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Due date optimization in multi-objective scheduling of flexible job shop production

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A B S T R A C T

The manuscript presents the importance of integrating mathematical methods for the determination of due date optimization parameter for maturity optimization in evolutionary computation (EC) methods in multi-objective flexible job shop scheduling problem (FJSSP). The use of mathematical modelling methods of due date optimization with slack (SLK) for low and total work content (TWK) for medium and high dimensional problems was presented with the integration into the multi-objective heuristic Kalman algorithm (MOHKA). The multi-objective optimization results of makespan, machine utilization and due date scheduling with the MOHKA algorithm were compared with two comparative multi-objective algorithms. The high capability and dominance of the EC method results in scheduling jobs for FJSSP production was demonstrated by comparing the optimization results with the results of scheduling according to conventional priority rules. The obtained results of randomly generated datasets proved the high level of job scheduling importance with respect to the interdependence of the optimization parameters. The ability to apply the presented method to the real-world environment was demonstrated by using a real-world manufacturing system dataset applied in Simio simulation and scheduling software. The optimization results prove the importance of the due date optimization parameter in highly dynamic FJSSP when it comes to achieving low numbers of tardy jobs, short job tardiness and potentially lower tardy jobs costs in relation to short makespan of orders with highly utilized production capacities. The main findings prove that multi-objective optimization of FJSSP planning and scheduling, taking into account the optimization parameter due date, is the key to achieving a financially and timely sustainable production system that is competitive in the global market.

A R T I C L E   I N F O

Keywords:
Flexible job shop scheduling problem (FJSSP);
Due date;
Makespan;
Capacities utilization;
Multi-objective optimization;
Evolutionary computation;
Multi-objective heuristic Kalman algorithm;
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1. Introduction

The production planning and scheduling of flexible job shop production (FJSSP) is extremely important if a company wants to ensure global competitiveness and sustainable business [1]. Optimization parameters that define short makespan of orders and enable high utilization of production capacities are meaningless if the expected order due dates are not guaranteed. Adequate planning and scheduling of due dates, which are usually very tight, expresses the need for a detailed discussion of the scheduling orders importance from the point of due dates. The research question presented in the research work refers to the importance of mathematical modelling of the due dates optimization objective in the multi-objective FJSSP optimization problem.

The importance of scheduling FJSSP from the point of the due dates has a significant impact on other optimization parameters that FJSSP deals with.

According to the literature, the problem of scheduling orders in job shop production has long been known, defined and discussed in detail. The initially used scheduling priority rules [2] only allowed the theoretical solution of single-objective optimization problems, which the developers transferred to dynamic job shop production environments by means of simulation modelling approaches [3]. The set of mathematical methods for modelling due date parameter is extensive [4]. Their suitability for individual use is demonstrated by the specificity of the optimization problem and its complexity [5]. The complexity of scheduling is reflected in several supporting parameters that influence the correct assessment of the due date parameter from the average job tardiness, the number of tardy jobs and the total tardy jobs costs leading to time and financial losses of the company [6]. Given the complexity presented, which is defined in FJSSP as NP - hard, the use of evolutionary computation methods (EC) is one of the effective ways of achieving optimal optimization results [7, 8]. The optimization problem of scheduling due dates in flexible manufactured systems [9] has encountered many limitations in the research due to conflicting optimization goals and the use of different mathematical modelling methods [10]. The researchers have limited it to optimization parameters that define the due date of jobs [11], assuming independence from other optimization parameters [12], which significantly influence production flexibility [13]. The dynamic change in FJSSP production due to dynamic customer demand and high-mix low-volume production [14, 15] cites Pareto-based optimization approaches as suitable optimization approaches [16]. The use of fuzzy approaches [17], which satisfactorily solve the optimization problem of FJSSP production, usually treats the problem only on a single-level of primary optimization criteria and limits the multi-level structure of the FJSSP problem [18]. Heuristic methods [19, 20], which allow a detailed devaluation of the optimization approach and the satisfactory optimization method, are usually limited by the transfer of the optimization results to a real-world or simulation environment [21, 22]. The need for an efficient optimization method that allows the planning and scheduling of the FJSSP problem with the optimization parameter of due dates is the key to achieving a comprehensive optimization approach [23]. However, the research results must allow for the devaluation of both test and realistic datasets for appropriate integration of the proposed methods into the real-world production environment [24].

In the presented research work, we want to present the importance of integrating mathematical methods for determining due dates into the existing EC method. The research work tries to overcome the existing limitations of the FJSSP research problem, which does not deal with the optimization parameter of planning and scheduling orders with the due date parameter. The mathematical modelling with known total work content (TWK) and slack (SLK) methods and their integration into the proposed EC algorithm MOHKA allows to evaluate the importance of the FJSSP multi-objective optimization with parameters that ensure short makespan, high utilization of production capacities and the achievement of tight due dates.

