum machine idle time. The resultant optimal distribution of the maximum job tardiness is presented in Figure 12 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 13 from which it is noticed that the duration of the fourth task of job 4 on machine 1 has the greatest effect on the resultant optimal mean of the maximum machine idle time.

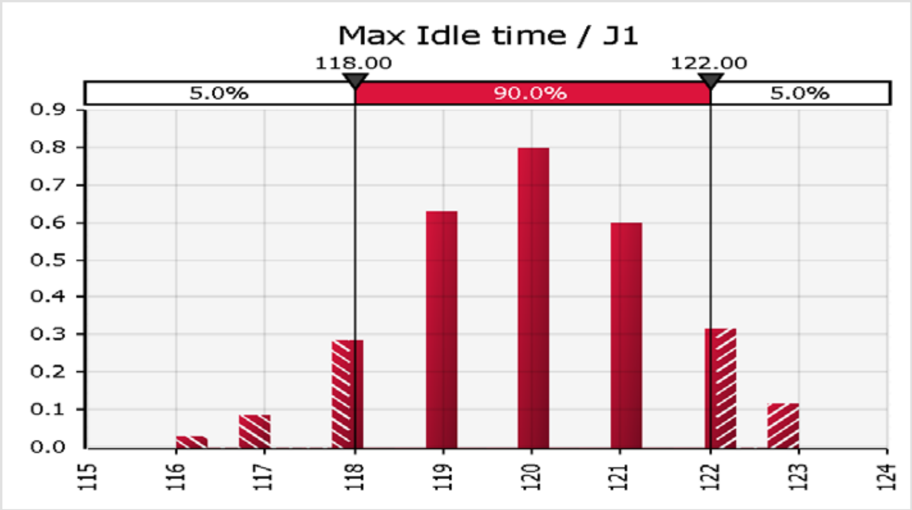

Figure 12. Optimal maximum machine idle time distribution

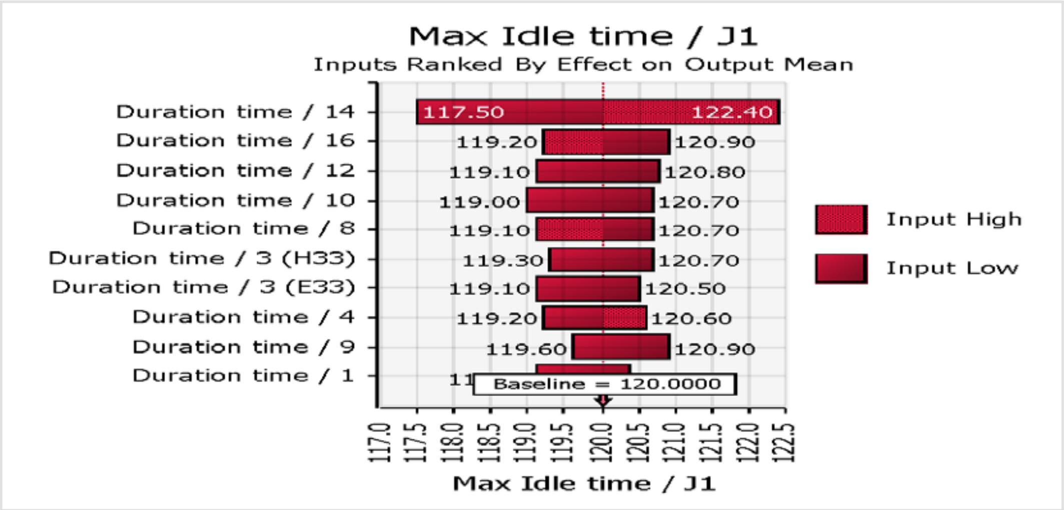

Figure 13. Inputs ranked by the effect on the maximum machine idle time

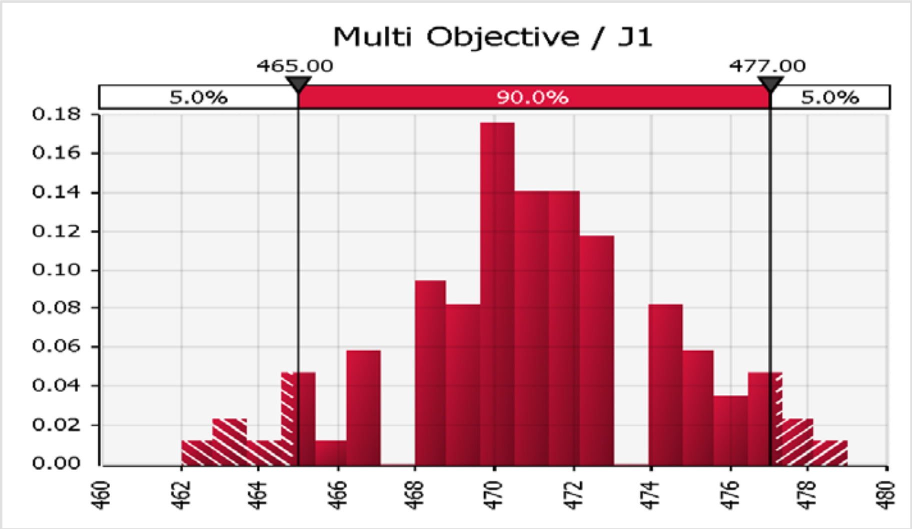

