Selection of Objective MCDM Frameworks for Production Planning and Facility Layout Problems

Madhusudhan Thimmappa
Faculty of Mechanical Engineering, Technical University of Liberec

Abstract

This paper presents a practical way to select and compare Multi-Criteria Decision Making (MCDM) frameworks for industrial engineering problems. The main aim is to avoid direct expert weighting, because in real cases experts may not be available or may not be able to give reliable weights. Therefore, objective weighting methods are used. CRITIC and Entropy are selected for weight calculation, and TOPSIS, VIKOR and ELECTRE are selected for ranking. These methods are combined into six frameworks. The frameworks are tested on two problems. The first one is the Flexible Job Shop Scheduling Problem (FJSSP), where Brandimarte MK02 and MK07 are used. Two genetic algorithm settings are tested R+R and Cp+CtMin. For each setting, both the start population and the final population are evaluated. The second problem is the Facility Layout Problem (FLP), where the 6-1-1 benchmark instance is used. This instance contains six workshops, an entrance and exit system, pick-up and drop-off points, material flow values and aisle space limits. The MCDM results are compared by Spearman score, rank reversal, sensitivity analysis, Euclidean distance, mean absolute rank difference and Friedman test. The results show that Entropy-ELECTRE is most suitable for the tested FJSSP cases, while Entropy-VIKOR is most suitable for the tested FLP case. The paper also shows that comparison measures should be evaluated by their ability to clearly separate the frameworks.

Keywords: MCDM, CRITIC, Entropy, TOPSIS, VIKOR, ELECTRE, FJSSP, FLP, comparison methods

1. Introduction

Industrial engineering decisions are usually made under several conditions at the same time. In production planning, a schedule may be good in one criterion but weak in another. For example, one schedule can have a short makespan, but it can still create high tardiness or poor machine use. In facility layout design, one layout can reduce transport distance but leave poor free space for later changes. Because of this, one criterion is usually not enough to choose the best solution.

Multi-Criteria Decision Making (MCDM) is useful in this situation because it gives a structured way to compare alternatives using several criteria together. However, selecting the MCDM method is also a decision problem. Different methods can give different rankings for the same alternatives. This is why the method should not be selected only because it is popular or easy to use. It should be tested on the real data of the problem.

The motivation of this work is to find MCDM framework combinations that do not depend on direct expert weighting. Expert weighting methods are common, but they can be difficult in practice. Sometimes experts are not available. Sometimes it's not reliable. Sometimes different experts may also give different weights. For this reason, this paper focuses on objective weighting methods, where the weights are calculated from the decision matrix.

Two common industrial engineering problems are used. The first one is the Flexible Job Shop Scheduling Problem (FJSSP). In this problem, production schedules are compared. The second one is the Facility Layout Problem (FLP). In this problem, layout alternatives are compared. These two problems were selected because both are practical, both include several criteria, and both are common in production planning and design.

The paper follows a simple logic. First, objective weights are calculated. Second, the alternatives are ranked by selected MCDM methods. Third, the ranking results are compared using several comparison measures. The final framework is selected based on the full comparison, not only on one result table.

2. Framework design

The main abbreviations used in the framework are CRITIC - Criteria Importance Through Intercriteria Correlation, Entropy, TOPSIS - Technique for Order Preference by Similarity to Ideal Solution, VIKOR - Multi-Criteria Optimization and Compromise Solution, ELECTRE - Elimination et Choix Traduisant la Réalité.

The tested MCDM framework has two parts. The first part is the weighting method. This part decides the importance of each criterion. The second part is the ranking method. This part uses the criteria values and weights to rank the alternatives. In this work, CRITIC and Entropy are used as weighting methods. TOPSIS, VIKOR and ELECTRE are used as ranking methods. By combining them, six frameworks are obtained.

Table 1 MCDM frameworks

Weighting method	Ranking methods	Frameworks used
CRITIC	TOPSIS, VIKOR, ELECTRE	CRITIC-TOPSIS, CRITIC-VIKOR, CRITIC-ELECTRE
Entropy	TOPSIS, VIKOR, ELECTRE	Entropy-TOPSIS, Entropy-VIKOR, Entropy-ELECTRE

This design makes it possible to study two things. First, it shows how the weighting method changes the final ranking. Second, it shows how the ranking method behaves with the same set of weights. This is useful because the final result can depend on both parts of the framework.