2. Problem description

In the optimization problem of planning and scheduling of the flexible job shop production (FJSSP), the three most frequent optimization parameters are shown in Eq. 1, Eq. 2 and Eq. 3:

- Makespan

$$MC = max\{C_j \mid j = 1, \ldots, n\}, \tag{1}$$

- Total workload of all machine

$$TW = \sum_{i=1}^{n} \sum_{j=1}^{n_i} \sum_{k=1}^{m} p_{ijk} x_{ijk}, k = 1, 2, \ldots, m \tag{2}$$

and

- The workload of the most loaded machine

$$MW = max \sum_{i=1}^{n} \sum_{j=1}^{n_i} p_{ijk} x_{ijk}, k = 1, 2, \dots, m \tag{3}$$

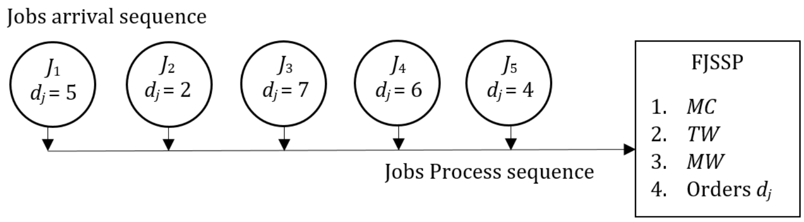

Fig. 1 Jobs arrival sequence with different due dates

Where the C_j is completion time of job j, n represents number of jobs and m the number of machines. These three optimization parameters relate to the time of jobs completion and the achievement of the highest possible utilization of the machines. In the highly dynamic job shop production, a very important parameter is the due date of jobs d_j, which in most cases are very tight. Fig. 1 shows the job arrival sequence of five jobs, where each job must be executed with a different due date in the production system defined as FJSSP. The optimization of the jobs process sequence must be carried out with regard to the multi-objective nature of FJSSP, whereby three parameters must be minimized (MC, MW, d_j) and one parameter must be maximized (TW).

In this case, each job j has a certain number of operations O_i, which must be performed on the available machine m from the given set of machines capable of performing an individual operation. The process time of the operation p_{jk} varies in relation to the assigned machine capable of performing the individual operation O_i. The optimization algorithm must arrange the job process sequence in such a way that it handles all four optimization parameters accordingly. Example: If the conventional priority rule Earliest Due Date (EDD) was used, the job process sequence would be J_2, J_5, J_1, J_4 and J_3. This job process execution sequence deals only with one optimization parameter d_j, which is defined as follows: The due date of job j represents the estimated dispatch date of job j (dispatch date promised to the customer). Completion of job j after the due date (promised to the customer) is allowed, but represents an additional financial penalty for the company. When considering the optimization parameter d_j, important related goals must be specified. The priority objective is to reduce the maximum lateness, which is defined as in Eq. 4:

$$L_{max} = max(L_j, \dots, L_n), \tag{4}$$

where the lateness of an individual job j defined by the Eq. 5

$$L_j = C_j - d_j \tag{5}$$

depends on the completion time of the job j and the assumed delivery time of the job d_j.

The timed L_{max} can be more easily defined with the parameter number of tardy jobs. This optimization parameter only defines whether the individual job j missed the estimated delivery time or not. Tardiness of job j is defined as presented by Eq. 6:

$$T_j = max(C_j - d_j, 0), \tag{6}$$

and the corresponding target function defined by Eq. 7.

$$\sum_{j=1}^{n} T_j \tag{7}$$

Due to the shortcomings of the above optimization function, which refers to some very tardy jobs, it is useful to determine the importance weights of jobs j by w_j. The higher the weight, the more important the job is.

The assumption in the present research work refers to: the given weight w_j refers only to the importance of an individual job j, which can be weighted directly by the planning team of the manufacturing system. However, the importance of the multi-objective decision making between the four optimization parameters (MC, TW, MW and d_j) does not determine the importance of the correlation between them, since this is performed with the evolutionary computation method MOHKA, which presents solutions of the optimization problem with Pareto optimal solutions.

3. Due date modelling

To model due dates of jobs, a random dataset is generated (according to the FJSSP characteristics) and divided into three groups with regard to their complexity dimensions:

- Low dimensional optimization problem, in the present manuscript the dataset J_5, M_{11}, O_{66} has been configured to evaluate MOHKA capabilities in relation to the optimization results of conventional priority rules.
- Middle dimensional optimization problems are represented by two datasets, a theoretical dataset J_{10}, M_{11}, O_{122} and a real-world dataset J_{15}, M_{10}, O_{84}, which was used in the FJSSP case study section.
- High dimensional optimization problems are represented by datasets J_{15}, M_{11}, O_{176} and J_{20}, M_{11}, O_{240}, respectively.