Figure 14. Optimal multi-objectives (Equal weights) distribution

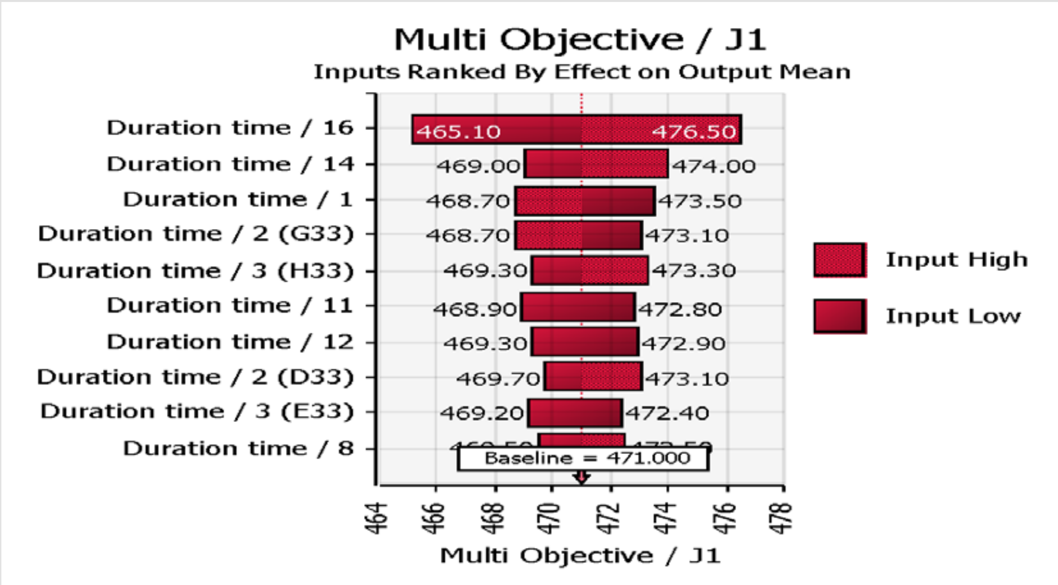

Figure 15. Inputs ranked by the effect on the multi-objectives (Equal weights)

4.4. Multi-objectives (Equal Weights)

In the fourth case, the problem has been solved to minimize the fourth objective that has been presented in Equation 4. The resultant optimal distribution of the fourth objective is presented in Figure 14 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 15 from which it is noticed that the duration of the last task of job 5 on machine 3 has the greatest effect on it.