2.1 CRITIC weighting

CRITIC is an objective weighting method [1]. It gives higher importance to criteria that have larger variation and lower correlation with other criteria. In simple words, a criterion receives a higher weight when it helps to separate the alternatives and does not repeat the same information as another criterion.

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - r_{jk}) \tag{1}$$

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{2}$$

where C_j is the information content of criterion j, σ_j is the standard deviation of criterion j, r_{jk} is the correlation between criteria j and k, and w_j is the final weight. CRITIC is useful in this paper because some criteria can be partly related. For example, in layout problems, material handling cost and movement distance can be connected. CRITIC helps reduce the effect of repeated information [1].

2.2 Entropy weighting

Entropy is also an objective weighting method, but it uses a different idea [2]. It gives more importance to criteria whose values are more different between alternatives. If all alternatives have almost the same value for one criterion, that criterion is not very useful for decision-making, so it receives a smaller weight.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \quad (4)$$

$$k = \frac{1}{\ln m} \quad (5)$$

$$d_j = 1 - e_j \quad (6)$$

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (7)$$

where x_{ij} is the value of alternative i under criterion j, p_{ij} is the normalized proportion, ej is the entropy value, d_j is the diversification degree, and w_j is the final weight. Entropy is useful when the researcher wants a simple data-based weighting method. Its limitation is that it does not directly check correlation between criteria [2].

2.3 TOPSIS, VIKOR and ELECTRE ranking

TOPSIS ranks alternatives by looking at their distance from the ideal and the worst solution [3]. A good alternative should be close to the ideal solution and far from the worst solution. This makes TOPSIS easy to explain and easy to use in practical evaluation.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \quad (8)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (9)$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (10)$$

VIKOR is used when a compromise solution is needed [4]. It considers the group utility value and the individual regret value. This is useful when criteria conflict and no alternative is clearly best in all criteria.

$$S_i = \sum_{j=1}^{n} w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \quad (11)$$

$$R_i = \max_j \left[w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \quad (12)$$

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (13)$$

ELECTRE uses pairwise comparison. It checks whether one alternative can outrank another [5]. It uses concordance to show support for this statement and discordance to check if there is a strong reason against it. This is useful when a very weak value in one criterion should not be completely hidden by good values in other criteria.

$$C(a,b) = \sum_{j \in J(a,b)} w_j \tag{14}$$

$$D(a,b) = \max_{j \in \bar{J}(a,b)} \frac{|\, g_j(b) - g_j(a) \,|}{R_j} \tag{15}$$

3. Selection of Comparison Method

After the six MCDM frameworks are applied, their ranking results are compared. The aim is not to see which framework selects the best alternative, but also to check how the full ranking behaves. For this reason, different comparison measures are used. Each measure checks the ranking from a different side [6].

Table 2 Comparison measures used after ranking

Measure	Short name	Main purpose	Expected better result
Spearman score	SS	Checks similarity with the common ranking pattern	Lower distance
Rank reversal	RR	Checks if ranking changes when alternatives change	Lower
Sensitivity analysis	SA	Checks ranking change under 5%, 10%, and 15% data changes	Lower
Euclidean distance	ED	Checks full rank distance	Lower
Mean absolute rank difference	MAR	Checks average movement of ranks	Lower
Friedman test	FT	Checks average rank performance	Lower

Spearman score (SS) is used to check how close each framework ranking is to the common ranking pattern. If the value is better, it means that the framework gives a ranking similar to the general result of the other frameworks [7].

Rank reversal (RR) checks whether the ranking changes when the set of alternatives is changed. A good framework should not strongly change the order of the remaining alternatives when one alternative is removed [6].

Sensitivity analysis (SA) checks what happens when the input data changes slightly. In this paper, the criteria values are changed by 5%, 10%, and 15%. This also works as a robustness check, because a reliable framework should keep a similar ranking under small data changes.

Euclidean distance (ED) measures how far one ranking is from the reference ranking. It gives more importance to larger rank differences. A lower value means that the ranking is closer to the reference ranking.

Mean absolute rank difference (MAR) checks the average movement of rank positions. It shows how much the alternatives move, on average, compared with the reference ranking. A lower value means smaller rank changes.

Friedman test (FT) is used to compare the average rank performance of the frameworks. It gives an additional statistical view of how the frameworks behave across the tested cases.