Due date optimization parameter modelling is performed with TWK (Total WorK content) method by the Eq. 8.

$$d_j = at_j + K_x \cdot \sum\nolimits_{i \in o_j} p_{i,j,k} \tag{8}$$

The tightness coefficient of the order due date K_x (allowance factor) determines the tightness of the delivery times. In the current literature [7] for the TWK method and determination of the tightness coefficient of the permissible deviation of the delivery time for the EC method, values in the range of $3 \le K_x \le 5$ are given. The smaller the value of the tightness coefficient, the narrower the due date of the order j is. The experiments in the manuscript use the value of the coefficient $K_x = 3$. The due date modelled according to the TWK method depends on the arrival time of the order j (at_j), total time of processing of all operations (p_{ijk}) and the described tightness coefficient. The MOHKA algorithm schedules the job orders according to four optimization criteria, including the due date d_j. The adequacy comparison of the proposed MOHKA method is performed with two comparison algorithms: Multi-objective particle swarm optimization (MOPSO) [25] and Bare-bones multi-objective particle swarm optimization (BBMOPSO) [26]. These two algorithms do not use an integrated mathematical decision model to terminate orders according to the due date criterion, this criterion is calculated numerically in the experiment at the end of the optimization results. As stated in the initial research question, the due date parameter in the FJSSP optimization problem is not well researched, especially when it comes to using the EC method to obtain optimal solutions. All algorithms in the experiment use the same initialization parameter: population size ($N_s = 300$), maximum number of archived nondominated solutions ($N_a = 100$), and maximum number of algorithm iterations ($MaxIter = 300$).

The optimization parameter for scheduling jobs by due date is analysed using three criteria: number of tardy jobs, average job tardiness and tardy jobs cost. The tardy jobs costs is modelled as shown in Eq. 9, where the initial job cost (J_{cost}) are multiplied by the constant value of three, divided by the value constant K_s, and multiplied by subtracting the completion time C_j and the due date d_j.

$$L_{cost} = \frac{3 \cdot J_{cost}}{K_S} \cdot \left(C_j - d_j\right) \tag{9}$$

A constant value of three determines three times the cost of tardy jobs compared to the cost of in-time completed jobs. The value constant K_S is automatically determined by the orders makespan. The parameter J_{cost} is determined numerically according to the characteristics of the machines performing an individual job operation.

The modelling of the due dates and the achievement of the other three optimization parameters were carried out using conventional methods (priority rules) and the heuristic GSBR method, with the aim of evaluating the efficiency of the conventional scheduling methods compared to the proposed MOHKA EC method. The comparison is performed in the software environment Lekin. As the Lekin software environment only allows the optimization of datasets of up to one hundred operations in the FJSSP optimization problem, the evaluation is performed with a randomly determined dataset classified as low dimensional optimization problem J_5, M_{11}, O_{66}. A randomly generated dataset does not contain data where two or more operations are performed on the same machine within a single order, limitation of Lekin.

In contrast to larger datasets, where in the TWK method is used to model due dates, the SLK (slack) method [4] is recommended for smaller datasets, which can model due dates by the Eq. 10.

$$d_j = at_j + \sum\nolimits_{i \in o_j} p_{i,j,k} + K_y \tag{10}$$

The time reserve constant K_y determines the looseness-tightness of due dates, in the SLK method the determination of the time reserve constant of the due date is given by the literature values $4 \leq K_y \leq 16$. In the presented research work the value $K_y = 8$ is used. The K_y must be calculated individually for the specific optimization problem.

3.1 Performance testing

To test the performance of the MOHKA algorithm for due date job scheduling, four randomly generated benchmark datasets and one real-world dataset all of which describe a multi-objective FJSSP optimization problem were used. The datasets were created using the interdependency function between different parameters describing the optimization problem. We divided these benchmark datasets into three groups according to the complexity of the optimization problem.

3.2 Using TWK and SLK methods

The division of the datasets used in different groups according to their complexity provided the basis for testing two different due date modelling methods. TWK method for middle and high dimensional optimization problems and SLK method for low dimensional optimization problems. The use of TWK and SLK methods for different datasets is supported by the mathematical formulation of the individual methods. With the presented classification approach, the complexity of the optimization problems can be evaluated more precisely in order to determine the advantages and limitations of the due date methods capabilities. The proposed MOHKA algorithm performed the optimization of datasets with four parameters of a flexible production system: makespan (MC), total workload of all machines (TW), maximum workload of an individual machine (MW) and added due date (d_j) parameter. The obtained optimization results were compared with two multi-objective particle swarm based optimization algorithms MOPSO and BBMOPSO. The experiments were performed on a personal computer with Intel i7 processor and 16 GB internal memory.