4.5. Multi-objectives (Double Weighted Makespan)

In the fifth case, the problem has been solved to minimize the fourth objective that has been presented in Equation 5. The resultant optimal distribution of the fourth objective is presented in Figure 16 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 17 from which it is noticed that the duration of the last task of job 5 on machine 3 has the greatest effect on it.

4.6. Multi-objectives (Double Weighted Maximum Job Tardiness)

In the sixth case, the problem has been solved to minimize the fourth objective, which has been presented in Equation 6. The resultant optimal distribution of the fourth objective is presented in Figure 18 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 19 from which it is noticed that the duration of the last task of job 5 on machine 3 has the greatest effect on it.

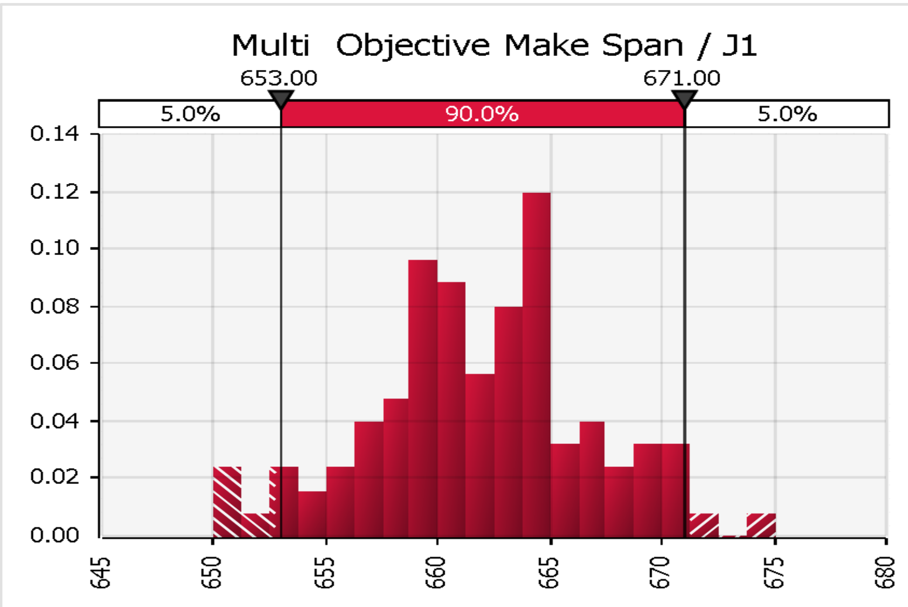

Figure 16. Optimal multi-objective (double weighted makespan) distribution

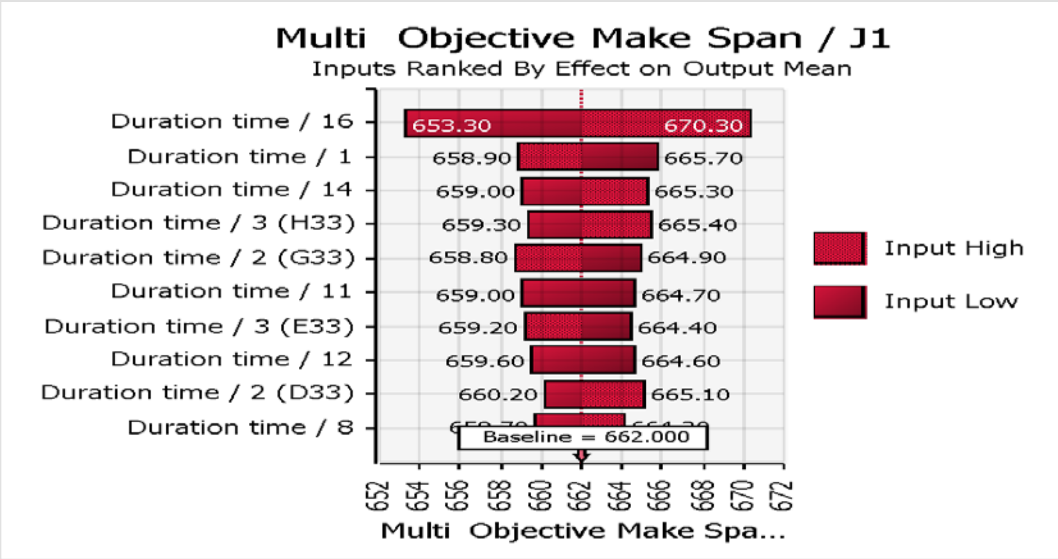

Figure 17. Inputs ranked by the effect on the multi-objectives (double weighted makespan)