The comparison measures are also evaluated by their range. If one measure has a wide range, it separates the frameworks more clearly. If the range is very small, the framework values are close to each other, and that measure is not strong enough for final selection by itself. Therefore, the final decision should not depend on only one comparison method.

4. Implementation and validation

The calculations were first checked on small examples before they were used for the final benchmark data. This step was important because a small mistake in criteria direction, normalisation or weight calculation can change the complete ranking. For this reason, the implementation was not used directly without checking.

CRITIC and Entropy were first calculated manually in Excel. The same data were then calculated in Python. When the Excel and Python results matched, the weighting part was accepted. For TOPSIS, VIKOR and ELECTRE, the input matrix, criteria directions, normalisation, weights and final ranking outputs were checked step by step.

The final calculations were carried out in Python in Visual Studio Code. The same structure was used for both FJSSP and FLP. This made the comparison easier.

Table 3 . Main validation checks used before the final comparison

Part checked	Reason for checking
Decision matrix	To make sure the same data were used in all methods
Criteria direction	To keep minimisation and maximisation correct
CRITIC and Entropy weights	To compare Excel and Python results
Final output	To confirm that the rankings were reasonable and consistent

5. FJSSP benchmark setting

The scheduling part is based on the Brandimarte FJSSP benchmark. Two models are used MK02 and MK07. These two instances were selected to test the frameworks on more than one scheduling condition. The schedules used as alternatives come from genetic algorithm results, not from manual preparation [8].

Two genetic algorithm settings are selected. The first setting is R+R. This setting uses random rules during schedule generation. It gives more varied and less guided schedules. The second setting is Cp+CtMin. This setting uses critical path information together with completion time minimisation. It gives more guided schedules and usually moves the results closer to good local solutions [9, 10].

The same two settings are applied to both MK02 and MK07. For each setting, the start population and the final population are analysed. The start population means the first generation before the genetic algorithm improves the schedules. The final population means the last generation after the improvement process. This makes it possible to compare the MCDM frameworks before and after optimization [9, 10].

Table 4 FJSSP testing setup

Item	Used setting in the paper
Benchmark instances	Brandimarte MK02 and MK07
Schedule-generation settings	R+R and Cp+CtMin
Population stages	Start population and final population
Weighting methods	CRITIC and Entropy
Ranking methods	TOPSIS, VIKOR and ELECTRE
Comparison measures	SS, RR, SA, ED, MAR and FT

Four criteria are used in the FJSSP evaluation. Makespan shows the total completion time of the schedule. Total tardiness shows how much the jobs are delayed. Total processing time shows the processing work assigned in the schedule. Average machine utilisation shows how much of the available machine time is used. Makespan, tardiness and processing time are minimized, while utilization is maximized.

Table 5 FJSSP criteria used in the MCDM evaluation

Criterion	Direction	Meaning
Makespan	Minimise	Total time needed to finish all jobs
Total tardiness	Minimise	Total delay of jobs after their due dates
Total processing time	Minimise	Total processing work in the schedule
Average machine utilisation	Maximise	Average use of available machine time

6. FJSSP results

The detailed FJSSP evaluation was carried out for MK02 and MK07, for both R+R and Cp+CtMin, and for both start and final populations. After these detailed results, the average values were prepared. shows the total average result. The values are expressed as distance from the best result of each comparison measure. Therefore, lower values are better.

Table 6 FJSSP total average comparison, distance from best result (%)

Framework	SS	RR	SA	ED	MAR	FT	Total avg.
CRITIC-TOPSIS	0.2	59.1	2.7	3.5	2.3	6.5	**12.4**
CRITIC-VIKOR	15.8	52.1	2.7	69.9	71.4	2.8	35.8
CRITIC-ELECTRE	11.0	0.5	0.3	54.5	58.1	9.9	22.4
Entropy-TOPSIS	4.4	51.8	2.1	14.5	14.8	1.8	14.9
Entropy-VIKOR	3.1	49.9	2.3	8.8	8.7	2.5	**12.5**
Entropy-ELECTRE	1.9	6.9	0.9	6.6	5.3	6.3	**4.7**
Range	15.7	58.6	2.5	66.4	69.2	8.1	

Entropy-ELECTRE gives the best total average value, 4.7%. This framework is strong because it performs well in stability-related measures and also gives low distance-based values. In simple words, the ranking does not change strongly when the alternatives or data values change.

