Improved Genetic Algorithm Approach Based on New Virtual Crossover Operators for Dynamic Job Shop Scheduling

KAOUTHER BEN ALI1, ACHRAF JABEUR TELMOUDI2, (Member, IEEE), AND SAID GATTOUF1

1SMART Lab, ISG, University of Tunis, Tunis 2000, Tunisia
2LISIER Laboratory, The National Higher Engineering School of Tunis, University of Tunis, Tunis 1008, Tunisia

Corresponding author: Achraf Jabeur Telmoudi (achraf-j.telmoudi@ieee.org)

ABSTRACT The realtime manufacturing system is subject to different kinds of disruptions such as new job arrivals, machine breakdowns, and jobs cancellation. These different disruptions affect the original schedule that should be updated to maintain the system's performance. An effective re-scheduling is required in this situation to make better utilization of the system resources. This paper studies the dynamic job shop scheduling problem. The problem is known as strongly NP Hard optimization problem where new jobs are unconditionally arrived at the system. Hence, to deal with system changes and performing hard tasks scheduling, we propose an evolutionary genetic algorithm based on virtual crossover operators. Experimental results are compared with state-of-the-art heuristics and metaheuristics dedicated for evaluating large scale instances. Simulation results show the efficiency of the proposed virtual crossover operators integrated into the genetic algorithm approach.

INDEX TERMS Dynamic job shop scheduling problem, genetic algorithm, crossover operators, makespan, dispatching rules, metaheuristics.

I. INTRODUCTION

Scheduling is a scientific domain concerning the allocation of tasks (e.g., jobs, services) to resources (e.g., machines). The objective of a scheduling problem is to maximize or minimize a desired objective in an optimal manner to perform measures such as the makespan, the total tardiness, the cost, etc. Operation research and artificial intelligence fields are the most referred to the literature of scheduling problems. Their goal is to solve the question of how to move forward in the production process that is considered the basic step of the process. Scheduling can be viewed as two types: static and dynamic. Static scheduling (called as deterministic) constructs a complete schedule of tasks on candidate machines through a well known data. However, dynamic scheduling considers tasks arrival one by one during the system execution.

The production scheduling encounters many challenges due to production environment changes that are considered dynamic in nature (job arrivals, job cancellation, machine breakdowns, etc.) and cause a high degree of complexity during the scheduling. Hence, the industrial process must be optimized in terms of different performance criteria. An illustrative workflow of scheduling in the manufacturing system is presented in Fig. refeval. The manufacturing system starts processing after the arrival of production orders. An effective schedule is required to maximize production effectiveness and gain profits. The most frequent industrial objective is the minimization of the makespan $C_{max}$; well known as the completion time of the last job at the system.

Different scheduling problems are classified based on their complexity in different production lines: flow shop, job shop, and open shop, etc. Obviously, the job shop is one of the most complicated NP-Hard combinatorial optimization problems. The goal of the job system is to find a processing order of a set of textitn jobs on textitm machines where different jobs may have a separate processing sequence. Each operation will be processed on a candidate machine during a fixed processing time [1], [2]. The interest in a real-time system with unexpected events is of great importance where the
Several approaches inspired by the above-presented methods are developed to maximize the performance of scheduling problems in considered systems. In the following, we will focus our interest on recent optimization techniques applied in the literature to solve the Dynamic JSSP. The contributed work in [23] has studied the problem of Dynamic JSSP by re-scheduling randomly job arrivals with the performance of three sub-objectives: the discontinuity rate of job arrivals, the deviation of the makespan from its initial solution, and the deviation of an updated sequence of machines. To solve the problem, the authors have proposed an updated version of the PSO (Particle Swarm Optimization) algorithm. The proposed algorithm is developed based on the following improvements: (i) modification of decoding scheme, (ii) adaptation of a new approach for population initialization, and, (iii) proposition of a novel particle movement method. Through extensive simulations with generated re-scheduling instances, the proposed modified PSO has shown its efficiency. It has given significantly better results than the three compared metaheuristics selected from the state-of-the-art.

