

Contribution

Develop a novel multi-objective optimisation model and Simulation-Particle Swarm Optimisation, which considers makespan, stability and robustness for Robust Stochastic Permutation Flow Shop Scheduling problem (SPFSP) under different real-time events such as machine breakdown, new job arrivals, and stochastic processing time of jobs.

Scheduling Problem

Scheduling is a decision-making process that is vital in many manufacturing systems. It deals with the assignment of a set of jobs to a set of machines with the goal to optimise one or more objectives (Pinedo, 2012).

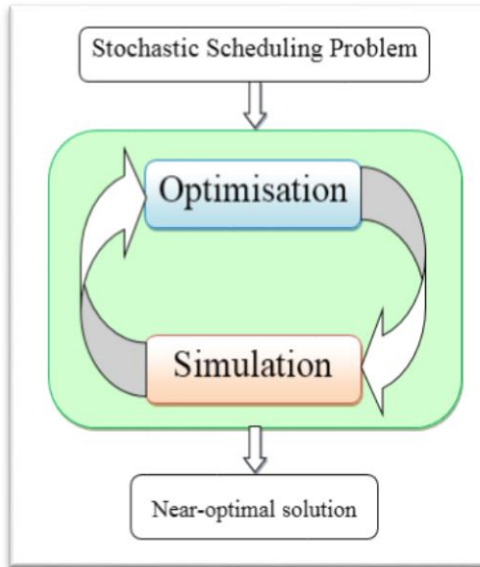


The Proposed Methodology

- The predictive-reactive approach is applied to solve the Permutation Flow Shop Scheduling problem under different real-time events.
- At the reactive phase, the Particle Swarm Optimisation algorithm is used to generate robust solutions for the Permutation Flow Shop Scheduling problem under different real-time events.
- The Monte-Carlo Simulation approach is applied to calculate the expected makespan for the Stochastic Permutation Flow Shop Scheduling problem.



Particle Swarm Optimisation (Tasgetiren et al., 2004)



Simulation-Optimisation approach (Juan, et al, 2014)

Mathematical Model

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

Where S^* refers to the new schedule after the time of disruption t_d and $\alpha + \beta + \gamma = 1$.

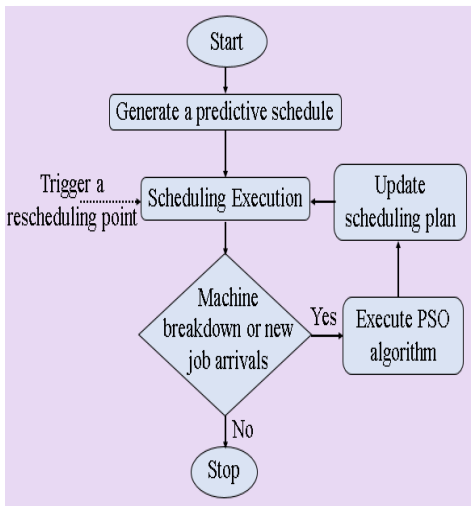
$U_n(S^*) = \sum_j CR_{mj'}$ is the real makespan in real scheduling.

$I_n(S^*) = \sum_i \sum_j \sum_r |CR_{ij'} - CP_{ij'}|$ is the stability measure, where $CR_{ij'}$ is the real completion time and $CP_{ij'}$ is the predicted completion time of job j' on machine i according to the initial schedule.

$R_n(S^*) = |\sum_j CR_{mj'} - \sum_j CP_{mj'}|$ is the robustness measure where $\sum_j CP_{mj'}$ is the predictive makespan according to the initial schedule. n the number of jobs, m the number of machines,

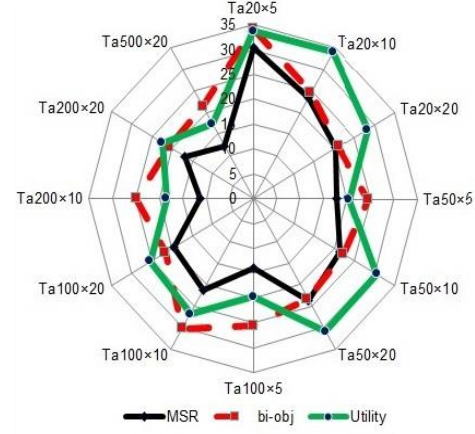
n is the number of jobs, m is the number of machines, $i = \{1, 2, \dots, m\}, j = \{1, 2, \dots, n\}, r = \{1, 2, \dots, n\}$

n' is the number of jobs that have not been processed on any machine yet and the newly arrived job and j' the set of n' jobs.



Predictive-Reactive Approach

Experimental Results



This figure shows the Relative Percentage Deviation for Tillard's instances with weight (0.166, 0.166, 0.666), where MSR is the proposed multi-objective model, bi-obj is a bi-objective model proposed by (Katragjini et al., 2013) and Utility is the classical model of makespan.

Conclusion

We proposed a multi-objective optimisation model that considers utility, stability and robustness measures for robust stochastic Permutation Flow Shop Scheduling problem under different real-time events. A predictive-reactive approach with novel Simulation-Particle Swarm Optimisation method are applied for this problem. Also, different sets of weights (α, β, γ) have been chosen to represent the relative importance of each objective in the proposed model. The results have demonstrated that the proposed multi-objective model and solution methods outperform the results of the other models.

References:

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