Original Research

Workers Scheduling in Production Logistics in a Job Shop Production System

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Received: 19 March 2025 / Accepted: 6 July 2025 / Published online: 6 July 2025

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Abstract
This paper presents a Genetic algorithm for solving a multi-objective deterministic mixed integer nonlinear programming modeling of the workers scheduling problem in production logistics in a job shop production system. The proposed model integrates multiple decisions into the workers scheduling problem. In this model, production planning is independent of the influence of human resources management. In the other word, production planning is fixed and workers scheduling is based on it. This model explicitly taking into consideration the individual competencies and preferences of each worker, also the workers and competency requirements relate to each assembly activity. The objective of the introduced model is to allocate employees to assembly activities while minimizing human resources costs and workers dissatisfactions. To benchmark the performance of this Genetic algorithm, optimal solutions obtained through a mathematical model resolution using commercial solver CPLEX are used. Results show that this Genetic algorithm can produce high-quality and efficient solutions in a short computational time.

Keywords – Genetic algorithm; Mixed integer programming; Multi-objective; Optimization; Worker’s scheduling; Un-paced asynchronous assembly lines.

INTRODUCTION

In the last decades, personnel scheduling problems have studied so much. In many organizations, cost of work force is one of the most important costs. Therefore, economics of these organization will revival to decrease of this cost, even as much as a small percent.

Employee scheduling provides a working time-table for each employee of an organization. It helps an organization to have timely requests for services or products. Employee scheduling deals with the number of employees with special skills to determine demands and specify people assigned for a work shift and their tasks during this period.

In recent decades, the employee’s preferences are more considered as a research trend on scheduling employee that it is because of increasing their work efficiency by considering their preferences and final organization efficiency. Therefore, in this paper, we focus on workers scheduling in production logistics in a job shop production system.

In a job shop production system, production operations are performed in sequence at different stations with varying length of time. Large production lines sequentially producing a variety of complex products often require tens up to hundreds of workers. The number of workers required at each station varies depending both on the product currently produced and the activities assigned to that station. Owing to product changeovers and the specific manpower competency requirements associated to each product at each station, there are often large waves of workers moves among stations, which cause significant disruptions to operations, deteriorating the overall productivity of the line and causing dissatisfaction among the workers [1].

This paper considers a mathematical model of two levels of flexibility (shift start times and daily break times) in a job shop production system. In this center, the activities are conducted continuously that varies to length time but in a deterministic manner. Each employee is competent to perform certain activities and four preferences are considered for employees. The experimental results for solving this new model have demonstrated, that it is possible to reach the optimal solution using a commercial solver for small cases, but for larger cases because of high solution time it is necessary using a meta-heuristic optimization approach.

In this paper, a Genetic algorithm is presented for solving this model. The aim is to decrease solution time of this model that it is necessary for workers scheduling in real environments.

Workers scheduling problems are particular cases of resource allocation problems [2]. Nowadays, it is no secret that the human resources are too important and organizations require highly capable and motivated labor force to survive in this competitive and complex environment. Researches indicate that employee's flexibility in scheduling problems has a great effect on improving employee efficiency. This is because of a positive impact on the work environment including increased employee incentives and reduced amount of absence and delay [3]. Therefore, in recent decades, employee’s preferences are more considered as a research trend on scheduling employee.

In this regard, some studies are conducted in the areas of health [4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21, 22,23,24], transportation [25] and production centers [1,26]. Sabar et al [1] present workers scheduling model that the allocation of workers has to be made according to criteria such as required and available competencies, preferences and mobility in the paced assembly center. Complied with classification of Boysen et al [27], assembly lines based on line control classify into three categories: paced, un-paced asynchronous, un-paced synchronous and also based on number of models classify into three categories: single model, mixed model, multi model. Sabar et al [1] take to consideration workers scheduling problem in the context of a paced multi-model assembly center. Sabar et al [1] present a mathematical model in a large assembly line environment where the pace setting takt time between individual products units is preset equal to at least a few minutes. They take into account individual competencies, mobility and preferences. Workers can be cross-trained and allowed to move between workstations in order to fulfil assembly tasks. In [1], when a worker enter to center, should be assigned to one of five states including assembly activity, secondary activity, movement, idle and break state. Duration of each state is equal to a period. According to [1], in many contexts, the allocation of employees has to be made according to criteria such as required and available competencies, preferences and mobility but nevertheless the importance of these criteria, there is no workers scheduling model that takes into consideration all of them until 2008. According to [28] from 2004 onwards, papers are written by considering preferences for employees. The most of papers are about nurse scheduling that takes into consideration to select shift as selective preference. Therefore, based on [1] and [28] and our knowledge, there is no personnel scheduling model in large production centers by considering all of these criteria that are expressed in this model