Moreover, in the work of Zhou et al. cited in [24], they have proposed effective scheduling policies (SPs) generated through off-line learning and implemented on online evolved SPs for fast application. They have proposed three types of hyper-heuristic methods for the co-evolution of the machine assignment and job sequencing rules to solve the multi-objective Dynamic JSSP. The used methods are genetic programming with two sub-populations, genetic programming with two sub-trees, and genetic expression programming with two chromosomes. Experimental results showed the superiority of the proposed method called (CCGP-NSGA II) in terms of efficiency and competitiveness; comparing against other evolutionary approaches. Other studies have presented different inspired hyper-heuristics approaches such as the work of Park et al. [3] that have proposed a new genetic programming based hyper-heuristic. The proposed approach is based on a systematic analysis of diverse popular combination schemes and decision making of different elements to be evolved by genetic programming. The analysis method has shown a significant influence on the behaviors of generated ensembles through different combinations.

To minimize the makespan in a Dynamic Job System, the authors of the work cited in [18] have developed a hybrid genetic algorithm called the GAKK algorithm. This method consists of combining the new KK heuristic with the GA. The main idea of this approach is to combine the population generated by the KK heuristic with 25% of the initial generated population for the execution of the hybrid algorithm. The provided experimentations have shown efficient results for large sizing problem instances in terms of Cmax minimization and running time. In addition to the previous works, the research cited in [25] has suggested a hybrid genetic algorithm with a tabu search approach for solving the Dynamic JSSP. The problem is investigated under two sub-constraints: machine breakdowns and random job arrival. Both of schedule efficiency and schedule stability are measured to validate the
Among many metaheuristics used for solving the Dynamic JSSP, the Greedy Randomised Adaptive Search Procedure (GRASP) has been studied by Baykasoglu with different optimization objectives. In [26], Baykasoglu and Karaslan addressed a Dynamic JSSP with machine capacity constraints. Moreover, the GRASP inspired approach is proposed under constraints related to order due dates and sequenc of dependent setup times. The problem is evaluated based on four performance criteria (mean tardiness, makespan, mean flow time, and schedule instability). Simulation results have shown the efficiency and the feasibility of the proposed method to solve the problem in real-time as well as the rescheduling problem. Similar to the studied research works being published in [27] and [28], the authors have proposed a multi-start and constructive search algorithm applied to solve an interesting industrial dynamic job shop floor case called parallel heat treatment furnaces; likewise in [29]. The obtained results have proved the high performance of the proposed method in terms of energy consumption and incomes.

The present study considers a dynamic job shop environment to minimize the makespan. Comparing to the studied works presented in the literature, this paper proposes an approach based on a genetic algorithm with new virtual crossover operators. The new proposal is dedicated to enabling a fast reaction of the genetic operators facing dynamic changes. The following this work is organized as follows: Section 2 describes the used notation and formulation of the developed objective function. Section 3 describes the proposed GA approach based on virtual crossover operators for solving sequencing operations. Computational results and their interpretations are discussed in Section 4. Finally, Section 5 presents the conclusion and lines for future research.

II. NOTATIONS AND PROBLEM FORMULATION

Due to the occurrence of external and/or internal events illustrated in Fig.2, the dynamic scheduling is required to absorb the impact of disruptions (arrival of new jobs, machine breakdowns, etc.) that affect the original schedule. In this context, the high frequency of environment changes involves extremely complicated processing during the system’s execution that needs powerful algorithmic techniques. The current study is addressed to find an effective schedule with the minimum makespan within a dynamic job shop system. Clearly, the dynamic job shop is an extension of the well-known job shop problem where during the execution of n jobs on m machines, new job arrivals may appear randomly at a time t. Each job has one or more operations with a fixed processing time where their relationships can be modeled with precedence constraints. If the actual operations have been processed or being processed, their schedule could be changed with the fact of perturbations. That is why rescheduling is required sometimes to update the schedule. A further explanation of the dynamic job shop is given as a sequence of static job-shop problems. Consequently, the completion time of the whole system is the makespan of the last static sub-problem presented at the system.

The considered assumptions are considered as follows:

(i) Each machine can perform only one operation of any job at a time.

(ii) An operation of a job could be performed by only one machine at a time.

(iii) An operation of a job cannot be performed until its preceding operation is completed.

(iv) Machines are considered preemptive and activities are interrupted (if any dynamic event occurs).

(v) A job cannot be cancelled.

(vi) Machines are available at time zero.

We consider a Dynamic JSSP being formulated as a sequence of static sub-problems. Table 1 defines the used notations in the mathematical model.