CRITIC-TOPSIS and Entropy-VIKOR are close to each other. CRITIC-TOPSIS has a total average of 12.4%, and Entropy-VIKOR has 12.5%. CRITIC-TOPSIS is useful when ranking similarity is important. Entropy-VIKOR gives a more balanced result across several measures. CRITIC-VIKOR gives the weakest result because its ED and MAR values are high, which means its rank positions are far from the common ranking pattern.

The FJSSP result also shows that the comparison method matters. Rank reversal, Euclidean distance and mean absolute rank difference have wide ranges. These methods separate the frameworks clearly. Sensitivity analysis and Friedman test have smaller ranges, so they are better used as supporting checks.

7. FLP benchmark setting

The layout part uses the 6-1-1 FLP benchmark instance [11]. The model contains six workshops placed in a limited facility area of 40 x 26 m. Each workshop has a fixed size, a pick-up point and a drop-off point. The facility also has one entrance and one exit. Material flow values describe how strongly the workshops are connected.

This problem is more realistic than a simple distance layout problem because the transport paths are not treated as zero-width lines. The aisles take real space. Therefore, the layout must be evaluated not only by movement cost, but also by the space used by aisles, the number of turns in paths and the remaining regular free space [11].

Table 7 FLP testing setup

Item	Used setting in the paper
Benchmark instance	6-1-1 FLP instance
Number of workshops	Six workshops
Facility size	40 x 26 m
Logistics points	Pick-up points, drop-off points, entrance and exit
Alternative source	Constructive algorithm results
Evaluation criteria	MHC, ACMC, NTurns and MaxSQ

The FLP alternatives are compared using four criteria. Material handling cost (MHC) measures the cost of moving materials between workshops. Aisle/access corridor measure (ACMC) measures the aisle or access space used by the transport system. Number of turns (NTurns) counts direction changes in material paths. Maximum remaining square space (MaxSQ) shows the largest regular free square area left in the layout. MHC, ACMC and NTurns are minimised. MaxSQ is maximised.

Table 8 FLP criteria used in the MCDM evaluation

Criterion	Direction	Meaning
MHC	Minimise	Cost or effort of material movement
ACMC	Minimise	Space used by aisles and access corridors
NTurns	Minimise	Number of direction changes in paths
MaxSQ	Maximise	Largest remaining regular square free space

8. FLP results

The FLP evaluation uses the same six MCDM frameworks as the FJSSP part. *Table **9*** shows the direct comparison values for the 6-1-1 benchmark. For Spearman score, robustness and sensitivity, higher original values mean better behaviour. For Euclidean distance, MAR and Friedman average, lower values are better.

Table 9 . FLP framework evaluation for the 6-1-1 benchmark

Framework	Spearman	Robust. %	Sensitivity	ED	MAR	Friedman
CRITIC-ELECTRE	0.868	75.3	**0.988**	14.2	2.44	3.50
CRITIC-TOPSIS	**0.895**	20.9	0.740	11.6	1.98	**2.95**
CRITIC-VIKOR	0.629	82.1	0.996	23.9	4.14	3.70
Entropy-ELECTRE	0.854	**90.4**	0.998	12.8	2.16	3.25
Entropy-TOPSIS	0.821	20.4	0.746	14.4	2.52	3.05
Entropy-VIKOR	0.896	77.7	0.993	**11.3**	**1.80**	3.30

Entropy-VIKOR gives the highest Spearman score, 0.896, and CRITIC-TOPSIS is almost the same with 0.895. This means that both rankings are close to the common ranking pattern. For rank reversal robustness and sensitivity, Entropy-ELECTRE gives the best values. This means that it is the most stable framework when the alternative set or the input data changes.

For Euclidean distance and MAR, Entropy-VIKOR gives the best result. This shows that its rank positions are closest to the reference ranking. CRITIC-TOPSIS is also strong in these two measures, but its stability values are weaker. To make the final comparison easier, the values were converted into distance from the best result, as shown in *Table **10***.

Table 10 FLP total average comparison, distance from best result (%)

Framework	SS	RR	SA	ED	MAR	FT	Total avg.
CRITIC-ELECTRE	3	17	1	25	36	0	**13.6**
CRITIC-TOPSIS	0	77	26	2	10	3	19.7
CRITIC-VIKOR	30	9	0	111	130	10	48.4
Entropy-ELECTRE	5	0	0	13	20	12	**8.2**
Entropy-TOPSIS	8	77	25	27	40	19	32.8
Entropy-VIKOR	0	14	0	0	0	25	**6.7**
Range	29.9	77.5	25.9	111.1	130.0	25.4	

Entropy-VIKOR gives the best total average result, 6.7%. Its main strength is ranking similarity and ranking distance. It performs very well in Spearman score, Euclidean distance and MAR. Entropy-ELECTRE is second, with 8.2%. Its main strength is stability, because it is best in rank reversal and sensitivity analysis.

