HEDGING MANUFACTURING SYSTEMS AGAINST ASSORTED RANDOM DISRUPTIONS IN A DYNAMIC ENVIRONMENT

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ABSTRACT

Manufacturing facilities need flexible production scheduling systems to increase productivity and reduce operational or production costs. These production costs become high when production systems are subject to unforeseen disruptions. Due to the complexity and dynamic nature of these systems, they are constantly haunted by large amount of random disruptions. Occurrence of these unannounced disruptions normally triggers rescheduling of production operations to take place.

This study presents a literature review related to the subject matter presented herein, and also addresses the challenges of avoiding and/or coping with production disruptions. A model is developed and simulated. The starting point of this research is to measure stability of the production schedules which also serves as a subject matter in this paper. This paper presents a new concept with simulation results as a case study. The manufacturing facility consists of five machines and for the scope of the study only machine breakdowns and material shortages are considered. The results show how the rescheduling parameters and the emerged disruptions affect the efficiency and mainly stability of the schedule execution.

Keywords: Dynamic Scheduling, Rescheduling, Manufacturing Disruptions, Schedule Stability
1 INTRODUCTION

Scheduling plays an important role in achieving optimal production performance in a timely manner, which is important in today’s highly competitive manufacturing environment. In manufacturing facilities, scheduling systems usually operate in highly dynamic and uncertain environments in which unforeseen disruptions prevent the execution of production schedules from achieving optimal performances. Examples of such disruptions include machine breakdowns, rush orders, order cancellations, due-date changes, scrap and waste due to machine malfunctions (Vieira et al., [1]). Even though real problems are dynamic and stochastic in nature, most of the solutions in the literature use static and deterministic models. In theory, most scheduling problems, even those with deterministic and static assumptions are nondeterministic polynomial time (commonly known as NP-hard) or mathematically intractable. For that reason, heuristic procedures are generally recommended for practical applications. Practitioners often view the ignorance of uncertainty and the dynamic elements of the scheduling process as the major source of the gap between scheduling theory and practice (Vieira et al., [1]). In the last two decades, researchers have closed this gap by proposing several scheduling systems under various names: on-line scheduling, dynamic scheduling, real-time scheduling, etc., [2]. Some of these systems have been developed using artificial intelligence and expert system tools from computer science as well as operations research tools. Reactive scheduling has emerged as an alternative approach to cope with uncertainty under stochastic environments. This approach becomes even more necessary to address problems associated with disrupted systems.

Most previous studies on rescheduling literature consider only two goals defined for the rescheduling actions ([1] & [2]):

- Make the schedule feasible again,
- Improve the efficiency of performance measures due to adaptation of the schedule to the situation occurred.

The purpose of this paper is to develop a tool to understand the philosophy of reactive scheduling better in terms of what major decisions are made during rescheduling process and how these decisions lead to different scheduling policies. Other papers in the literature which review the scheduling process under uncertain scenarios: Herroelen and Leus [3], for example, review the literature as a collection of techniques that are used to generate and revise schedules. Aytug et al., [4] includes taxonomy on uncertainty. Vieira et al., [1]’s study is considered to be closer to the approach presented herein. Their review is more general as they cover the entire rescheduling process whereas the emphasis in this paper is specifically on stability concepts. The emphasis in this paper is on unraveling what major decisions lead to these two policies (i.e. proactive and reactive policies) and on how stability concepts are used to cope with uncertainty.
2 RESCHEDULING OF MANUFACTURING OPERATIONS

Internal disruptions such as machine breakdowns, order changes, hot jobs, are difficult to fore-predict due to the stochastic behavior of the system, though, reaction from the scheduling system is still a requirement. Emergence of other disruptions like urgent orders, shortage of raw materials, late deliveries, employee strikes, etc., also cause the schedule to be modified, and are classified as the external disruptions. Above mentioned disruptions and others if not properly managed, lead to a system performance that is far-worse than optimal system performance.

In case of production control in dynamic environment, having stochastic parameters which are uncertain, two strategies are defined: 1) dynamic scheduling (on-line scheduling) solutions, and, 2) predictive-reactive scheduling (off-line scheduling) techniques. The latter mean calculating a predictive schedule suitable for addressing a static problem; and continuously updating this existing schedule in order to adapt a schedule to changing circumstances (Vieira et al., [1]).

Vieira et al., [1] present a summary in chronologic order of studies that analyze scheduling and rescheduling problems in a dynamic and stochastic environment. Research results on scheduling with uncertainties such as completely reactive, robust scheduling and predictive-reactive approaches are categorized and presented by Aytug et al., [4]. These give a broad overview on production schedule execution in the face of uncertainties. Pinedo [5] categorizes the scheduling techniques based on the stochastic or deterministic characteristics of the problem.

In highly dynamic and stochastic production environments, production schedules cannot be used for the entire scheduling horizon without any change because of unforeseen disruptions that may alter the state (or optimality) of the system. Schedule revision becomes a necessity at some point to retrieve optimal settings. Rescheduling is driven by two pressing questions: when to reschedule and how to reschedule? Sabuncuoglu and Goren [6] answered these immediate questions through“predictive scheduling”. This study take a valiant approach by expanding this for a “reactive scheduling” environment.