Objective Function:

\[ \text{Minimize } C_{\text{max}} \] (1)

Subject to:

1) Constraint on the start time of each operation \(O_{i,j}\)

\[ C_{\text{max}} = \max_i (s_{t_{i,j}} + p_{i,j}), \quad \forall i \leq n, j \leq \lambda_i \] (2)

2) Make-span calculation

3) Precedence constraint between operations

\[ s_{t_{i,j}} + p_{i,j} \leq s_{t_{i',j'}} + p_{i',j'} \] (3)

4) Machine capacity constraints (inspired from [30])

\[ \zeta[i, j, i', j'] + \zeta[i, j, i', j'] \geq \varepsilon_{ijk} + \varepsilon_{ijk} - 1 \] (4)
### III. GENETIC ALGORITHM BASED VIRTUAL CROSSOVER OPERATORS

To solve the Dynamic JSSP, we present in Fig 3 a flow chart that describes the global approach. It starts with an initial job shop problem following the initial data and the parameters. The GA is applied step by step following the processing in Fig 4. Once the schedule is planned for application, the decision process is activated. If no real-time job(s) arrive unconditionally at the system during system execution, the current schedule is considered as the final output. Otherwise, the process of the current state is pre-empted. Therefore, new job(s) are scheduled by respecting the precedence constraints. The current schedule is continued performing until (tx) is finished. Indeed, the new job(s) are added to the rest of the previous schedule. Hence, a new JSSP is initialized based on updated data and, then, the application of the adopted GA is activated. For a finite number of iteration, the same process is applied for achieving the best schedule with a minimum Cmax value.

The efficiency of the GA is based on the recombination process that plays the main role to obtain results with high performance. Genetic operators (selection, crossover, and mutation) are leading the intensification and diversification goals. Each operation that represents a gene of a chromosome is allocated on a candidate machine. The studied objective function is the minimization of the completion time of the last processed operation. Applied to Dynamic JSSP, the methodology consists of creating chromosomes with a number of genes equals to \(\sum_{i=1}^{n} \lambda_i\). After that, each operation is assigned randomly to a machine and placed on a gene of the chromosome. The objective is to minimize the maximum completion time of all operations.

The flow chart of Fig 4 describes the proposed GA approach used to solve the Dynamic JSSP with new job arrival. The algorithm starts with the initialization of input data and GA parameters for the system execution. The initial population is generated randomly to provide good initial solutions. As well as, to get various chromosomes with the best genes information. The contributed GA approach is applied based on the following main steps (selection, crossover, mutation, and evaluation). For the selection process, the roulette wheel selection operator is applied to choose the best parents for reproduction. For intensification purposes, the crossover operator is applied. The selected parents are combined with random chromosomes to create new offsprings. The proposed crossover operators are called virtual operators; a new shape of crossing between genes information which does not consider the physical nature of crossing by regards to the dynamic characteristic of the job environment. Two kinds of virtual crossing over are proposed based on two points and three-point crossing over. Then, the chosen swap operator is applying on a selected chromosome to perform diversification purposes. The principle of the swap operator consists of switching randomly two genes from the selected chromosomes. After that, the provided solutions will be evaluated to select the best chromosome(s) at the current iteration.

The last step consists of testing the performance of the selected chromosome(s), provided by the current iteration (based on its (their) makespan), vs. the chromosomes with the less makespan value of all previews iterations. If one of the termination criteria is reached, the algorithm will be stopped by sending the best solutions to the output. The termination criteria are: (criterion 1) the makespan remains constant for five successive iterations, or (criterion 2) a finite number C of iterations are reached. Otherwise, the iteration solutions will be stored for trying to improve in the next generations by comparing previous results to the next ones. Hence, to enhance solutions results of the next iteration, 20% of initial the population will be constituted by stored solutions will be evaluated to select the best chromosome(s) at the current iteration. The recombination process plays a crucial role in the performance of the evolutionary GA. According to a widely accepted representation for crossover operators, information already existing in the parent solutions should be recombined without introducing new information. For the Dynamic JSSP problem, the precedence relations of operation to other operations projected for the same machine is of great importance. This information should be passed to produce competitive offspring. In this process, crossover operator plays an important role for intensification purpose. To comprehend the GA process, it is necessary to understand the role of the crossover operator.