3.3 Results for the TWK method

The results in Table 1 show the high reliability of scheduling jobs with the TWK method, taking into account due dates with the MOHKA optimization algorithm. Its success in scheduling jobs with tight due dates, low average job tardiness potentially low tardy jobs cost and short orders makespan.

The middle dimensional dataset J_{10}, M_{11}, O_{122} caused no problems for all three evolutionary computation algorithms in scheduling orders for tight due dates of the TWK method with the tightness coefficient of $K_x = 3$. No job has missed the scheduled due date, which in turn did not result in additional tardy jobs costs in the manufacturing system. Since only the referential MOHKA optimization algorithm takes into account the mathematical architecture of the TWK method, we see that the results of the multi-objective optimization have a positive effect on the achievement of the minimum orders makespan. Makespan is the shortest in the MOHKA algorithm with up to 188 h, in contrast to MOPSO and BBMOPSO, where the makespan is 227 h and 206 h, respectively.

When the dimension of datasets increases from middle dimensional to high dimensional optimization problems, the difference between the optimization results of comparison and reference algorithms is more pronounced, presented on Fig. 2. In dataset J_{15}, M_{11}, O_{176}, the MOHKA algorithm terminates orders in such a way that three orders are late for the expected due date with an average job tardiness of 19 h, resulting in a tardy jobs costs of 2272.2 EUR. The MOPSO algorithm terminates orders so that only two orders miss the expected due date, but with higher average job tardiness of 45.5 h, which means a 139% higher average job tardiness than the MOHKA algorithm. A longer average job tardiness leads to higher tardy jobs costs, which amount to EUR 2966.5 in the MOPSO algorithm. The BBMOPSO algorithm had the most difficulties in scheduling the J_{15}, M_{11}, O_{176} dataset because up to one-third of the orders have missed the scheduled due date, with an average job tardiness of 20.6 h and high tardy jobs costs of 3558.5 EUR. This corresponds to an increase of 56.6% in the costs of tardy jobs compared to the MOHKA algorithm. The results show that the MOHKA algorithm is also most successful with the order makespan parameter of 289 h, which is 2.8% shorter than the BBMOPSO algorithm and 17% shorter than the MOPSO algorithm. Based on the optimization results described above, we can assume how important the scheduling of the dynamic FJSSP with the parameter of due date is, especially if the complexity of the optimization problem increases.

The hypothesis is confirmed for the high-dimensional dataset J_{20}, M_{11}, O_{240}, in which the reference MOHKA algorithm dominates over the results of the two comparison algorithms presented of Fig. 3. The lowest number of tardy jobs with an average job tardiness of 31.1 h compared to 44.4 h and 46.8 h for MOPSO and BBMOPSO, corresponding to 42.8% and 50.5% higher number of tardy jobs. Given the higher number of tardy jobs and the longer average job tardiness, the costs of tardy jobs is also higher for the two comparison algorithms than for the reference MOHKA algorithm, which amounts to 7,318.1 EUR. With the MOPSO algorithm, the tardy jobs costs amount to 13,585.6 EUR, while with BBMOPSO they amount to 33,070.1 EUR, which represents an increase of 85.6% and 351.9%, respectively, in the costs of tardy jobs that have exceeded their scheduled due date. The presented results prove the high importance of mathematical modelling with the parameter of due date optimization, as they have a decisive influence on the makespan and financial justification of a highly dynamic manufacturing. A suitable mathematical model of the multi-objective optimization problem is also reflected in the achievement of short order makespan. For the high dimensional dataset J_{20}, M_{11}, O_{240} the reference MOHKA algorithm achieved a makespan of 341 h and the two comparison algorithms 389 h and 397 h. Appropriate multi-objective decision making allows for an evenly balanced operation of the manufacturing system regarding to the makespan, machine utilization and achievement of tight order due dates.

