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Simulation Particle Swarm Optimisation for Stochastic Permutation Flow Shop Scheduling Problem under Different Disruptions

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Abstract—**This paper considers the permutation flow shop scheduling problem (PFSP) under stochastic processing time and in the presence of different types of real-time events. A multi-objective optimisation model and a novel predictive-reactive approach based Simulation-Particle Swarm Optimisation algorithm is designed and adapted for this problem. This algorithm hybridised the Monte-Carol Simulation (MCS) technique with the Particle Swarm Optimaisation algorithm to deal with the the stochastic behavior of the problem. Also, a deterministic version of the benchmark set proposed by [1] is adapted and used to test the aforementioned problem and solution method. Furthermore, the survival analysis based on the Kaplan-Meier estimator is used to analyse the behaviour of stochastic and dynamic solutions.**

Index Terms—**Permutation Flow Shop Scheduling; Multi-objective Optimisation Model; Predictive-Reactive Approach; Simulation-Particle Swarm Optimisation Algorithm**

I. Introduction

The scheduling in a manufacturing environment has received a special attention for its wide real applications. In real-world scheduling systems, there are two main sources of uncertainties that lead to different scheduling environments, which are; dynamic and stochastic. When there are some variables that are considered as unknown and follow a probability distribution, the scheduling in this case is named as stochastic scheduling [2]. The PFSP problems in stochastic environment (SPFSP) have received increasing interesting in the literature of scheduling, due to the nature of most real problems where the data and information cannot be known in advanced. However, the stochastic and dynamic scheduling problems have less consideration comparing to the deterministic PFSP. Stochastic scheduling models have been mainly introduced since the 1980s where researches have traditionally concentrated on non-anticipative policies which intent to minimise the criteria in expectation. [3] showed that for the scheduling problem of m immediately available jobs with random variable service times. It is certain that such problems can be reduced to equivalent deterministic problems. [4] investigated the analytic properties in scheduling of various classes of policies, also for special cases the optimal policies were determined. [5] derived additive performance bounds for a parallel machine without release dates in stochastic environment. [6] studied a stochastic 3-machines scheduling problem in Johnsons flow shops with the objective of minimising the expected total completion time. [7] addressed the flow shop scheduling problem (FSP) with minimisng the expected total completion time under machine breakdowns in stochastic environment. The authors presented a method that converts a scheduling problem under breakdowns into a finite sequence of problems without-breakdowns. [8] applied a hypothesis-test method incorporated into a Genetic Algorithm for solving the FSP problem under stochastic environment and to avoid premature convergence of the Genetic Algorithm. [9] provided an interesting review of many classical Combinatorial Optimisation Problems COP in a stochastic environment such as; stochastic scheduling, stochastic VRP and stochastic reservations. [10] proposed a job sequencing rule which includes Talwars and Johnsons rules for the 2-machines FSP so as to minimise the total completion time. In this problem, the processing times are assumed independently and follow the Weibull distribution. [11] proposed a class of PSO algorithm with SA and hypothesis test to solve the FSP with no-wait constraint in stochastic environment, where the criterion is to minimise the total completion time. The developed PSO algorithm showed better feasibility, effectiveness and robustness when compared to other proposed algorithms. [12] applied heuristics for the stochastic FSP and general distributions for processing times. [13] dealt with a scheduling problem of a real-world offline stochastic FSP with limited buffers. The impatience of a job is consider as an uncertain due date and both of the processing times and due dates are stochastic variables. The criteria is to minimise the expected weighted number of tardy jobs. [14] proposed a developed B&B method for the single-machine stochastic scheduling problem in order to minimise the total expected earliness and tardiness costs. [15] considered the setup and processing times as stochastic variables for the problem of a 2-machines production FSP with the criterion of minimising the total completion time. [16] proposed some heuristics from the literature for the PFSP under stochastic processing times in order to minimise the expected total completion time.