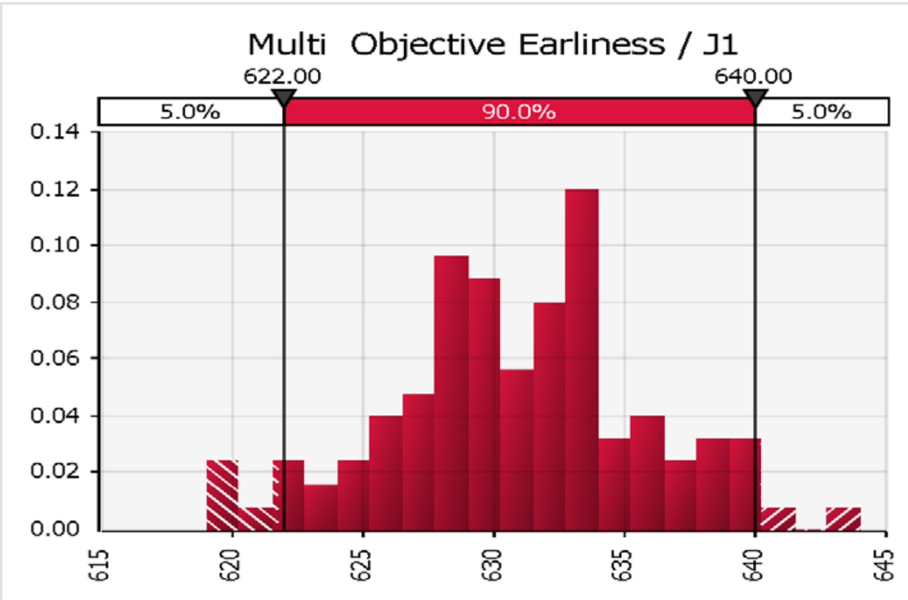

Figure 18. Optimal multi-objective (double weighted maximum job tardiness) distribution

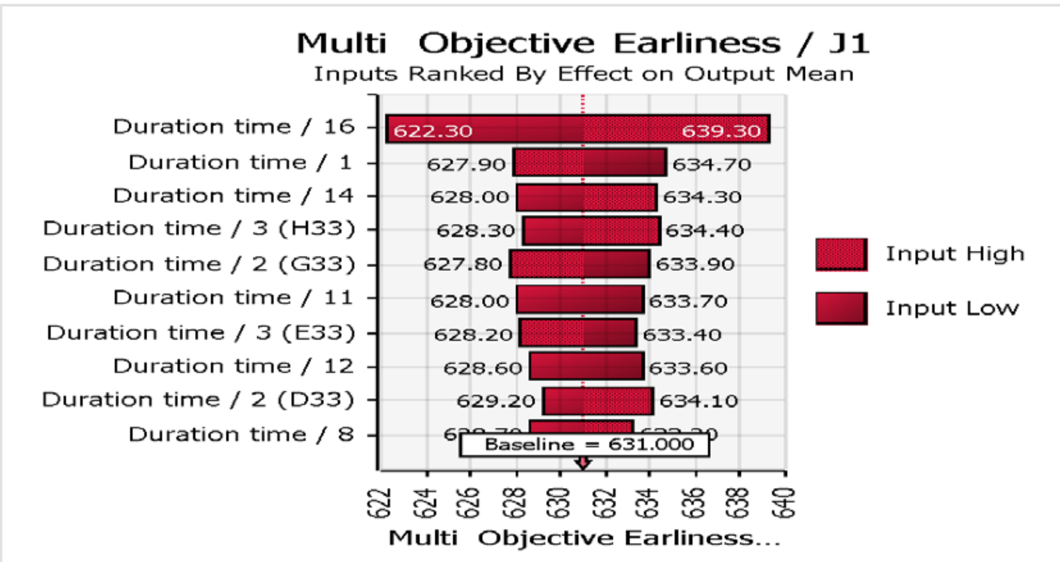

Figure 19. Inputs ranked by the effect on the multi-objectives (double weighted maximum job tardiness)