In the following subsections, four new crossover operators will be described. We are going to propose new virtual

| TABLE 1. Description of the used notations. |
|-----------------|-----------------|
| Notation | Definition |
| (i) Indices |
| \(J_i\) | \(i^{th}\) job, \(1 \leq i \leq n\) |
| \(O_{ij}\) | \(j^{th}\) operation of the \(i^{th}\) job, \(1 \leq i \leq n, 1 \leq j \leq \lambda_i\) |
| \(O_{ij,k}\) | Precedence constraint with \(O_{ij}\) |
| \(M_k\) | \(k^{th}\) machine, \(1 \leq k \leq m\) |
| (ii) Parameters and variables |
| \(\lambda\) | denotes the number of operations/ Job |
| \(n\) | Total number of jobs |
| \(m\) | Total number of machines |
| \(\lambda_i\) | Number of operations at job \(J_i\) |
| \(O_{ij,k}\) | A set of operation proceed on machine \(M_k\) |
| \(C_{max}\) | The makespan value |
| \(p_{ij}\) | The processing time of \(O_{ij}\) |
| \(p_{i,j'j''}\) | The processing time of \(O_{i,j'j''}\) |
| (iii) Decision variables |
| \(\varepsilon_{i,j,k}\) | \(\xi[i,j,i',j']=1; \varepsilon_{i,j,k}=1\) if operation \(O_{ij}\) is processed on machine \(k\); 0 Otherwise |
| \(s_{ij}\) | The starting time of operation \(O_{ij}\) |
| \(s_{i,j'j''}\) | The starting time of operation \(O_{i,j'j''}\) |
| \(\xi[i,j,i',j']=1\) if \(O_{ij}\) is processed before \(O_{i,j'j''}\) on \(k\); 0 Otherwise |

\[
O_{ij} \cap O_{i'j''} \in \Omega M_k \quad (5)
\]

and

\[
st_{ij} + p_{ij} - (1 - \xi[i,j,i',j'])L \leq st_{i'j''} \quad (6)
\]
crossover operators based on the behavior inheritance of best selected parents by their offsprings. The aim is to test their influence on the performance of the GA and implicitly on makespan minimization. All along the next subsections, we will use the same chromosome presented in Fig.5 to explain step by step the principle of the two proposed crossover operators applied with two points and three points crossover.

Starting by the given example: considering a job shop problem with two jobs $J_1$, $J_2$ and three machines $M_1$, $M_2$, $M_3$:

$$
J_1 = \left[ O_{1,1}, O_{1,2}, O_{1,3}, O_{1,4}, O_{1,5} \right] = (1, 3), (3, 2), (2, 1), (3, 4), ((2, 3))
$$

$$
J_2 = \left[ O_{2,1}, O_{2,2}, O_{2,3}, O_{2,4}, O_{2,5} \right] = (2, 2), (1, 2), (3, 5), (2, 3), ((3, 3))
$$

Each operation $O_{i,j}$ is presented by a pair of numbers ($k$, $p$); where $k$ is the index of the allocated machine for processing an operation and $p$ is the processing time of that operation.

In the above example, the size of the chromosome is equal to 10 genes.

**A. PROPOSED MIN-MAX CROSSOVER OPERATORS**

The process of reproduction starts by selecting two parents’ chromosomes. The principle of the two first proposed crossover operators, called respectively, Min-Max 2 points (Fig.6) and Min-Max 3 points (Fig.7) is described as follows:

- For the Min-Max 2 points: Random selection of 2 points crossover.
- For the Min-Max 3 points: A random selection of 3 points crossover.
- Calculate the absolute processing time $P_{a,c,s}$ of each segment of the two parents chromosomes:

$$
P_{a,c,s} = \sum_{i=1}^{P_s} P_{(i^{th}, s^{th})}
$$

where

- $P_s$ denotes the length of the segment $s$. $P_{i,s}$ is the processing time of the $i^{th}$ gene of the $s^{th}$ segment of the chromosome $c$.
- Arrange of three absolute processing times as the following: For Min-Max 2 points: minimum (min), medium (med), and maximum (max).

![Flow chart of the proposed approach for dynamical job sequencing.](image-url)
For Min-Max 3 points: minimum (min), medium 1 (med 1) medium 2 (med 2), and maximum (max).

- Switching each segment of each parent chromosome between both of them based on their positions:
  - For Min-Max 2 points: min by min, med by med, and max by max.

- For Min-Max 3 points: min by min, med 1 by med 1, med 2 by med 2, and max by max.

- Sequencing of the new offsprings with respect to precedence constraint relationships.