The terms Optimisation for Simulation or Simulation for Optimasation are commonly mentioned in the field of stochastic COPs [17]. Both the comprehensive surveys of [18] titled Optimisation via Simulation, and [19], which is titled Simulation Optimisation (Sim-Opt), reflect the two terms mentioned previously. The main aim of hybridising simulation and optimisation is to handle the COPs in the presence of stochastic components. Figure 1 illustrates the

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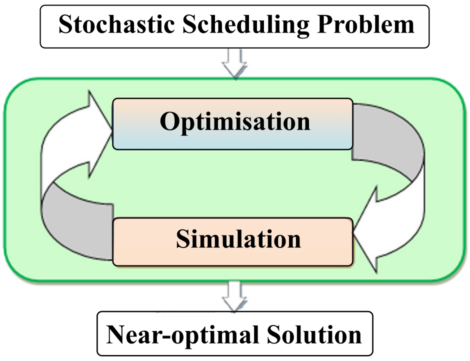

Fig. 1. Overview scheme of the Sim-Opt approach

scheme of the Sim-Opt approach. Recently, in stochastic scheduling, the Sim-Opt is used where heuristics or meta-heuristics are applied for the optimisation part. The concept of Simulated Annealing (SA) algorithm has been developed into an algorithm that can be used to solve a variety of optimisation problems. This is shown in work by [20], where SA was used to optimise parameters for an automated manufacturing system simulation. [21] presented the Simulation-Iterated Local Search approach that extends the Iterated Local Search algorithm by combining simulation to provide the algorithm with the ability of dealing with stochastic COPs in a natural way. [22] presented a Sim-heuristic approach for solving the PFSP under uncertain processing times. [23] integrated routing metaheuristics with MCS for solving the VRP with stochastic demands; [24] presented a review of Sim-heuristics by extending metaheuristics to deal with stochastic COPs. In this paper, the PFSP under stochastic processing time and different dynamic disruptions including; machine breakdowns and new job arrivals is considered, where a multi-objective model is used to preserve the problem stability and robustness. The reminder of this paper is as follows, Section II concentrates on the multi-objective model that used for the proposed problem. Section III shows the hybridisation of the MCS approach and PSO algorithm, which lead to the Sim-PSO approach. The experimental results are given in section IV. Finally, the conclusions and future works are listed in section V.

II. A MULTI-OBJECTIVE OPTIMISATION MODEL FOR ROBUST DYNAMIC PFSP

In this paper, a multi-objective optimisation model proposed by [25] is presented. This model is designed for the PFSP of size $n \times m$ ($jobs \times machines$) in the presence of different real-time events. The model considers very important performance measures including utility, stability, and robustness. The proposed multi-objective optimisation model (MSR) is given as follows:

$$Min \quad MSR = \alpha U_n(S^*) + \beta I_n(S^*) + \gamma R_n(S^*) \tag{1}$$

where α, β and γ are the objective weights and $\alpha + \beta + \gamma = 1$, $U_n(S^*)$ is the real makespan, $I_n(S^*)$ is the stability objective and $R_n(S^*)$ is the robustness objective.
The first measure, utility, is defined as a classical makespan measure, which is used to indicate the degree of optimisation of the problem. It is required to define two makspans in this model, which are; the real and predictive makespans. To define these makespanes, for given processing times $p_{i\pi_j}$ for jobs $j = 1, 2, ..., n$ on machines $i = 1, 2, ..., m$, and a job permutation $\pi = \pi_1, \pi_2, ..., \pi_n$ that sequenced n jobs through m machines using the same permutation, the C_{ij} denotes the completion time of job π_j on machine i. The calculation of completion time for jobs j on machines i is given as follows:

$$C_{11} = P_{11}$$
$$C_{1j} = C_{1,j-1} + P_{1j}$$
$$C_{i1} = C_{i-1,1} + P_{i1}$$
$$C_{ij} = max\{C_{i,j-1}, C_{i-1,j}\} + P_{ij} \quad \forall i = 2, .., m, \quad j = 2, .., n$$