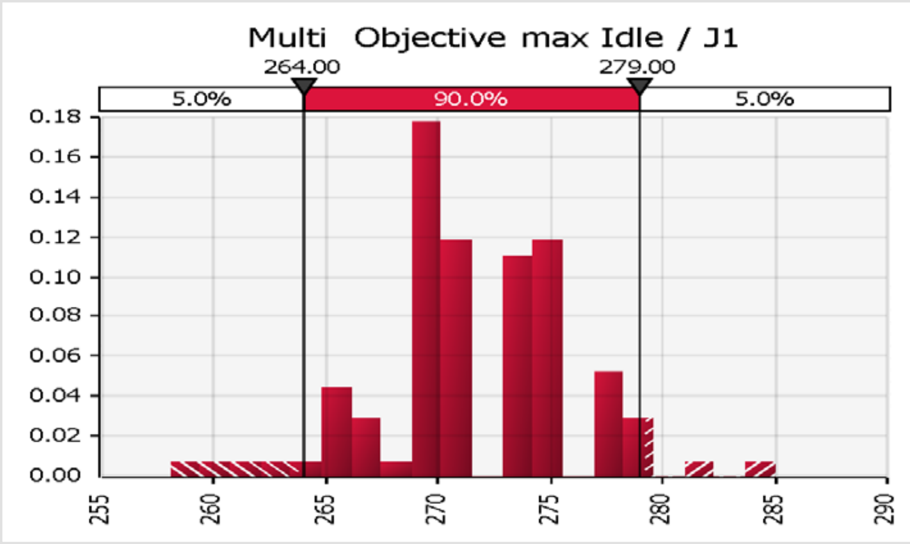

Figure 20. Optimal Multi-objective (double weighted maximum machine idle time) distribution

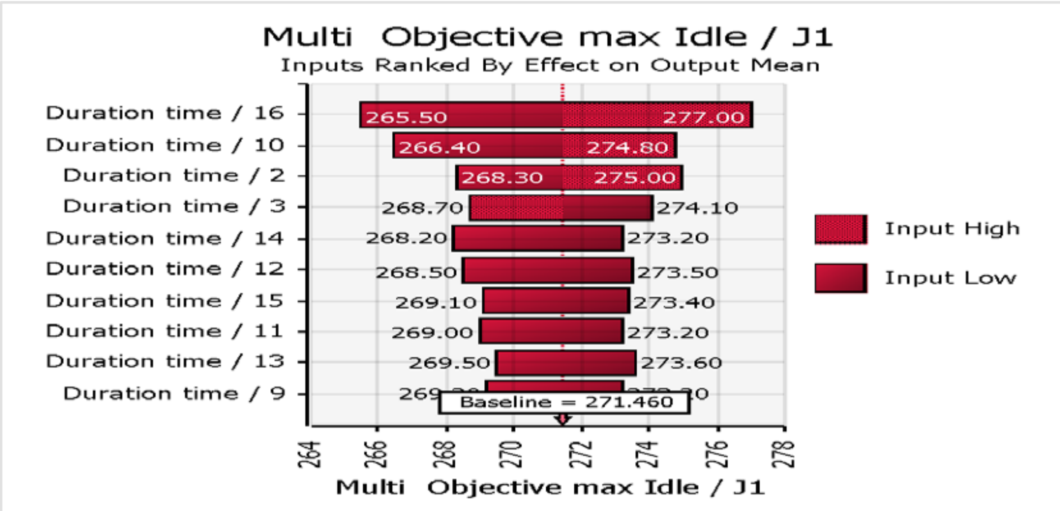

Figure 21. Inputs ranked by the effect on the multi-objectives (double weighted maximum machine idle time)