**Performance Analysis of the Min-Max crossover operators:**

Unlike all crossover operators established in the literature where a physical exchange is performed, the significant advantage of the present new method is the behavioral
crossing aspect of genes that do not considers the physical crossing between the selected parents. The proposed operator can be viewed or called a virtual crossover. Indeed, it consists of applying local permutations of the positioning of the chromosome segments. Consequently, the new offsprings will be reconstructed based on the excellent quality behavior of the opposite parent. The application of the virtual crossover permits the combination of the behavior of crossed chromosomes to estimate the possible best solutions. One more important aspect is to perform the internal performance analysis of the scheduling parameters vs. the local reproducibility evolution of fixed segments. The major disadvantage of this approach is that identical reproduction genes can occur when parents are with the same quantitative arrangement of segments. This inconvenience becomes negligible by increasing the number of crossover points.

B. PROPOSED MEAN/Min-MAX CROSSOVER OPERATORS

The Mean/Min-Max crossover consists of an exchange of the behavior between two parents based on the mean of absolute processing time of chromosomes segments. In Fig.8 and Fig.9, we illustrate through an example the following steps, one by one, of the two proposed crossover operators, called Mean/Min-Max 2 points and Mean/Min-Max 3 points.

- For Mean/Min-Max 2 points: Random selection of 2 points crossover.
- For Mean/Min-Max 3 points: Random selection of 3 points crossover.

- Calculate the mean of the absolute processing time $P_{a_{c,s}}$ of each segment of the two parent chromosomes:

$$\mu(P_{a_{c,s}}) = \frac{\sum_{i=1}^{P_{s}} P_{i,s}}{n_{c,s}}$$

where: $n_{c,s}$ is the number of genes of the $s^{th}$ segment of the chromosome $c$.

- Arrangement of the three means of the absolute processing times as the following: -For Mean/Min-Max 2 points: minimum (min), medium (med), and maximum (max).
- For Mean/Min-Max 3 points: minimum (min), medium 1 (med 1), medium 2 (med 2), and maximum (max).

- Switching the chromosome segment position between the two parents: -For Mean/Min-Max 2 points: min by min, med by med, and max by max.
- For Mean/Min-Max 3 points: min by min, med 1 by med 1, med 2 by med 2, and max by max.

- Sequencing of the new offsprings with respect to precedence constraint relationships.

Performance Analysis of the Mean/Min-Max crossover operators:

The Mean/Min-Max 2 points crossover keeps the same advantages as described above. Nevertheless, we consider the Mean/Min-Max method is better due to its ability to reduce identical reproductions, considering the more stringent and detailed assessment of segments. We note that the two used proposed crossover operators are used based on the changing of genes information for 2 and 3 points crossover operators whereas the total processing time is calculated and exchanged between parent1 and its corresponding in parent2. For the second operator, we calculate the mean processing time and exchanging genes information between the two parents. For both methods, new offsprings are created.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. INSTANCES AND PARAMETERS SETTING

To evaluate the performance of the GA, 26 benchmarking random instances with different sizing problems (small, medium and large) are generated. We denote by $n'*m$ the problem size; where $n'$ is the total number of jobs (including new job arrivals) executed on $m$ machines. The number of operations
for a job follows the uniform discrete distribution within the interval \([1, 10]\) and \([1, 20]\). The processing time of each job follows the uniform distribution of \([1, 100]\). While increasing the size, problems become more complex. The first one is of 25 jobs and 5 machines. The last instance contains 300 jobs treated by 25 machines. The size of the first and the last generated problems are denoted respectively by \((25*5)\) and \((300*25)\).

To evaluate the approach, the 26 generated instances are structured in the following three subsets:

- Small problem-size (Small P-size) where the number of jobs is strictly less than 50: \(25*5, 25*10, 30*5, 35*10, 35*15, 40*5, 40*10, 45*5,\) and \(45*10\).
- Medium problem-size (Medium P-size) where the number of jobs is between 50 and 100: \(50*10, 55*10, 60*5, 70*5, 70*10, 75*5, 75*10, 80*5, 80*10, 90*5,\) and \(95*10\).
- Large problem-size (Large P-size) where the number of jobs is strictly superior to 100: \(100*10, 115*5, 120*10, 130*10, 220*25,\) and \(300*25\).