MODEL FORMULATION

This paper focuses on solving shift scheduling problem in production logistics in a job shop production system. In this production system, production operations are performed sequentially at different stations with different durations. The production line has several workstations. In this system, production activities are performed continuously that varies length of time but deterministic periods of time. Two flexibility levels (shift start times and daily break times) for workers are considered. Each worker is competent to perform certain activities and four preferences are considered for worker. These selective preferences are the shift duration, assignable activities, the number of transfers between activities and start times for breaks.

The solution presented in this paper allocates workers to production activities while minimizing human resource costs and dissatisfaction. For validating the performance of the model, a small problem to theoretical data is solved by CPLEX. Due to workers scheduling problems are NP-Hard. Solution times of exact approaches are high and this is not acceptable even for small problems. By considering large assembly lines with many workers and requiring the generation of solutions in short times and in order to indicating that this proposed model is applicable in real environments, in this research, this model also is solved by Genetic algorithm that outcome results demonstrate efficiency this model.

This research focuses on the production logistics in a workshop production system where there are multiple workstations and multiple products are produced. There are different production times for activities at each station. Therefore, there are several storage locations before the stations for continuous operation of the stations without stopping.

At different stations, various activities are performed on these products (where necessary). Number of required workers in each station is different depending on activities associated with the station and type of products. There are often huge wave of workers moving between stations due to changes in product lines and individual competencies required for each product and each activity at each station. This leads to stop operation, reduced productivity of production line and employee's dissatisfaction.

This study presents a metaheuristic solution for a new mathematical modeling of workers scheduling in a job shop production system. In this model, for workers is considered preferences in four cases, which are:
1 - The duration of daily work.
2 - Preferred activities.
3 -The preferred number of workers movement between stations.
4 - Break starting time.

In this model, employees are assigned to work on the production activities of different products at different stations in order to minimize operating costs and employee dissatisfaction via maintaining production planning. Operating costs include following cases:
1 - Worker presence costs during ordinary working hours and overtimes.
2 – Costs associated with reduced or increased number of workers in the system.
3 – Costs associated with the worker assigning to the activities.
4 – Revenue for assigning workers to an effective secondary activity (non-productive), in the organization.
5 – Costs associates with worker's idle state.
6 - Worker transfer cost.

Workers' dissatisfaction includes:
1 - Penalty cost associated to the deviation (positive or negative) from the preferred number of transfers for each worker.
2 - Penalty cost associated to the deviation from the total work duration preferred by each worker.
3 - Penalty cost associated to the worker dissatisfaction for his assignment to the activity.
4 - Penalty cost associated to the worker deviation (positive or negative) from the preferred break starting time.

This method considers the possibility to assign workers to assembly activities, secondary activities (non-productivity activities), break starting time, workers movement between stations and workers idle state when a worker has started his shift. Starting time of each activity and duration of it is specified.

Research pre-assumptions:
• A large multi-product production system with specific activity at each station is considered.
• There is a program for workers scheduling in one shift.
• Multi product model are produced in this center.
• There are different times for the production activities on each product in each of the stations.
• For each product, the task to be fulfilled is specified.
• One or more workers are required for each activity.
• Each worker can perform multi activity during the day.
• Competencies of each worker are defined.
• Workers are allowed to move between work stations to fulfilling the assigned activities.
• Each worker must have required competency for the assigned activity.
• Each worker who starts his activities and enters the center may be in one of these five states: production activity, idle, assigned to the secondary activity, movement between activities and rest.
• The duration of preferred working hours, number of preferred movements, preferred start times for rest and favorite activities of each worker is determined.
• The duration of allowed normal working, overtime and rest time for each worker is specified.
• Penalty for deviation from the number of transfers, total work duration and type of activity preferred by worker, and preferred start time to rest during the workday for each worker is determined.
• A worker can be reallocated to another activity only at the end of each activity.
• The movements taken into account are those that are realized between two assembly activities on different stations or between an idle state and an assembly state.
• Costs associated with duration of worker presence in regular working hours and overtime, per employee added or subtracted to the production line, duration of assigned to assembly activity, idle duration, duration of movement between assembly activities and revenue assigning to the second activity for each worker is determined.
• The maximum duration of worker idle time is determined
• Each worker only once during the day can start his shift.