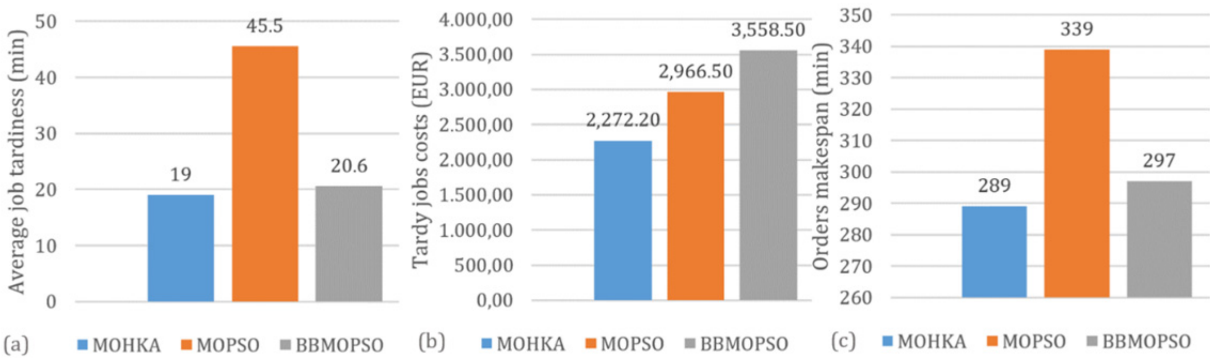

Fig. 2 Optimization results J_{15}, M_{11}, O_{176}: (a) average job tardiness, (b) tardy jobs costs and (c) orders makespan

Table 1 Algorithms optimization results

Algorithm	Dataset	Number of tardy job	Average job tardiness (h)	Tardy jobs costs (EUR)	Orders makespan (h)
MOHKA	J_{10}, M_{11}, O_{122}	0	0	0	188
	J_{15}, M_{11}, O_{176}	3	19	2,272.2	289
	J_{20}, M_{11}, O_{240}	7	31.1	7,318.1	341
MOPSO	J_{10}, M_{11}, O_{122}	0	0	0	227
	J_{15}, M_{11}, O_{176}	2	45.5	2,966.5	339
	J_{20}, M_{11}, O_{240}	10	44.4	13,585.6	389
BBMOPSO	J_{10}, M_{11}, O_{122}	0	0	0	206
	J_{15}, M_{11}, O_{176}	5	20.6	3,558.5	297
	J_{20}, M_{11}, O_{240}	18	46.8	33,070.1	397

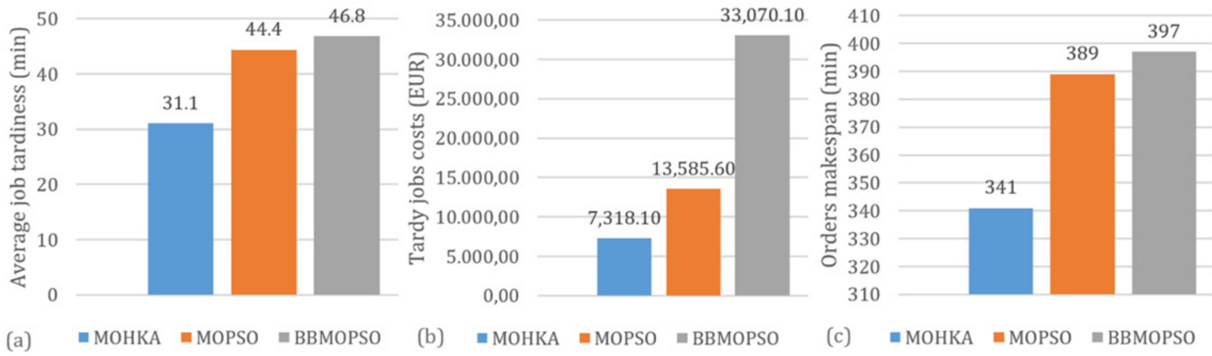

Fig. 3 Optimization results J_{20}, M_{11}, O_{240}: (a) average job tardiness, (b) tardy jobs costs, and (c) orders makespan

3.4 Results for the SLK method

With the aim to compare the solutions of the MOHKA algorithm and the solutions of conventional priority rules, a comparison of the results of the MOHKA optimization with the results of job scheduling in the Lekin software environment was performed for the low dimensional optimization problem of J_5, M_{11}, O_{66}.

Table 2 shows the optimization results of a randomly generated J_5, M_{11}, O_{66} dataset of five jobs with a total of sixty-six operations performed on eleven machines. The optimization was performed with the MOHKA optimization algorithm in the software environment MATLAB and seven optimization approaches in the software environment Lekin. Of the seven optimization approaches, six are conventional priority rules and one is a heuristic algorithm named General Shifting Bottleneck Routine (GSBR). For the optimization of due dates the SLK method with a time reserve constant of $K_y = 8$ was used.