4.7. Multi-objectives (Double Weighted Maximum Machine Idle Time)

In the seventh case, the problem has been solved to minimize the fourth objective, which has been presented in Equation 7. The resultant optimal distribution of the fourth objective is presented in Figure 20 and processing times of the tasks have been ranked by the effect on the output mean of the makespan as shown in Figure 21 from which it is noticed that the duration of the last task of job 5 on machine 3 has the greatest effect on it.

5. Conclusion

In this study, a multi-objective job-shop scheduling model under uncertainty is developed to optimize makespan, maximum job tardiness and the maximum idle time of machines under risk. The model considers multi-jobs and multi-machines. Each task has a specific due date and random processing times of specific probability distribution. The model is solved using both Evolver and @RiskOptimizer.

The accuracy of the model has been verified through logical analysis of its results. Throughout the gotten results, it may be concluded that it is necessary to reduce the variation of the task’s processing times by applying more training of the personnel and removing or at least reducing the resources of variation to get more stable schedules.

References

[1] G. Zhang, X. Shao, P. Li, and L. Gao, "An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem," *Computers & Industrial Engineering*, vol. 56, pp. 1309-1318, 2009.

[2] K.-L. Huang and C.-J. Liao, "Ant colony optimization combined with taboo search for the job shop scheduling problem," *Computers & operations research*, vol. 35, pp. 1030-1046, 2008.

[3] A. Udomsakdigool and V. Kachitvichyanukul, "Multiple colony ant algorithm for job-shop scheduling problem," *International Journal of Production Research*, vol. 46, pp. 4155-4175, 2008.

[4] M. S. Al-Ashhab, Munshi, S., Oreijah, M., & Ghulman, H., "Job Shop Scheduling Using Mixed Integer Programming," *International Journal Of Modern Engineering Research*, vol. 7, p. 7, 2017.

[5] K. R. Baker and B. Keller, "Solving the single-machine sequencing problem using integer programming," *Computers & Industrial Engineering*, vol. 59, pp. 730-735, 2010.

[6] M. Dell'Amico and M. Trubian, "Applying tabu search to the job-shop scheduling problem," *Annals of Operations research*, vol. 41, pp. 231-252, 1993.

[7] A. Ponsich and C. A. C. Coello, "A hybrid differential evolution—tabu search algorithm for the solution of job-shop scheduling problems," *Applied Soft Computing*, vol. 13, pp. 462-474, 2013.

[8] H. R. Lourenco, "Job-shop scheduling: Computational study of local search and large-step optimization methods," *European Journal of Operational Research*, vol. 83, pp. 347-364, 1995.

[9] M. Faccio, J. Ries, and N. Saggiorno, "Simulated annealing approach to solve dual resource constrained job shop scheduling problems: layout impact analysis on solution quality," *International Journal of Mathematics in Operational Research*, vol. 7, pp. 609-629, 2015.

[10] D. Sha and C.-Y. Hsu, "A hybrid particle swarm optimization for job shop scheduling problem," *Computers & Industrial Engineering*, vol. 51, pp. 791-808, 2006.

[11] T.-L. Lin, S.-J. Horng, T.-W. Kao, Y.-H. Chen, R.-S. Run, R.-J. Chen, *et al.*, "An efficient job-shop scheduling algorithm based on particle swarm optimization," *Expert Systems with Applications*, vol. 37, pp. 2629-2636, 2010.

[12] L. Gao, G. Zhang, L. Zhang, and X. Li, "An efficient memetic algorithm for solving the job shop scheduling problem," *Computers & Industrial Engineering*, vol. 60, pp. 699-705, 2011.

[13] R. Cheng, M. Gen, and Y. Tsujimura, "A tutorial survey of job-shop scheduling problems using genetic algorithms—I. Representation," *Computers & industrial engineering*, vol. 30, pp. 983-997, 1996.