• Each worker only once during a day can take each type of rest in each shift.
• Minimum working duration for each worker presence at the time of the beginning of his shift is determined.

The model solved in this paper with the Genetic algorithm is presented in [29], and readers can study the indicators, sets, parameters, variables, objective function, and constraint set in [29].

GENETIC ALGORITHM

In this research is used binary coding meaning that all variables are introduced as binary, therefore there is a binary string for each solution. In random initial population, solution time is high and some constraints are violating. For resolving this problem, initial population is considered a feasible solution. Constrains are written in m-files at Matrix formation that are loading in program. For violating of constraints, objective function penalties as much as values of that constraint is violated and a fixed number (this fix number in this numerical example is 200). Fitness function is objective function and stopping condition is 100 generations.

Mutation rate, crossover rate and size of population have extra effect on efficiency of algorithm. For example, if mutation rate is set too high, owing to high mutation increase probability of new information entering but genetic information of elite individuals will die out. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of Genetic algorithms. For example, small population sizes might lead to premature convergence and yield substandard solutions. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time. The finding of optimal parameters need to high computational time. In this research, for computing of proper values (not necessarily optimal) for these parameters (crossover rate, mutation rate and population size) is used trial and error method procedure.

Mutation rates in Genetic algorithm usually ranges from 0.01 to 0.20 and crossover rate ranges from 0.8 to 0.99. Different values of these two parameters in the specified rates are considered as algorithm values in order to determine these parameters. The algorithm was performed for each value. For a good approximation for each pair of the parameters, the program runs 20 times, and the mean response for these parameters are considered as evaluation criterion.

According to the obtained results, the proper values for the algorithm parameters are equal to the mutation rate of 0.02 and crossover rate of 0.88 and population size is considered 200. After each run, a graph and a table can be seen observed. As Fig. 1 represents, the obtained diagram is the result of 20 times run of this algorithm for appropriate values of the parameters (not necessarily optimal).

In this figure, it can be observed that in all iterations, the mean of objective function value from 80 generations onwards have obtained an approximate stability. Therefore, considering 100 generations for algorithm stop does not seem far from reality. In the case of population size, the different values are tested. The number of appropriate (not optimal) is considered 200. Table I and Table II represent changes in the mean of the objective function and mean of solution time based on different values of the parameters.

According to these tables, optimal parameters of the algorithm can be found.

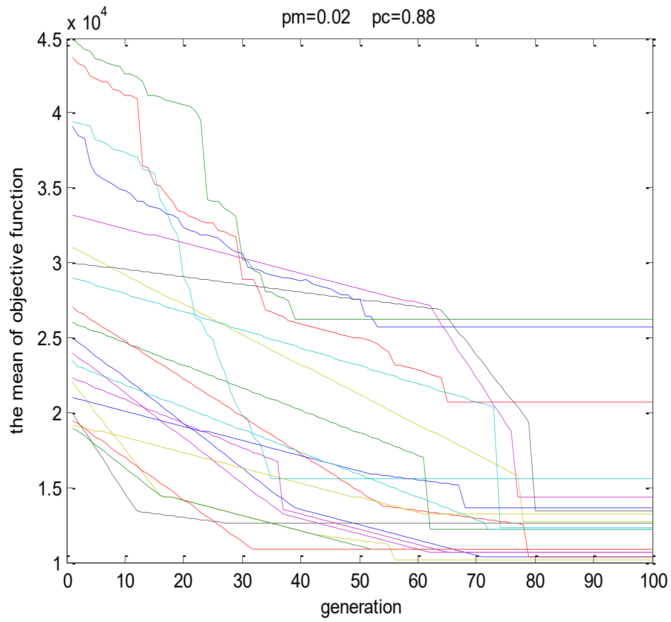

FIGURE 1.
THE ANSWERS OBTAINED FROM EACH EXECUTION OF THE ALGORITHM WITH PM=0.02 AND PC=0.88.