The results show a high reliability of production jobs scheduling by the optimization algorithm MOHKA. In the considered dataset MOHKA terminates jobs so that two orders miss the scheduled due dates with an average job tardiness of 9.5 h and a tardy jobs costs of 2,651 EUR. With the six priority rules we see that the five priority rules, with the exception of the SPT priority rule, terminate orders in such a way that all five orders miss the scheduled tight due date. The average job tardiness is higher than 309.5% for the CR priority rule to 505.3% for the LPT priority rule than for the MOHKA algorithm. There are also significantly higher tardy jobs costs. The only algorithm that has partially approximated the results of the MOHKA algorithm is the heuristic GSBR algorithm, where four orders are tardy with an average job tardiness of 9.4 h. Due to two additional delayed jobs, the tardy job cost are 39.8% higher than in the MOHKA algorithm. There is also a significant difference in achieving a short makespan of orders, where the MOHKA algorithm terminates work jobs so that they are completed in a makespan of 99 h, and all other algorithms terminate orders with makespan between 208 h (GSBR) and 256 h (CR).

The presented optimization results prove the high ability to terminate production orders with the MOHKA algorithm and to achieve tight due dates from low dimensional optimization cases (with SLK method) to middle and high dimensional optimization cases (with TWK method) compared to optimization solutions according to MOSPO, BBMOPSO and priority rules.

Table 2 MOHKA vs. priority rules optimization results

Algorithm	MOHKA	EDD	MS	FCFS	LPT	SPT	CR	GSBR
Number of tardy job	2	5	5	5	5	4	5	4
Average job tardiness (h)	9.5	34.8	47.6	41.6	48	32.4	29.4	9.4
Tardy jobs costs (EUR)	2,651	11,325.1	14,682.2	13,320	14,436.1	10,570.1	8,905	3,706.2
Orders makespan (h)	99	211	211	215	217	233	256	208

3.5 Real-world case study

With the proposed method for modelling the due date for FJSSP, which was tested on randomly generated benchmark datasets, we proved the high ability to solve multi-objective optimization problems. The initial experiment, which was conducted on randomly generated datasets, was extended to a real-world case study for the FJSSP manufacturing system to evaluate MOHKA efficiency in determining due dates.

The fourth section presents the ability to solve a multi-objective optimization problem of a real-world manufacturing system (the dataset from a real-world environment is called RW_PS). The first part of the section presents the input data of the manufacturing system that has been prepared to describe FJSSP. Working with the company to prepare relevant and credible input data offers the opportunity to achieve reliable optimization results by testing the proposed EC scheduling methods. The RW_PS dataset consists of fifteen job orders that are executed on ten machines with eighty-four operations. The optimization results obtained with the MOHKA algorithm were compared with the optimization results of the MOPSO and BBMOPSO algorithms. The proposed integration approach of transferring the optimization results to the conventional simulation environment was used to transfer the optimization results, the order of the due dates of the job sequence, to the simulation model of the real-world manufacturing system.

Manufacturing system input data

Selected data were obtained from a Central European medium-sized company that manufactures individual orders for different customers. Orders received in the company by the customer must be performed on specific, available machine within the manufacturing system concerning four optimization parameters MC, TW, MW and d_j (FJSSP problem). The orders consist of two types of products with different process times, machine operating costs (O_c), machine idle costs (I_c) and fix location of machine is known by x and y location. Input data are given in Table 3. Compared to the test random generated datasets described in section 3, the additional complexity of the RW_PS optimization problem is added by two different product types, which add one dimensional complexity to the optimization problem.

In a real-world manufacturing system, machines marked M_1 to M_{10} perform the following operations:

- M_1 and M_2 for raw material cutting,
- M_3 to M_5 CNC machining,
- M_6 and M_7 welding,
- M_8 and M_9 assembling and
- M_{10} final control operation.

The main task of the optimization algorithm is to optimally determine the job sequence of operations on the available machine. The algorithm must determine which of the machines is capable of performing the individual operations according to the four optimization criteria. The simulation model was built in the Simio software environment, in which a transfer method for integrating optimization results from the MOHKA method to conventional simulation decision logic was used [18]. Using the MOHKA algorithm, we solved the FJSSP optimization problem, so we decided to extend our existing optimization results with a suitable simulation model. Fig. 4 shows a simulation model of a real-wold manufacturing system running on an order job sequence determined by the MOHKA optimization algorithm.