2.1 When to reschedule?

“When to reschedule” has to do with the timing of scheduling decisions and is triggered only when a system is upset following various unforeseen disruptions. It determines system responsiveness to various kinds of disruptive factors. As rescheduling frequency increases, the system responsiveness also increases. There are several ways to decide on timing of scheduling decisions, namely; periodic scheduling, continuous scheduling and adaptive scheduling. Periodic scheduling, schedules the system periodically; the period length can be constant or variable. In the constant case which is often used in practice, revisions are made at the beginning of each fixed-time interval. However, according to the variable-time interval method, scheduling decisions are made after a certain amount of schedule is realized,[7]. Another alternative could be to revise the schedule following a certain number of random events. For example, the schedule can be updated after each major machine breakdown, or
when a new important job arrival occurs. This method of scheduling is called continuous scheduling, [8]. Another method is adaptive scheduling; the decision is triggered following a predetermined amount of deviation from the original schedule. For example, a revision is made when the total difference in completion times between the initial and actual schedules exceeds some threshold value, say 30 minutes. Similarly, schedules can be revised after a certain amount of deviation from the planned throughput, flow-time, tardiness or any other performance measure.

2.2 How to reschedule?

“How to reschedule” determines the ways in which schedules are generated and/or updated. There are four related issues: the first one has to do with scheduling scheme. It can either be offline scheduling, online scheduling or a combination of the two (i.e., hybrid). Offline scheduling refers to scheduling all operations of available jobs for the entire scheduling period, before executing the schedule; in online scheduling, decisions are made one at a time, during the execution of schedule, [9]. Dispatching rules in a dynamic environment serve as a good example of online scheduling. For the sake of scope, only these two scheduling schemes are considered.

An online approach accommodates considerable flexibility in the schedule to compensate for unforeseen system disturbances but lacks the global perspective provided by an offline approach. Therefore, analyzing both approaches’ strengths and weaknesses and identifying the circumstances under which one performs better than the other is valuable. It is known that offline scheduling is superior to online scheduling in a static environment. However, in a dynamic environment, offline scheduling is still better, but the difference between the performances of these scheduling schemes is not as large as in the static case, [7]. However, further analysis of offline scheduling and online scheduling methods is needed in a dynamic and stochastic environment that includes the consideration of stability which is the subject matter of this study.

Another issue is the amount of information or data available during the reschedule process. When all the required information is available, the scheduling is said to be “full scheduling” and is called “partial scheduling” when there is low confidence about the accuracy of the far-fetched future information. In this case only near future information is used to populate revised schedule. With this policy, the system scheduler leave the system and letting it recover from disruptions.

Sabuncuoglu and Bayiz [10] reports that full scheduling is superior to partial scheduling in a static environment because of its global perspective and avoidance of myopic decision-making but more expensive to perform than its counterpart. On the other hand, the relative performance of full scheduling and partial scheduling in a dynamic and stochastic environment is needed for stability measurement.
2.3 Stability Measure

In this study ‘stability measurement’ is concerned with the difference between initial and realized/actual schedules, and between their respective homogeneous performances. For the sake of this study we extend the definition of “stability” to encompass performance measures as well, as opposed to a study by Sabuncuoglu and Goren [6] who defined stability by excluding their performance parameters. A schedule whose realization does not deviate much from the initial schedule in the face of disruptions is called “stable schedule”. A schedule also serves as a plan for other production activities, such as determining delivery dates, releasing times, planning requirements for secondary resources such as machines, number of employees, etc.,[11]. Any deviation from the initial schedule can disrupt the plans for such activities and increase system nervousness. Thus, stability is an important performance metric in practice. Alagöz and Azizoglu [12] study stability measure as the number of jobs processed on different machines in both schedules (original and revised schedules).

Rescheduling is a difficult multi-objective to deal with effectively in highly dynamic settings. While aiming at optimizing overall system efficiency taking into account classical performance measures (i.e. earliness, tardiness, etc.), the impact of disruptions induced by moving jobs arbitrarily during rescheduling event is mostly neglected. Wu et al.,[11] and Cowling & Johannson [13]defined stability as the deviation between job starting times for both schedules and again the difference between jobs sequences (i.e. the original and revised schedule).

2.4 Rescheduling Dynamics

In practice, a classical production scheduling process is as follows: An initial schedule (predictive scheduling) is generated to serve as a production process guide for future production activities. In a highly dynamic environment, aforementioned random disruptions do occur on the production floor triggering rescheduling (reactive scheduling) of operations which is concerned with revising already existing schedule to restore near-optimal performance levels. The schedule which is actually executed on the production floor is called the ‘realized/actual schedule’. This schedule may substantially differ from the initial schedule, depending on the degree or intensity of disruptions.

Finally, the scheduler should decide on which performance metric to use for schedule performance measures. Classical performance measures such as flow-time, throughput, are widely used in literature and often preferred in practice. The productivity or efficiency factor is employed as a common performance measure for analysis and experimentation in this paper.