TABLE I.
AVERAGE SOLUTION TIME AND FITNESS RESULTING FROM CHANGING POPULATION SIZE FOR 20 RUNS

Number of generations	**Population size**	**Percentage of mutation (pm)**	**Percentage of crossover**	**Average solution time**	**Average fitness of generations**
100	50	0.2	0.8	1978	17154
100	100	0.2	0.8	2809	16362
100	150	0.2	0.8	5980	15241
100	200	0.2	0.8	9305	12646
100	250	0.2	0.8	12259	13139
100	300	0.2	0.8	18367	12942

TABLE II.
CHANGES IN THE AVERAGE OBJECTIVE FUNCTION AND ALGORITHM EXECUTION TIME IN TERMS OF MUTATION AND CROSSOVER RATES

Percentage of Crossover	**Percentage of mutation (pm)**	**Average value of the objective function for 20 runs**	**Average solution time for 20 runs (in seconds)**
0.8	0.01	14175.5	9900
0.85	0.02	13365	10500
0.9	0.05	16541.5	9180
0.95	0.1	18163.5	9720
0.99	0.15	17524	10170
0.88	0.02	12410.5	9498
0.85	0.01	14786	9954
0.9	0.02	13862.5	10890
0.95	0.05	15326.2	10776
0.99	0.1	18364.5	9690
0.8	0.15	17326.5	9336
0.85	0.2	17896	11010

0.9	0.01	16395.5	9480
0.95	0.02	15836	9840
0.99	0.05	21635	9948
0.8	0.1	19362.5	10164
0.85	0.15	19684.2	10518
0.9	0.2	23615.2	11184
0.95	0.04	16539.5	11718
0.99	0.17	17388.5	9096

As it is shown in Table II, changes in the average solution time ranges from 0%to 22% and changes in the mean value of the objective function ranges from 0%to 47%. According to this table, the shortest average time to solve the problem is related to crossover rate (0.99) and mutation rate (0.17). However, these values are not acceptable based on the standard deviation of 40% of the mean value of the objective function. Highest mean value of the objective function is related to the crossover rate (0.88) and mutation rate (0.02) with 9%-time deviation of its minimum solution time. due to the small amount of time deviation, these values as parameters for the algorithm is intended.

According to the results, the appropriate values of the mutation rate are 0.02, the crossover rate is 0.88, and the initial population is 200.

In the runs performed for the appropriate parameter values (population size 200, mutation rate 0.02, and crossover rate 0.88), according to Fig. 1 the average value of the objective function has reached approximate stability in all iterations from generation 80 onwards. Therefore, considering this stability, considering 100 generations to stop the algorithm does not seem far from reality.

Evaluate the proposed method

A numerical example introduced to validate and assess the performance of the model and its efficiency. Then the empirical results are analyzed.

Two workstations considered for this production center. Three product models will be produced in the center. There are different times for each activity on any of the products in both stations. The production activities will be performed on three products at both stations. A setup time is considered in each station for changing every product. This timing is considered for a working day. The allowed normal working hour for each employee is 9 hours along with 15 minutes as rest time in the first half of the day, 30 minutes rest time in the middle of the day for lunch and 15 minutes rest time for the second half of the workday. One worker is required to perform each activity. Minimal duration of worker presence at center when starts his shift is 2 hours. The defined parameters are in accordance with [29].

In [29], this model is solved with the CPLEX software. This problem has defined for 2 stations, 3 products and 7 workers that requires 8744 variables (8478 zero or one variables and 266 integer variables) ,764 linear limits and 77 nonlinear limits. CPLEX version 12.1 and a computer processor Intel (R) core (TM) i7cpu (8 GB Memory Ram) is used to solve the problem. The number of iterations and solution time for this numerical example are 2,147,483,648 and 769,453.3 seconds, respectively. The optimal objective function value is equal to.

In this paper, this problem with same parameters [29] also is solved by Genetic algorithm. MATLAB version 7.1 and a computer processor Intel (R) core (TM) i7cpu (8 GB Memory Ram) is used to solve the problem.

The solution time for this numerical example by Genetic algorithm is 9480 seconds. The amount of objective function value is equal to 10432.5 and results of employee scheduling are in accordance with Table III.