Where $P_{ij} = p_{i\pi_j}$. Then the makespan of the PFSP is defined as follows:

$$\sum_j C_{mj} \leq C_{mn}, \forall \pi$$

Hence, the first objective is defined as follows:

$$U_n(S^*) = \sum_{j'} CR_{mj'} \tag{2}$$

Where $\sum_j CR_{mj'}$ is the makespan in the real schedule.
m is total number of machines.
n' is the number of the jobs sequence that have not been processed yet and the job in progress on the first machine, including the newly arrived job at the disruption time t_D.
$j' = \{1, 2, ..., n'\}$ the index of n' jobs.
S^* refers to the new schedule for the partial subsequnce of jobs that have not been processed yet on the first machine at the time of disruption t_D. It should be noted that the S^* has n' number of jobs and n' depends on the disruption type, e.g., if there is new job arrived to the system then n' will be the number of not processed jobs, the job in process on the first machine and the new arrived job.
The stability measure is defined as the deviation of the completion time of each job in the baseline sequence and the new schedule. The stability performance is defined as follows:

$$I_n(S^*) = \sum_i \sum_j |CR_{ij'} - CP_{ij'}| \tag{3}$$

where $CR_{ij'}$ refers to the real completion time in the real schedule, and $CP_{ij'}$ represents the predicted completion time of a job j' on machine i according to the planned baseline solution.

The third performance measure is robustness, which is defined as the difference of the total completion time between the new schedule and the baseline one and it is given by the following equation:

$$R_n(S^*) = |\sum_{j'} CR_{mj'} - \sum_{j'} CP_{mj'}| \tag{4}$$

where $\sum_{j'} CP_{mj'}$ is the predicted value of makespan according to the planned baseline solution.
To enable a fair comparison between models, the MSR model is normalised as follows:

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$$NMSR = \alpha NU_n(S^*) + \beta NI_n(S^*) + \gamma NR_n(S^*) \quad (5)$$

Where $NU_n(S^*)$, $NI_n(S^*)$ and $NR_n(S^*)$ are the normalised objectives of makespan, stability and robustness respectively. The normalised makespan is giving by the following equation:

$$NU_n(S^*) = \frac{U_n(S^*) - Min(U_n)}{Max(U_n) - Min(U_n)}$$

Where $Max(U_n)$ and $Min(U_n)$ are the upper and lower bounds respectively for the makespan at the moment of disruption t_D. The calculation of $Min(U_n)$, $Max(U_n)$ and $NI_n(S^*)$ are given in details in [25]. The objective $NR_n(S^*)$ is calculated as follows:

$$NR_n(S^*) = \frac{R_n(S^*) - Min(R_n)}{Max(R_n) - Min(R_n)} \quad (6)$$

Where $R_n(S^*)$ represents the robustness measure after the disruption time t_D, $Max(R_n)$ is the robustness upper bound and $Min(R_n)$ is the robustness lower bound [25].

III. The Simulation-PSO framework

Following an analysis, we propose that the processing times follow the Log-Normal distribution. In this case, a random variable p_{ij} (of processing time) follows a Log Normal probability distribution where μ and σ are parameters if $\log(p_{ij})$ follows a Normal distribution $N(\mu, \sigma)$. To transform the stochastic problem into dynamic version of deterministic processing times, we assume that the deterministic processing time of job i is the expected value of the probability distribution which characterised the unknown processing time of the same job. After this, the expected values of makespan for the PFSP is estimated by employing the MCS technique. The MCS phase will be repeated running as many times as we require to obtain an enough reliable estimation. Thus, the steps of the Sim-PSO approach can be given as follows:

1) For stochastic FSP in a permutation scheduling, let us first consider stochastic processing times P_{ij} of jobs i and on machines j where the jobs number are n and the machines number are m. Each stochastic processing time P_{ij} follows the Log Normal distribution with known mean $E[P_{ij}]$.
2) In the dynamic PFSP scheduling where the processing times are constant values, we consider the processing times p_{ij} as constant values given by $p_{ij} = E[P_{ij}]$.
3) For the dynamic PFSP under different real-time events, we generate an initial scheduling sequence (solution) by using the predictive-reactive based PSO algorithm with the MSR model.
4) Improve the initial generated schedule by applying a classical Local Search (LS) algorithm, then the new improved solution is consider as a new initial solution for the dynamic problem.
5) Apply a simulation for short runs (for example 250 iterations), to obtain the estimated expected stochastic solution of the dynamic PFSP.
6) Employ the ILS technique [26] to improve the best of dynamic and stochastic solutions obtained so far.
7) Employ a simulation with long runs (e.g. 1000000 runs) to obtain good expected stochastic makespans related to the best dynamic and stochastic solutions.