With the goal of optimizing a job shop system with frequent dynamic changes, the makespan value of each static sub problem is calculated and, then, the whole completion time is performed at the end of the process. In this study, the proposed GA approach is applied to different sizing generated random instances. The obtained results are compared against the following state of the art heuristics and metaheuristics:

- GA1: Simple GA with one-point crossover operator (used in \([31]\)).
- GA2: Simple GA with two-point crossover operator.
The generated results are compared vs. all selected operators (four types) is applied while executing the GA approach. The simulation results show the efficiency of the proposed GA approach based virtual crossover operators for solving the Dynamic JSSP. In the following, we give all compared approaches used for simulations:

- **GA1Cmax**: MinMax GA with 2 points crossover combined with the swap operator mutation.
- **GA2Cmax**: MinMax GA with 3 points crossover combined with the swap operator mutation.
- **GA3Cmax**: Mean/MinMax with 2 points crossover combined with the swap operator mutation.
- **GA4Cmax**: Mean/MinMax with 3 points crossover combined with the swap operator mutation.

**Mean 1**: The average makespan of the set of the Small problem-size.

**Mean 2**: The average makespan of the set of the Medium problem-size.

**Mean 3**: The average makespan of the set of the Large problem-size.

**G-Mean**: The average makespan of the set of the 26 instances. We show a marginal quality with 7 optimal solutions from the instance (60*5) and three solutions for the GA2Cmax with the instances (100*10) and (220*25). One solution for the GA3Cmax using the instance (60*5) and three solutions for the GA2Cmax with (50*10), (70*5), and (80*5) instances.

These results show the performance of the 3-point virtual crossover operator to enhance the performance of the GA to solve the Dynamic JSSP with random arrival of new jobs.
TABLE 3. Experimentation results of the proposed GA based virtual crossover (VC) operators VS. metaheuristics and dispatching rules in terms of minimum Cmax.

| Problem size | Data n | GA1\_Cmax | GA2\_Cmax | GA3\_Cmax | GA4\_Cmax | GA1 | GA2 | GRASP | HGAT | GAKK | MOPOS | SPT | LPT | EDD |
|--------------|--------|------------|------------|------------|------------|-----|-----|-------|------|------|-------|-----|-----|-----|
| SMALL P-SIZE | 259 | 280 | 275 | 268 | 270 | 371 | 308 | 299 | 292 | 297 | 268 | 384 | 380 | 389 |
| 35\_10 | 198 | 192 | 187 | 194 | 252 | 212 | 205 | 207 | 207 | 205 | 269 | 282 | 285 |
| 35\_15 | 242 | 243 | 233 | 237 | 349 | 273 | 254 | 270 | 283 | 258 | 362 | 354 | 359 |
| 40\_5 | 179 | 178 | 171 | 183 | 228 | 216 | 201 | 199 | 203 | 193 | 237 | 233 | 239 |
| 40\_10 | 80 | 78 | 69 | 94 | 166 | 116 | 103 | 103 | 106 | 106 | 183 | 179 | 173 |
| 45\_5 | 105 | 91 | 98 | 115 | 207 | 136 | 122 | 127 | 131 | 115 | 210 | 215 | 202 |
| 45\_10 | 371 | 364 | 380 | 392 | 409 | 422 | 392 | 371 | 388 | 399 | 451 | 446 | 442 |
| 50\_5 | 174 | 171 | 170 | 181 | 251 | 209 | 195 | 193 | 185 | 191 | 238 | 232 | 229 |

Indeed, for 10 problems among 11 (90.9% of total cases), best results were obtained when we combine the proposed GA approach with one of the virtual crossover operators based 3 points crossover. This is due to the performance of the 3-point crossover in the reduction of producing identical genes through the virtualization of crossing over. These results confirm our opinion when we have discussed the proposed GA based new crossover operators in previous subsections. Also, we can interpret that the GA approach combined with virtual 2 points crossover operators do not give the best makespan values for the medium class of problems (only for small P-size). In Figure 10, the given values of Mean 2 and mean 3 confirms the efficiency of the proposed virtual crossover operators vs. methods developed in the literature (seen in Table 3). Obviously, the obtained means values (for medium and large P-size) of the $GA4_{C_{max}}$ method demonstrate the global performance of the proposed Mean/Min-Max with 3 points crossover operator to reach an acceptable solution results. For the set of problems with large size, the Min-Max 2 points methods give only

FIGURE 10. Comparisons in terms of average makespan results using various problems size.
33.33% best solutions of total cases and about 66.66% based Mean/Min-Max 3 points.