TABLE III.
COMPUTATIONAL RESULTS OBTAINED FROM THE GENETIC ALGORITHM FOR A NUMERICAL EXAMPLE

	W3	W6	W2	W1	W4	W5	W7
p1	a023	a027	a012	a001	a023	a027	a027
p2	a024	a082	a013	a002	a024	a097	a097
p3	a072	a061	a014	a003	a034	a062	a043
p4	a039	a008	a015	a074	a112	a009	a020
p5	a004	a103	a038	a036	a067	a010	a021
p6	a094	a048		a016	a005	a011	a022
p7	a026			a017	a006	a052	a053
p8	a027			a018	a007		
p9	a042			a043	a044		
p10	a019			a110	a111		
p11	a103			a048	a048		
p12	a048						

As it is shown in Table III workers number 1,2, 3 and 4 start their work in the morning shift and workers number 5, 6 and 7 start their work in the afternoon shift. Workers numbers 1, 3, 4 and 7 are present in the center for 2 shifts while workers number 2 ,5 ,6 and 7 are present for one shift. Workers number 5 and 7 workers are present in the center for 7 periods while workers number 1 and 4 are present in the center for 11 periods. Workers number 2, 3 and 6 are present in the center for 5,6 and 12 periods. The start of rest time in the first half day for workers number 1, 2, 3 and 4 is at 10:45, 11:00,10:15 and 10:00, respectively. No rest time is considered in the morning for workers number 5, 6 and 7 because they are not present in the center in the first shift. Lunch break is considered for workers who are working in two shifts. Start time for rest of workers number 1, 3 and 4 for lunch break is at 13:30, 13:00, 13:35. The start of rest time in the third half day for workers number 1, 3 and 6 is considered at 14:30 and for workers number 5 and 7 is considered at 16:00 and 15:51 respectively. Working hours for workers number 1, 2, 3, 4, 5, 6 and 7 equals to 405, 195, 405, 405, 255, 165 and 246 minutes, respectively. Idle state duration for each employee, time duration assigned to the second activity and movement duration are presented in this Table.

Table IV indicates the results of solution by CPLEX and Genetic algorithm solvers in terms of the amount of objective function and solution time. According to this table, solution time by using CPLEX solver is very high and this is an indication of the fact that the optimal solutions cannot be used in the real environment for employee scheduling. However, the number of stations, products and workers in the large production lines are more than this solved numerical example.

Table V indicates the evaluation of two solution methods by considering deviation from the optimal objective function value and problem solution time.

The results showed that Genetic algorithm increased the objective function (cost) up to 24.73% (worse than before), but the resolution time improved as much as 98.77%. workers scheduling in the production and service environments requires a short time solution. Therefore, Genetic algorithm provides high quality solutions in acceptable time for workers scheduling in real environments.

TABLE IV.
RESULTS FROM THE C-PLEX SOLVER AND THE GENETIC ALGORITHM

Problem solving methods	The objective function	Solution time (in seconds)
CPLEX	8362	769453.34
Genetic Algorithm	10432.5	9480

TABLE V.
THE AMOUNT OF DEVIATION FROM THE OPTIMAL OBJECTIVE FUNCTION VALUE AND THE LENGTH OF THE SOLUTION TIME

Positive deviation from the optimal objective function value (the amount of deteriorated objective function)	Negative solution time deviation (decrease in solution time duration)
24.73%	98.77%

In the following, to further evaluate the proposed model, fifteen problems in three categories of small, medium and large have been solved. Since the time to solve the small numerical example presented in [29] using the CPLEX software was very high, these numerical examples have been solved only with the genetic algorithm. According to the results obtained from the previous section, in solving these fifteen problems, the number of initial populations is 200, the number of generations is 100, the mutation rate is 0.02, and the crossover rate is 0.88. A feasible solution has been used to generate the initial population because if a random initial population is used, some of the constraints may be violated due to the high number of constraints, but by creating a feasible initial population that applies to the constraints and considering the penalty for violating the constraints, none of the constraints have been violated. And the results will be analyzed in terms of the length of the solution time according to the number of constraints and variables. Tables VI, VII and VIII show the parameters and results of the numerical examples considered.