The LS algorithm has been applied in different steps in the Sim-PSO approach, the proposed LS algorithm used in this research has been used by [27] among others.
The MCS is employed to estimate the expected makespan value that related to the given solution. The approach steps are given in the following points:

a. Generate a random variate for all jobs processing times using the Log Normal distribution.
b. The random variates obtained from the proposed probability distribution are employed to generate a random stochastic makespan observations.
c. These steps are iteratively repeated and the obtained observations are employed to estimate the expected makespan, variance or quartiles.
d. An efficient operator of the perturbation process, which is the enhanced swap operator and the acceptance criterion of Demon-like procedure are used in the Sim-PSO approach. For more details about the acceptance criterion and the perturbation process we refer to [28] and [29].

Moreover,

IV. Experiment Results

In this section, the experimental results and statistical study for the approach are given and discussed. The predictive-reactive based PSO is hybridised with the MCS approach and the MSR model are used to solve the SPFSP under different real-time events. Java eclipse is used to implement all the experiments on a PC of Intel Cori5 2.6 GHz with 6GB of memory RAM. The proposed Sim-PSO approach starts with solving the dynamic part of the problem (PFSP under machine breakdown and new job arrivals disruptions) using the predictive-reactive based PSO algorithm with the MSR model, then, the MCS is applied to calculate the stochastic makespan. Since we apply a multi-objective optimisation model, different weights are used, these weights are assumed to be; $(0.333, 0.333, 0.333)$, $(0.498, 0.498, 0.002)$ and $(0.166, 0.166, 0.666)$. For the instances introduced by [1] (PFSP under machine breakdown and new job arrivals disruptions), we suppose the processing times p_{ij} as the expected processing time $P_{ij} = E[p_{ij}]$ follow the Log-Normal distribution. In this paper, we consider small, medium and large Taillard benchmark [30] of size 20×5, 50×10 and 200×20 $(jobs \times machines)$. Each instances from the same size consists of 10 different problems. [1] have reported the PFSP with different real-time disruptions including machine breakdown and new job arrivals. In this experiment, each problem has been run for five independent times. Also, we consider the limit $t_{max} = n \times m \times 0.03$ in seconds to stop the approach. The Log-Normal distribution has two parameters, namely; μ_{ij} and σ_{ij} parameters. These parameters are given in the equations below from the Log-Normal distribution properties.

$$\mu_{ij} = ln(E[P_{ij}]) - 0.5 \times ln\left(1 + \frac{V[P_{ij}]}{E[P_{ij}]^2}\right)$$

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TABLE I
THE AVERAGE DYNAMIC AND STOCHASTIC RPD FOR WEIGHTS W_1-W_3 AND $k = 0.1$

	$n \times m$	DRPD	SRPD
W_1	20×5	25.762	25.76
	50×10	29.287	29.2
	200×20	19.863	19.86
W_2	20×5	25.684	25.21
	50×10	30.122	28.76
	200×20	19.697	19.43
W_3	20×5	21.114	20.353
	50×10	23.903	23.888
	200×20	14.976	14.517

$$\sigma_{ij} = \left| \sqrt{ln\left(1 + \frac{V[P_{ij}]}{E[P_{ij}]^2}\right)} \right|$$

We will consider the scenario where the variance are relatively low particularly $k = 0.1$ [22]. Once the best solution is found, the average relative percentage deviation of dynamic solution (DRPD) and the average relative percentage deviation of stochastic solution (SRPD) are calculated over 10 of Taillard problems from the same size $(n \times m)$. The average relative percentage deviation is given as follows:

$$RPD = \frac{M - Best_{Sol}}{Best_{Sol}} \times 100 \tag{7}$$

Where the value M represents the acquired solution using the proposed model and solution methods. $Best_{Sol}$ is the average of lower bound solution of 10's Taillard's instances that have the same number of jobs and machines. Table 1 show the results obtained in this experiment, for the SPFSP under different real-time events. Table 1 includes the results corresponding to one of the three weights W_i, $i = 1, 2, 3$. It shows the solutions corresponding to the variance where k is equal to 0.1 and both of the DRPD and SRPD are taken as average of 10 Taillard's instances from same size (20×5, 50×10 and 200×20). Finally, the Table has the relative percentage deviations for dynamic and stochastic solutions. From Table 1, we can conclude the following two points:

- The SRPDs corresponding to the best solution obtained from MCS are generally lower than the dynamic RPDs. Also, the difference between the DRPD and SRPD rises even for low level of uncertainty $k = 0.1$.
- The DRPD and SRPD are variants typical to different weights, hence, the SRPD corresponding to weight $W_3 = (0.166, 0.166, 0.666)$ are generally lower than other SRPD of other weights. For this, we select the the weight $W_3 = (0.166, 0.166, 0.666)$ for the next analysis study.