CRITIC-ELECTRE also has good stability, but its ED and MAR values are weaker. CRITIC-TOPSIS gives good similarity, but it is weak in robustness and sensitivity. Entropy-TOPSIS is weaker because of high rank reversal and sensitivity distance values. CRITIC-VIKOR gives the weakest total result because ED and MAR are very high.

In the FLP table, MAR and ED have the widest ranges. This means that these two measures are very useful for showing clear differences between frameworks. Rank reversal also has a wide range and is useful for stability checking. Spearman score, sensitivity and Friedman test are useful as additional checks, but they should not be used alone.

9. Discussion of both problems

The two problems do not give the same final framework. This is expected because FJSSP and FLP have different data behaviour. FJSSP contains generated schedules, and the schedules can change strongly between the first and final population. In this case, stability is very important. That is why Entropy-ELECTRE becomes the most suitable framework for the full FJSSP comparison.

The FLP case is different. The alternatives are layout solutions from the 6-1-1 constructive algorithm results. In this case, Entropy-VIKOR gives rankings that are close to the common ranking pattern and also have low rank distance. Therefore, Entropy-VIKOR is more suitable for the FLP comparison.

The result also shows that Entropy-based combinations are strong in the tested cases. Entropy-ELECTRE is best for FJSSP, and Entropy-VIKOR is best for FLP. However, this should not be taken as a general rule for all industrial problems. The conclusion is based only on the selected benchmarks. More instances would be needed before saying that Entropy is always the best objective weighting method.

Another important point is that the comparison method influences the interpretation. A method may look good under one comparison measure but weak under another. For example, a framework can be close to the consensus ranking but unstable under rank reversal. Because of this, the final selection should be based on more than one comparison method.

Using the range of comparison results is a simple and useful check. If a measure has a wide range, it gives more information because it separates the frameworks clearly. If a measure has a very small range, it means that all frameworks behave similarly in that measure. In that case, it is safer to treat the measure as supporting information.

10. Proposed simple selection procedure

Based on the study, the MCDM framework selection can be done in a simple sequence. The first step is to define the decision problem and the goal. The second step is to select criteria that describe the problem without repeating the same information. The third step is to generate or collect the alternatives. The fourth step is to normalise the data and set the direction of criteria. The fifth step is to choose weighting and ranking methods. The sixth step is to compare the rankings with several comparison measures. The final step is to select the framework and explain why it fits the problem.

Table 11 Simple methodology for selecting an MCDM framework

Steps	Simple meaning
1. Define the problem	Know what decision has to be made
2. Set criteria	Choose useful criteria and avoid repeated information
3. Prepare alternatives	Use existing or generated solutions
4. Prepare data	Normalise values and set min/max directions
5. Apply frameworks	Combine objective weights with ranking methods
6. Compare rankings	Use similarity, stability and distance measures
7. Select framework	Choose the framework supported by the results

This procedure is useful because it avoids choosing a method only by habit. It also gives a clear explanation of why one framework is selected. This is important in industrial engineering because the final result should be practical, understandable and supported by data.

11. Limitations and future work

The results should be read with some limits in mind. The FJSSP part uses MK02 and MK07, and the FLP part uses the 6-1-1 instance. These benchmarks are useful for testing the method, but they are still only selected cases. A larger study with more scheduling and layout instances would make the final recommendation stronger.

Another limitation is that the tested frameworks are based on two objective weighting methods and three ranking methods. But other methods can also be tested later. For example, more objective weighting methods or other outranking methods can be added to the same framework.

Future work should also include more practical criteria. In scheduling, energy use, worker workload or maintenance limits can be added. In layout design, safety, accessibility, future expansion and ergonomic factors can be included. The same comparison logic can still be used, but the criteria set should always be checked carefully before the final MCDM calculation.

12. Conclusion

This paper compared objective MCDM frameworks for production planning and facility layout problems. The purpose was to reduce dependence on expert weighting and to use data-based weights instead. CRITIC and Entropy were combined with TOPSIS, VIKOR and ELECTRE, which produced six frameworks.