TABLE VI

PARAMETERS AND RESULTS OF NUMERICAL EXAMPLES SOLVED IN SMALL SIZE

	Program run time	Best solution obtained	Number of variables	Number of constraints	Number of products	Number of stations	Number of available workers
Problem 1	9483	10432.5	8744	841	3	2	7
Problem 2	12000	9234	1944	1255	3	2	10
Problem 3	13800	8940	15544	1531	3	2	12
Problem 4	14510	8320	19944	1945	3	2	15
Problem 5	15130	8012	26944	2635	3	2	20

TABLE VII
PARAMETERS AND RESULTS OF NUMERICAL EXAMPLES SOLVED IN MEDIUM SIZE

	Program run time	Best solution obtained	Number of variables	Number of constraints	Number of products	Number of stations	Number of available workers
Problem 1	16680	14167	24240	2562	3	5	15
Problem 2	18200	13389	32320	3402	3	5	20
Problem 3	21120	12564	40400	4242	3	5	25
Problem 4	23760	12130	48480	5082	3	5	30
Problem 5	25134	11872	56560	5922	3	5	35

TABLE VIII
PARAMETERS AND RESULTS OF NUMERICAL EXAMPLES SOLVED IN LARGE SIZE

	Program run time	Best solution obtained	Number of variables	Number of constraints	Number of products	Number of stations	Number of available workers
Problem 1	28145	19867	90400	9958	3	8	50
Problem 2	29860	18201	99440	10948	3	8	55
Problem 3	30450	17830	108480	11930	3	8	60
Problem 4	31340	17340	117520	12928	3	8	65
Problem 5	31970	16840	126560	13918	3	8	70

The results of the solved problems show that the solution time increases with the size of the problem, but the length of the solution time is acceptable. Considering that the solutions do not violate any of the constraints of the problem, it can be said that the quality of the solutions is also acceptable considering the solution time. Tables IX, X, and XI show the percentage increase in solution time versus the percentage increase in the number of variables and constraints for small, medium, and large problems.

TABLE IX
PERCENTAGE INCREASE IN SOLUTION TIME IN SMALL PROBLEMS

	Percentage increase in solution time	Percent increase in number of variables	Percent increase in number of constraints
Second problem in relation to the first problem	26%	48%	49%
Third problem in relation to the second problem	15%	21%	21%
Fourth problem in relation to the third problem	5%	27%	27%
Fifth problem in relation to the fourth problem	4%	35%	35%

TABLE X
PERCENTAGE INCREASE IN SOLUTION TIME IN MEDIUM PROBLEMS

	Percentage increase in solution time	Percent increase in number of variables	Percent increase in number of constraints
Second problem in relation to the first problem	15%	33%	32%
Third problem in relation to the second problem	8%	25%	24%
Fourth problem in relation to the third problem	12.5%	20%	19%
Fifth problem in relation to the fourth problem	5.7%	16.6%	16.5%

TABLE XI
PERCENTAGE INCREASE IN SOLUTION TIME IN LARGE PROBLEMS

	Percentage increase in solution time	Percent increase in number of variables	Percent increase in number of constraints
Second problem in relation to the first problem	6%	10%	10%
Third problem in relation to the second problem	2%	9%	9%
Fourth problem in relation to the third problem	3%	8%	8%
Fifth problem in relation to the fourth problem	2%	7.6%	7.6%

Table XII shows the percentage of objective function improvement in five problems solved with the Genetic algorithm in three sizes.

TABLE XII
PERCENTAGE OF OBJECTIVE FUNCTION IMPROVEMENT

Problem size	Problem number	Percentage of improvement of the objective function
Small size problems	1	29%
	2	37%
	3	39%
	4	43%
	5	45%
Medium size problems	1	30%
	2	36%
	3	37%
	4	38%
	5	41%
Large size problems	1	26%
	2	30%
	3	34%
	4	36%
	5	38%

According to Tables IX, X and XI, increasing the number of variables and the number of constraints has increased the solution time almost linearly and sometimes less. This is while in exact solution methods such as CPLEX software that uses the branch and cut method to solve nonlinear mixed integer programming problems, the solution time of the problem increases exponentially with increasing the number of variables and constraints.

As can be seen in Table XII, the objective function improves with increasing the number of workers due to the possibility of creating greater satisfaction for the workers and reducing the deviation from the desired of the workers.

CONCLUSION AND FUTURE RESEARCH

This paper has introduced a Genetic algorithm for solving a mathematical modeling of the workers scheduling problem in production lines by considering competencies and preferences of each worker, as well as the workers and competency requirements associated with each activity. In this model, individual preferences are shifting duration, assignable activities, the number of transfers between activities and start times for breaks. This model has solved by CPLEX solver in [29]. Due to workers scheduling problems are NP-Hard. Solution times of exact approaches are high and this is not acceptable even for small problems. By considering large production lines with many workers and requiring the generation of solutions in short times and in order to indicating that this proposed model is applicable, in this research, this model also is solved by Genetic algorithm that outcome results demonstrate efficiency this solution method in terms of solution time.