Figures 2, 3 and 4 show the survival functions for different size instances selected previously with $k = 0.1$. The selected instances are of size 20×5, 50×10 and 200×20, respectively. The survival functions are related for both of the best dynamic and the best stochastic solutions, respectively. The survival function produced from the observed stochastic makespans when employing the stochastic solution. This function corresponds to the stochastic solution and is generally under the survival function corresponding to the dynamic solution. The dynamic solution is constructed from the observed stochastic makespans when the dynamic solution is used. It means in job schedule terms that the probability of keeping the job under operation will be generally lower when using the stochastic solution.

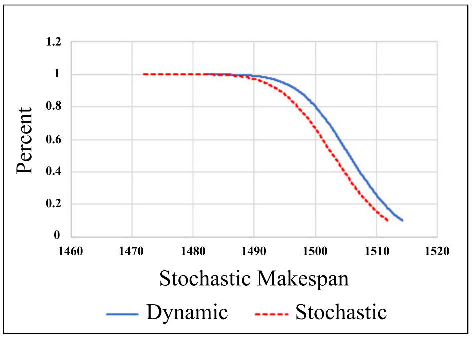

Fig. 2. Survival plot with intersecting solutions for problem 20×5 with $k = 0.1$ and weight W_3

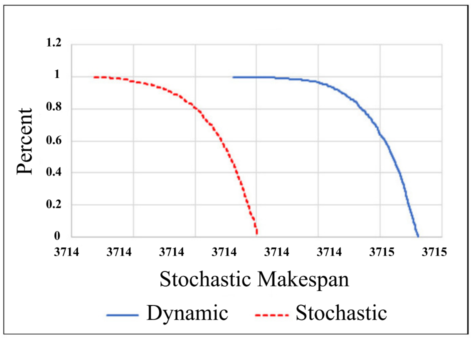

Fig. 3. Survival plot with intersecting solutions for problem 50×10 with $k = 0.1$ and weight W_3

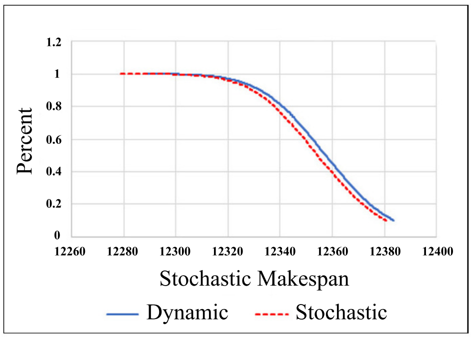

Fig. 4. Survival plot with intersecting solutions for problem 200×20 with $k = 0.1$ and weight W_3

V. CONCLUSION

a novel approach that hybridised predictive-reactive based PSO algorithm with the MCS technique (Sim-PSO) has presented in this paper. This approach has been proposed with the MSR model to solve the SPFSP under different real-time events including machine breakdown and new job arrival. The PSO algorithm has the ability to deal with dynamic and stochastic problems successfully, hence, the contribution of this paper is hybridising the PSO algorithm with the MSC to solve the SPFSP under different uncertainties. Another contribution of this paper is applying the MSR model to reduce instability and maintain robustness along with the Sim-PSO approach for the problem. Moreover, this paper indicates the analogy between work failure times and duration times from Survival Analysis so as to better compare alternative solutions. Consequently, some realisations of the Sim-PSO may produce makespan values over the duration of the experiment, so providing incomplete or censored observations. This statistical study shows that the the probability of ongoing jobs corresponding to the stochastic solution is generally lower than the dynamic one. In summary, this paper clarifies some of the advantages which can be gained when hybridising the PSO algorithm with the MCS technique in solving the SPFSP under different uncertainties. For future work, the proposed approach could compare with other methods to solve the SPFSP under different real-time events. Also, applying the Sim-PSO approach for other stochastic scheduling problems.

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