Table 3 Real-world manufacturing system characteristics

	Machine	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
	x_{loc} (m)	8	8	12.5	18.5	24.5	30.5	36	36	24.5	19.5
	y_{loc} (m)	9.5	4.5	0	0	0	0	5.5	10.5	16.5	12
Product 1	Processing time (min)	20	24	40	45	38	47	20	25	11	22
	O_c (EUR/h)	45	45	35	35	35	35	52	52	59	43
	I_c [EUR/h]	22.5	22.5	14	14	14	14	31.2	31.2	35.4	21.5
Product 2	Processing time (min)	22	22	43	43	43	43	23	23	12	25
	O_c (EUR/h)	43	43	36	36	36	36	53	53	59	45
	I_c [EUR/h]	21.5	21.5	14.4	14.4	14.4	14.4	31.8	31.8	35.4	22.5

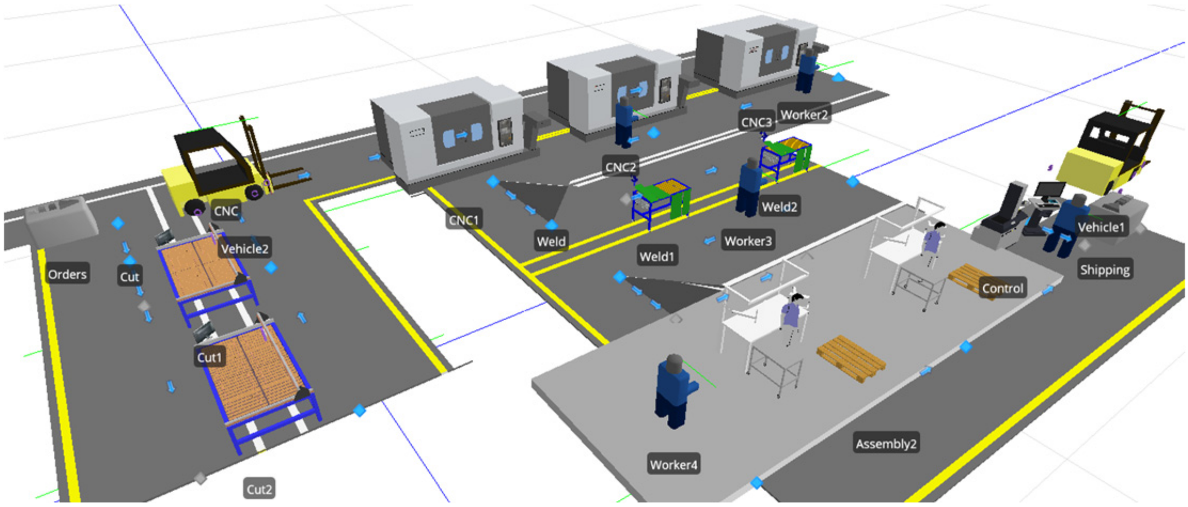

Fig. 4 Simulation model in Simio

Due date scheduling results

Table 4 and Fig. 5 show the results of optimizing the RW_PS dataset according to the order due date parameter. As shown in section 3, the TWK method with a tightness coefficient K_x = 3 was used when evaluating RW_PS dataset. The optimization results show that with the MOHKA optimization algorithm only one job missed a tight due date with an average job tardiness of 46 min. With the BBMOPSO optimization algorithm also, one job missed the due date, but job is tardy by an average job tardiness of 154 min, which corresponds to a 234% longer tardy time of the missed job than the tardy job with the MOHKA algorithm. In the MOPSO algorithm, two jobs are tardy with an average job tardiness of 58 minutes, which is 26.1% longer tardy time than the delay with the MOHKA algorithm. Since the value of tardy jobs costs is low, the percentage difference between them is significant. In this case, the MOHKA algorithm proves to be the most efficient, since it is the only algorithm able to take due dates into account as a decision criterion when determining the job sequence.

The tardy jobs costs in the MOPSO algorithm are 130.2% higher in the MOPSO algorithm than in the MOHKA algorithm. Even if only one job with the BBMOPSO algorithm missed the scheduled due date, this was delayed by a much longer time than the tardy job with the MOHKA algorithm. This is reflected in 230.7% higher tardy job costs. The makespan of orders is shortest with the MOHKA algorithm at 392.45 min, while the makespan of orders is longer by 2.1% longer with MOPSO and 7.6% longer with BBMOPSO. From the perspective of the multi-objective decision making process, we can conclude that the MOHKA algorithm provides a high degree of FJSSP scheduling capabilities even in real-world datasets, considering the ability to achieve a tight job due date.