Therefore, Genetic algorithm provides high quality solutions in acceptable time for workers scheduling in real environments. The numerical example of [29] solved and analyzed. Required results of this method are: (1) to apply the model, (2) this model can be utilized for larger problems, (3) to indicate that meta-heuristic optimization approaches are applicable for solving larger problems.

According to results and findings of this study, the most important recommendations that can be considered as a framework for future research include: (1) this study considered different definite and distinct duration for assembly activities. It is recommended to consider time duration for assembly activities in future researches of random variables, (2) it is recommended to define the competency of workers for production operations in a fuzzy manner in future researches, (3) other meta-heuristics and combined heuristic algorithms can be used for solving this model to analyze the obtained results, (4) this model can be used to provide a new model for workers scheduling in other centers, (5) in this study, a constant daily production planning and human resource planning is considered accordingly. It is recommended to use interaction between production planning and human resource planning for future researches.

REFERENCES

[1] Sabar, M., Montreuil, B., Frayret, J-M. (2008). Competency and preference-based workers scheduling in large assembly lines. International Journal of Computer Integrated Manufacturing, 21, 468-479. https://doi.org/10.1080/09511920701574842.

[2] M. A. O. Louly, "A goal programming model for staff scheduling at a telecommunications center,". *J. Math.* Model. Algorithms Oper Res, vol. 12, no. 2, pp. 167-178.2013. https://doi.org/10.1007/s10852-012-9200-x.

[3] Bailey, J. and Field, J. (1985). Workers scheduling with flexible shift models. Journal of Operations management, 5, 327–338.

[4] Aickelin, U., &Dowsland, K. A. (2004). An indirect Genetic Algorithm for a nurse-scheduling problem. Computers & Operations Research, 31, 761-778. https://doi.org/10.1016/S0305-0548(03)00034-0.

[5] Asgeirsson, E. I. (2014). Bridging the gap between self-schedules and feasible schedules in staff scheduling. Annals of Operations Research, 218, 51-69. https://doi.org/10.1007/s10479-012-1060-2.

[6] Awadallah, M., Khader, A., Al-Betar, M., &Bolaji, A. (2011). Nurse Rostering Using Modified Harmony Search Algorithm.Second international conference on Swarm, Evolutionary, and Memetic Computing, Springer Berlin Heidelberg, Lecture Notes in Computer Science, 7077, 27-37. https://doi.org/10.1007/978-3-642-27242-4_4.

[7] Bard, J., &Purnomo, H. (2005). Short-Term Nurse Scheduling in Response to Daily Fluctuations in Supply and Demand.Health Care Management Science, 8, 315-324. https://doi.org/10.1007/s10729-005-4141-9.

[8] Beliën, J., &Demeulemeester, E. (2008). A branch-and-price approach for integrating nurse and surgery scheduling.European Journal of Operational Research, 189, 652-668. https://doi.org/10.1016/j.ejor.2006.10.060.

[9] Bester, M. J., Nieuwoudt, I., & Van Vuuren, J. H.(2007). Finding good nurse duty schedules: A case study. Journal of Scheduling, 10, 387-405. https://doi.org/10.1007/s10951-007-0035-7.

[10] Bilgin, B., Demeester, P., Misir, M., Vancroonenburg, W., VandenBerghe, G., &Wauters, T. (2010). A hyper-heuristic combined with a greedy shuffle approach to the nurse rostering competition. International Conference on Practice and Theory of Automated Timetabling Viii.

[11] Brucker, P., Burke, E. K., Curtois, T., Qu, R., &VandenBerghe, G. (2010). A shift sequence-based approach for nurse scheduling and a new benchmark dataset. Journal of Heuristics, 16, 559-573. https://doi.org/10.1007/s10732-008-9099-6

[12] Burke, E., &Curtois, T. (2010). An ejection chain method and a branch and price algorithm applied to the instances of the first international nurse rostering competition, 2010. International Conference on Practice and Theory of Automated Timetabling Viii.