[14] Y. Wang, "A new hybrid genetic algorithm for job shop scheduling problem," *Computers & Operations Research*, vol. 39, pp. 2291-2299, 2012.

[15] M. Al-Ashhab, "Multi-Objective Job Shop Scheduling Using a Lexicographic Procedure."

[16] P. Quanke, W. Ling, and G. Liang, "Differential evolution algorithm based on blocks on critical path for job shop scheduling problems," *Journal of Mechanical Engineering*, vol. 46, pp. 182-188, 2010.

[17] H. M. Wagner, "An integer linear-programming model for machine scheduling," *Naval Research Logistics (NRL)*, vol. 6, pp. 131-140, 1959.

[18] A. S. Manne, "On the job-shop scheduling problem," *Operations Research*, vol. 8, pp. 219-223, 1960.

[19] A. Scaria, K. George, and J. Sebastian, "An Artificial Bee Colony Approach for Multi-objective Job Shop Scheduling," *Procedia Technology*, vol. 25, pp. 1030-1037, 2016.

[20] K. P. Yoon and C.-L. Hwang, *Multiple attribute decision making: an introduction* vol. 104: Sage publications, 1995.

[21] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and multidisciplinary optimization*, vol. 26, pp. 369-395, 2004.

[22] R. L. Becerra and C. A. Coello Coello, "Epsilon-constraint with an efficient cultured differential evolution," in *Proceedings of the 9th annual conference companion on Genetic and evolutionary computation*, 2007, pp. 2787-2794.

[23] M. Laumanns, L. Thiele, and E. Zitzler, "An efficient, adaptive parameter variation scheme for metaheuristics based on the epsilon-constraint method," *European Journal of Operational Research*, vol. 169, pp. 932-942, 2006.

[24] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multiobjective evolutionary algorithms: Empirical results," *Evolutionary computation*, vol. 8, pp. 173-195, 2000.

[25] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE transactions on evolutionary computation*, vol. 6, pp. 182-197, 2002.

[26] J.-F. Bérubé, M. Gendreau, and J.-Y. Potvin, "An exact ε-constraint method for bi-objective combinatorial optimization problems: Application to the Traveling Salesman Problem with Profits," *European journal of operational research*, vol. 194, pp. 39-50, 2009.

[27] M. Boulif and K. Atif, "An exact multiobjective epsilon-constraint approach for the manufacturing cell formation problem," in *Service systems and service management, 2006 International Conference on*, 2006, pp. 883-888.

[28] L. Grandinetti, F. Guerriero, D. Laganà, and O. Pisacane, "An optimization-based heuristic for the multi-objective undirected capacitated arc routing problem," *Computers & Operations Research*, vol. 39, pp. 2300-2309, 2012.

[29] M. Al-Ashhab, "Multi-Objective Job Shop Scheduling Using a Lexicographic Procedure," *International Journal of Engineering Science Invention (IJESI)*, vol. 7, p. 10, 2018.

[30] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*. MA: Addison-Wesley, Reading, 1989.

[31] D. Goldberg, "Genetic algorithms in search, optimization and Machine Learning Addison-Wesley Reading Google Scholar," 1989.

[32] D. Lei, "Simplified multi-objective genetic algorithms for stochastic job shop scheduling," *Applied Soft Computing*, vol. 11, pp. 4991-4996, 2011.

[33] J. Huang and G. A. Süer, "A dispatching rule-based genetic algorithm for multi-objective job shop scheduling using fuzzy satisfaction levels," *Computers & Industrial Engineering*, vol. 86, pp. 29-42, 2015.

[34] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," *IEEE Transactions on evolutionary computation*, vol. 1, pp. 53-66, 1997.

[35] L. Ke, Q. Zhang, and R. Battiti, "MOEA/D-ACO: A multiobjective evolutionary algorithm using decomposition and antcolony," *IEEE transactions on cybernetics*, vol. 43, pp. 1845-1859, 2013.