Table 4 Optimization results of real-world manufacturing system

Algorithm	MOHKA	MOPSO	BBMOPSO
Number of tardy job	1	2	1
Average job tardiness (min)	46	58	154
Tardy jobs costs (EUR)	14.9	34.3	46.3
Orders makespan (min)	392.45	400.48	422.21

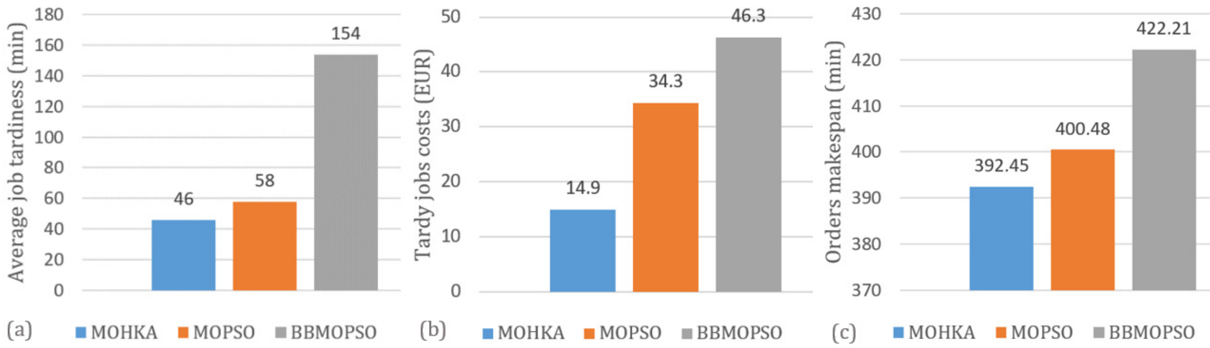

Fig. 5 Optimization results: (a) average job tardiness, (b) tardy jobs costs, and (c) orders makespan

4. Discussion and conclusions

Scheduling multi-objective FJSSP optimization problem is defined as a NP-hard optimization problem. The initial research question of scheduling FJSSP production with the optimization parameter of the due dates importance and taking into account the standard optimization parameters related to the makespan of orders and machine utilization, was evaluated in the presented research with the MOHKA optimization method and the SLK and TWK methods to model due dates. With increasing number of optimization parameters, the computational complexity of the optimization algorithm increases. The presented research work presents the integration of the mathematical structure of the SLK (for low dimensional optimization problems) and TWK methods (for medium and high dimensional optimization problems) into the optimization MOHKA algorithm, which is capable of scheduling FJSSP production. The proposed MOHKA algorithm was used to schedule test datasets with emphasis on achieving a tight due date of the orders. The optimization results were compared with the results of the optimization algorithms MOPSO and BBMOPSO, which terminate orders only at ordinary optimization parameters: *MC, TW and MW*. The disadvantage of the comparative optimization methods becomes apparent when we talk about medium and high dimensional optimization problems in the scheduling of FJSSP. The limited scheduling capabilities of the MOPSO and BBMOPSO algorithms are reflected in the limited mathematical structure of the algorithms, which do not consider the SLK and TWK methods as decision parameters in achieving optimally scheduled orders from the point of due dates. The optimization results of the reference MOHKA algorithm prove the high importance of the due date optimization parameter, since the proposed method optimizes order scheduling with regard to the two comparative algorithms for low, medium and high dimensional optimization problems. Since we are talking about multi-objective decision making and finding compromises between different (even contradictory) optimization parameters, the results of the MOHKA algorithm prove the high ability to reach all four optimization parameters equally and efficiently (*MC*, *TW*, *MW* and d_j). As evidenced the short order makespan, tight due dates, low average order tardiness and the associated low associated job tardiness costs are achieved. The answer to the question about the efficiency of evolutionary methods in multi-objective decision making compared to the conventional optimization approach of priority rules was given by the presented study, in which the optimization results of the MOHKA algorithm are compared with the optimization results of six priority rules and an integrated heuristic method in the Lekin software environment. The obtained results prove the high dominance of the optimization results of the evolutionary method MOHKA, which terminates the FJSSP production according to the used low-dimensional dataset for all optimization parameters most efficiently. Randomly generated datasets were the basis for carrying out the validation of the applicability of the proposed method in real-world manufacturing systems, whereby the satisfactory optimization results were demonstrated in the experiment. The scheduling of the FJSSP production to achieve tight due dates was carried out using the example of a dataset of a real-world manufacturing system. In this case, the TWK method, which is integrated into the decision logic of the MOHKA algorithm, proved the high ability to terminate the significance of real-world datasets importance in relation to the parameter of due date optimization.

Since the presented research work deals only with FJSSP, which is the main part of the research problem of multi-objective optimization job shop production, it is necessary to further investigate the importance of scheduling due dates in dynamic job shop production (DJSSP). Where the main features are dynamic order changes during the execution of the algorithm (at initialization stage the whole order dataset is unknown), machine failures during the execution of operations and the determination of the importance of orders need to be studied. Further research on the research problem of DJSSP would remove the limitations of current research, where the FJSSP optimization problem is based on the assumption of an initially known order dataset, an initially empty production system, a uniform meaning of orders, and known production capacities that do not change during operation.

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