[13] Burke, E. K., Curtois, T., Qu, R., &VandenBerghe, G. (2010). A scatter search methodology for the nurse rostering problem. Journal of the Operational Research Society, 61, 1667-1679. https://doi.org/10.1057/jors.2009.118.

[14] Burke, E. K., Curtois, T., van Draat, L. F., van Ommeren, J. K., & Post, G. (2011). Progress control in iterated local search for nurse rostering.Journal of the Operational Research Society, 62, 360-367. https://doi.org/10.1057/jors.2010.86.

[15] Fahle, T., &Bertels, S. (2006). A hybrid setup for a hybrid scenario: combining heuristics for the home health care problem. Computers & Operations Research, 33, 2866-2890. https://doi.org/10.1016/j.cor.2005.01.015.

[16] Gutjahr, W. J., &Rauner, M. S. (2007). An ACO algorithm for a dynamic regional nurse scheduling problem in Austria. Computers & Operations Research, 34, 642-666. https://doi.org/10.1016/j.cor.2005.03.018.

[17] Li, J. P., &Aickelin, U. (2004). The application of Bayesian optimization and classifier systems in nurse scheduling. Parallel Problem Solving from Nature - Ppsn Viii, Lecture Notes in Computer Science, 3242, 581-590.

[18] Lu, Z., &Hao, J.-K. (2012). Adaptive neighborhood search for nurse rostering. European Journal of Operational Research, 218, 865-876. https://doi.org/10.1016/j.ejor.2011.12.016.

[19] Maenhout, B., &Vanhoucke, M. (2011). An evolutionary approach for the nurse rerostering problem. Computers & Operations Research, 38, 1400-1411. https://doi.org/10.1016/j.cor.2010.12.012.

[20] Stolletz, R., & Brunner, J. O. (2012). Fair optimization of fortnightly physician schedules with flexible shifts. European Journal of Operational Research, 219, 622-629. https://doi.org/10.1016/j.ejor.2011.10.038.

[21] Thompson, J. M., & Parr, D. (2007). Solving the multi-objective nurse scheduling problem with a weighted cost function. Annals of Operations Research, 155, 279-288. https://doi.org/10.1007/s10479-007-0202-4.

[22] Topaloglu, S., &Ozkarahan, I. (2004). An implicit goal programming model for the tour scheduling problem considering the employee work preferences. Annals of Operations Research, 128, 135-158. https://doi.org/10.1023/B:ANOR.0000019102.68222.df.

[23] Wright, P. D., &Bretthauer, K. M. (2010). Strategies for Addressing the Nursing Shortage: Coordinated Decision Making and Workforce Flexibility. Decision Sciences, 41, 373-401. https://doi.org/10.1111/j.1540-5915.2010.00269.x.

[24] Wright, P. D., Bretthauer, K. M., & Cote, M. J. (2006). Reexamining the nurse scheduling problem: Staffing ratios and nursing shortages. Decision Sciences, 37, 39-70. https://doi.org/10.1111/j.1540-5414.2006.00109.x.

[25] Maenhout, B., &Vanhoucke, M. (2010). A hybrid scatter search heuristic for personalized crew rostering in the airline industry. European Journal of Operational Research, 206, 155-167. https://doi.org/10.1016/j.ejor.2010.01.040.

[26] [26] Sabar, M., Montreuil, B., &Frayret, J. M. (2009). A multi-agent-based approach for workers scheduling in assembly centres. Engineering Applications of Artificial Intelligence, 22, 1080-1088. https://doi.org/10.1016/j.engappai.2009.02.00009.

[27] Boysen, N., Fliedner, M., Scholl, A. (2008). Assembly line balancing: Which model to use when. International Journal of Producyion Economics, 111, 509-528. https://doi.org/10.1016/j.ijpe.2007.02.026.

[28] Van den Bergh, J., De Bruecker, P., De Boeck, L. (2013). Personnel scheduling: A literature review. European Journal of Operational Research, 226, 367-385. https://doi.org/10.1016/j.ejor.2012.11.029.

[29] Farahani, A., Farahani, H., Farahani, G., & Mousavi, S. (2022, September). Flexible personnel scheduling in large multi-product unpaced asynchronous assembly lines. In 2022 27th International Conference on Automation and Computing (ICAC) (pp. 1-6). IEEE. DOI: 10.1109/ICAC55051.2022.9911088.