The G-mean values demonstrate the efficiency of the four proposed virtual crossover operators vs. all compared methods. By comparing our proposal to the best metaheuristics cited in the literature, it is shown near results but globally there is a huge difference this is due to the variation of the job environment with dynamic perturbations. As well as for the used Priority Dispatching rules (P-dispatching rules) that have been seen very far from both the used metaheuristics and our proposal in terms of Cmax values. It is meaningful due to the role of metaheuristics in giving optimal solutions (marked with gray color in Table 3).

The global G-mean values of the proposed approach indicate that the experimentations outputs are appeared in an interval of small uncertainty due to the definition of the Dynamic JSSPs as a sequence of static JSSPs. However, the performance of each virtual crossover operator is proportional to the problem size and the best solution is given based on Mean/Min-Max 3 points crossover virtual operator.

**V. CONCLUSION AND FUTURE DIRECTIONS**

In this paper, a Dynamic JSSP is addressed with the objective to minimize the makespan with continuous jobs arriving in a manufacturing system while considering the sequencing of operations. A GA based metaheuristic approach is used to manage the job operating processing through the proposed new virtual crossover operators. Important formulations are presented in the context of developing the dynamic JSP with precedence constraints and a preemptive model during scheduling. Experimental results demonstrate that our proposal GA has a shorter makespan than the other compared algorithms when scheduling is performed with mean/min-max 3 points crossover operator. The proposed algorithm gives promoted solutions for small, medium, and especially large size problems according to the obtained global average makespan. To the best of our knowledge, there are few works that deal with this kind of optimization shop floor by regards to its hardness. Hence, we aim to continue working on extended methods capable to ensure system robustness in terms of schedule quality and time-consuming.

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KAOUTHER BEN ALI received the M.Sc. degree in computer science from the Higher Institute of Management of Tunisia, in 2015, where she is currently pursuing the Ph.D. degree in computer science. Her research interests include almost all the fields of operation research, combinatorial optimization problems and artificial intelligence for real-world applications.

Since 2017, she started working as a Researcher at the SMART Laboratory, Computer Science Department, Higher Institute of Management of Tunisia. The aim of her recent publications is to discuss new trends, review industrial needs, and present innovative solutions in production scheduling fields.

ACHRIF JABEUR TELMOUDI (Member, IEEE) received the M.Sc. degree in automation and systems engineering and the Ph.D. degree in electrical engineering from University of Tunis, Tunis, Tunisia, in 2006 and 2011, respectively.

Since 2011, he has been an Associate Professor in automation and industrial informatics with the Higher Institute of Applied Science and Technology of Sousse, University of Sousse, Tunisia. He is currently a member of the LISIER Laboratory, The National Higher Engineering School of Tunis, University of Tunis, Tunisia. His current research interests include planning and scheduling, discrete event systems, Petri nets, prediction, and system identification. He serves as a Guest Editor for the Journal of Systems and Control Engineering, the Transactions of the Institute of Measurement and Control, and Cybernetics and Systems. He is also an Associate Editor of the Journal of Systems and Control Engineering, the International Journal of Dynamics and Control, and the International Journal of Applied Metaheuristic Computing. He is also a regular Reviewer for more than 20 journals, including IEEE SMC: Systems, IEEE TRANSACTIONS ON ROBOTICS, IEEE TRANSACTIONS ON AUTOMATIC CONTROL, IEEE ACCESS, Neural Computing and Applications, Energy, Journal of Aerospace Engineering, Computers & Industrial Engineering, Journal of Systems and Control Engineering, Aircraft Engineering and Aerospace Technology, RAIRO—Operations Research, and so on.

SAID GATTOUFI received the Ph.D. degree in management from Sabanci University, Turkey, in 2002. He was an Associate Professor with the Operations Management and Business Statistics Department, Sultan Qaboos University, Oman, from 2005 to 2014. He is currently a Professor with the Higher Institute of Management of Tunisia, where he is also a Researcher with the SMART Laboratory. He is an active Researcher. His publications are frequently cited in well-reputed international journals, including the Journal of Operational Research Society, Socio-Economic Planning Science journal, International Journal of Flexible Manufacturing Systems, International Journal of Computer Mathematics, International Journal of Accounting and Finance, Journal of Risk Finance, and Journal of Business and Economics Research. He participated as an organizer, a presenter, and a keynote speaker in well-known conferences around the world. His main areas of research are the performance assessment and the analysis in management, in general, using data envelopment analysis (DEA) and its derived approaches.

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