[36] R. Kuo and W. Cheng, "Hybrid meta-heuristic algorithm for job shop scheduling with due date time window and release time," *The International Journal of Advanced Manufacturing Technology*, vol. 67, pp. 59-71, 2013.

[37] Z.-h. Jia, C. Wang, and J. Y.-T. Leung, "An ACO algorithm for makespan minimization in parallel batch machines with non-identical job sizes and incompatible job families," *Applied Soft Computing*, vol. 38, pp. 395-404, 2016.

[38] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on*, 1995, pp. 39-43.

[39] H. Hirano and T. Yoshikawa, "A study on two-step search based on PSO to improve convergence and diversity for Many-Objective Optimization Problems," in *Evolutionary Computation (CEC), 2013 IEEE Congress on*, 2013, pp. 1854-1859.

[40] F. Zhao, J. Tang, and J. Wang, "An improved particle swarm optimization with decline disturbance index (DDPSO) for multi-objective job-shop scheduling problem," *Computers & Operations Research*, vol. 45, pp. 38-50, 2014.

[41] L.-L. Liu, R.-S. Hu, X.-P. Hu, G.-P. Zhao, and S. Wang, "A hybrid PSO-GA algorithm for job shop scheduling in machine tool production," *International Journal of Production Research*, vol. 53, pp. 5755-5781, 2015.

[42] K. Shahnaghi, H. Shahmoradi-Moghadam, A. Noroozi, and H. Mokhtari, "A robust modelling and optimisation framework for a batch processing flow shop production system in the presence of uncertainties," *International Journal of Computer Integrated Manufacturing*, vol. 29, pp. 92-106, 2016.

[43] M. Gong, T. Hou, B. Fu, and L. Jiao, "A non-dominated neighbor immune algorithm for community detection in networks," in *Proceedings of the 13th annual conference on Genetic and evolutionary computation*, 2011, pp. 1627-1634.

[44] M. Costa and E. Minisci, "MOPED: a multi-objective Parzen-based estimation of distribution algorithm for continuous problems," in *International Conference on Evolutionary Multi-Criterion Optimization*, 2003, pp. 282-294.

[45] Y. Gao, L. Peng, F. Li, M. Liu, and X. Hu, "Eda-based multi-objective optimization using preference order ranking and multivariate gaussian copula," in *International Symposium on Neural Networks*, 2013, pp. 341-350.

[46] L. Wang, S. Wang, and M. Liu, "A Pareto-based estimation of distribution algorithm for the multi-objective flexible job-shop scheduling problem," *International Journal of Production Research*, vol. 51, pp. 3574-3592, 2013.

[47] B. Liu, Y. Fan, and Y. Liu, "A fast estimation of distribution algorithm for dynamic fuzzy flexible job-shop scheduling problem," *Computers & Industrial Engineering*, vol. 87, pp. 193-201, 2015.

[48] M. Sevaux and K. Sörensen, "A genetic algorithm for robust schedules in a one-machine environment with ready times and due dates," *Quarterly Journal of the Belgian, French and Italian Operations Research Societies*, vol. 2, pp. 129-147, 2004.

[49] C. W. Wu, K. N. Brown, and J. C. Beck, "Scheduling with uncertain release dates," *AICS'05*, p. 397, 2005.

[50] A. Alhindi and Q. Zhang, "MOEA/D with Tabu search for multiobjective permutation flow shop scheduling problems," in *2014 IEEE Congress on Evolutionary Computation (CEC)*, 2014, pp. 1155-1164.

[51] P. C. Chang, S. H. Chen, Q. Zhang, and J. L. Lin, "MOEA/D for flowshop scheduling problems," in *2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence)*, 2008, pp. 1433-1438.

[52] J. S. Alzahrani, "JOB SHOP SCHEDULING CONSIDERING MAKESPAN, PENALTIES OF MACHINE IDLING, AND JOB OUT OF TIME," *International Journal of Research - Granthaalayah*, vol. 7, p. 10, 2019.