For the FJSSP case, Brandimarte MK02 and MK07 were used. Two genetic algorithm settings were selected R+R and Cp+CtMin. Both start and final populations were evaluated. The best overall framework was Entropy-ELECTRE, mainly because it gave stable results and low total average distance.

For the FLP case, the 6-1-1 benchmark instance was used. The layout alternatives were evaluated using MHC, ACMC, NTurns and MaxSQ. The best overall framework was Entropy-VIKOR because it performed well in ranking similarity and distance-based measures. Entropy-ELECTRE was also strong when stability was the main concern.

The study confirms that one MCDM framework cannot be called the best for every problem. The suitable framework depends on the problem, the criteria, the data and the comparison method. Future work should test the same methodology on more benchmark instances and more generated alternatives. Additional criteria such as energy use, worker workload, safety or environmental impact can also be included.

References

[1] DIAKOULAKI, D.; G. MAVROTAS and L. PAPAYANNAKIS. Determining objective weights in multiple criteria problems: The critic method. online. *Computers & Operations Research*, vol. 22 (1995), no. 7, pp. 763–770. Available from: https://doi.org/10.1016/0305-0548(94)00059-H.

[2] SHANNON, C. E. A Mathematical Theory of Communication. online. *Bell System Technical Journal*, vol. 27 (1948), no. 3, pp. 379–423. Available from: https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

[3] HWANG, Ching-Lai and Kwangsun YOON. *Multiple Attribute Decision Making*. online. Lecture Notes in Economics and Mathematical Systems. Berlin, Heidelberg: Springer Berlin Heidelberg, 1981. Available from: https://doi.org/10.1007/978-3-642-48318-9.

[4] OPRICOVIC, Serafim and Gwo-Hshiung TZENG. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. online. *European Journal of Operational Research*, vol. 156 (2004), no. 2, pp. 445–455. Available from: https://doi.org/10.1016/S0377-2217(03)00020-1.

[5] ROY, Bernard. The outranking approach and the foundations of electre methods. online. *Theory and Decision*, vol. 31 (1991), no. 1, pp. 49–73. Available from: https://doi.org/10.1007/BF00134132.

[6] DERRAC, Joaquín; Salvador GARCÍA; Daniel MOLINA and Francisco HERRERA. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. online. *Swarm and Evolutionary Computation*, vol. 1 (2011), no. 1, pp. 3–18. Available from: https://doi.org/10.1016/j.swevo.2011.02.002.

[7] SPEARMAN, C. The Proof and Measurement of Association between Two Things. online. *The American Journal of Psychology*, vol. 15 (1904), no. 1, p. 72. Available from: https://doi.org/10.2307/1412159.

[8] BRANDIMARTE, Paolo. Routing and scheduling in a flexible job shop by tabu search. online. *Annals of Operations Research*, vol. 41 (1993), no. 3, pp. 157–183. Available from: https://doi.org/10.1007/BF02023073.

[9] KOBLASA, František and Miroslav VAVROUŠEK. Flexible Job Shop Schedule generation in Evolution Algorithm with Differential Evolution hybridisation. online. In: *39th International Conference on Mathematical Methods in Economics*. 9 - 10.9/2021. Czech University of Life Sciences Prague. ISBN 978-80-213-3126-6. Available from: https://mme2021.v2.czu.cz/en/r-16791-news-mme-2021/proceedings-of-the-39-th-international-conference-on-mme-202.html.

[10] KOBLASA, František and PETER BUBENÍK. *Využití optimalizačních metod v oblasti rozvrhování strojírenské výroby*. *Liberec: Technická univerzita v Liberci*. online. 2025. ISBN 978-80-7494-439-0. Available from: https://kniholib.cz/arl-li/en/detail-li_us_cat-0696255-Vyuziti-optimalizacnich-metod-v-oblasti-rozvrhovani-strojirenske-vyroby/.

[11] KOBLASA, František and Miroslav VAVROUŠEK. Facility Layout Problem with heterogeneous Material Handling System constraints. online. In: *PROCEEDINGS OF THE 41ST INTERNATIONAL CONFERENCE ON MATHEMATICAL METHODS IN ECONOMICS*. Czech Society for Operations Research. ISBN 978-80-11-04132-8. Available from: https://mme2023.vse.cz/mme_2023_proceedings.pdf.