2.5 Rescheduling Literature Conclusion

After examining the existing literature on “stability” it is fair to suggest and conclude the following ([1], [4], [6], [11], & [14]):
• Other approaches propose methods based on a multi-objective function that simultaneously consider both stability and productivity addressing a compromise between them (i.e. like that of Wu et al.,[11]),

• No results illustrate how close the changes between original or predetermined schedule and a revised schedule to the current time, and

• Schedule deviation is not expressed in terms of a “productivity” function as a common measure of performance; instead existing approaches are only limited to change in time. It is not easy to relate time factor with the “productivity” function using classical algorithms.

Apart from other objectives mentioned above, this study also seeks to address these shortcomings by modeling the stochastic fluctuations of stability function following a variety of random disruptions.

Recently, several studies deal with the effect of rescheduling from a stability measure point of view. In this paper, we analyze and propose control action taken by the scheduler on several rescheduling scenarios; we further present stability measure and schedule calculation method to be able to minimize the effect of the changes induced by the rescheduling while keeping productivity function also at the extreme.

3 METHODOLOGY
Regenerating production schedules frequently is costly and should be avoided if possible, except as a reactive counterpart to random disruptions. Notations employed for the present study are provided by Aytug et al.,[14]. Let the new schedule generation time be defined by the rescheduling point, rescheduling interval (RI) as the time between two consecutive rescheduling points. The strategy employed herein is that of “predictive-reactive” which includes three policy types, namely: event-driven, period and hybrid. Rescheduling in this study is event-driven, such that rescheduling of operations are only performed in the event of a disruption.

3.1 Disruption effect versus Threshold
In case of any disruptions the first decision when it comes to “rescheduling” is based on the estimated length of disruption. If the length is so short that the schedule is affected appreciably, the decision may be to continue without making any changes. If, on the other hand, a disruption affects schedule performance drastically, alternative algorithms are executed with the objective of modifying the schedule in a way that minimizes the effect of disruptions. For example, multiple durations may be considered, i.e. 20 minutes, 1 hour, and 2 hours. This randomly range selected with the expectation that disruptions shorter than 20 minutes may not always call for schedule modifications (rescheduling). Disruptions longer than 2 hours may frequently require regeneration of a new schedule. The potential modifications may include rescheduling of operations. If no acceptable solution is found, the scheduler regenerates a schedule. The decision process flow is depicted in figure 1 below:
The threshold is an important decision factor in rescheduling as it determines whether to reschedule or not, and ‘not’ to reschedule is an assurance of less impact on efficiency and stability measures.

3.2 Rescheduling Interval (RI)

As a continuation from the above explanation, figure 2 below presents a concept of event-driven rescheduling policy. It is depicted in figure 2 below that the impact of disruptions for both RI$^1$ and RI$^2$ are of varying degree, i.e. with RI$^1$ a new schedule is required as the impact is notably greater than the threshold value, and as for RI$^2$ an original schedule may still be followed since the impact is lower than the defined threshold$^2$. Practically, schedules should only be generated in every RI time interval. However, in real-life a scheduler should determine the feasibility of performing rescheduling activities following a logic presented above. Rescheduling is calculated right after disruption “A” as in the figure below (Figure 2). If disruption “B” as in the figure is envisaged to have a minor impact on operations downstream, then production rescheduling is not considered, i.e. a system to recover from

$^2$ Threshold in this paper is defined as a decisive value that determines whether to react to disruptions or not
deviation and the original schedule is followed until the next scheduling horizon (rescheduling is neglected because the effect induced by the disruption does not require modification in the schedule because it is still executable without notable degradation on the system performance). However, if disruption has severe effects on the production system (refer to disruption “A”), then “complete rescheduling” is considered in which all jobs from the original schedule that remained unprocessed are included in the pool of jobs waiting processing.

Figure 2: Impact of disruptions on manufacturing operations subject to random disruptions

4 CASE STUDY

In this section, the method used for measuring the stability of the production schedules is presented and case study results obtained through simulation are outlined. Methods presented herein should assist a scheduler to know whether to reschedule or not, and understand prior to rescheduling the impact a system might have following rescheduling of operations.

4.1 Stability Measure

In this section a new approach for measuring stability is presented and the latter sections present a simulation approach. Schedule stability is calculated for all available jobs in the system, that is jobs scheduled for processing. Each job is assigned with a weighting factor called a “disruption index” which can be given by expression (1) below:

\[
DI = (ST_2 - ST_1) + AI_j
\]

where:

- \(DI\) is the disruption index, or penalty function,
- \(ST_1\) is the starting time for an original schedule,
- \(ST_2\) is the starting time for a revised/new schedule, and
- \(AI_j\) is the actuality index per job.
Expression (1) above imply that the disruption index can be determined by first calculating the difference between starting times of both schedules (original and revised schedule); and then adding the actuality index and/or penalty factor to the difference. This actuality factor is related to a function associated with the deviation of job starting times from the current time. The penalty measure is only calculated in the event of a disruption, i.e. instances where starting time deviation is greater than zero (0) - this implies a schedule shift. As thus, a schedule with less penalty value can be considered a more stable schedule and most preferred. We calculate the mean value of the stability function for twenty different rescheduling points to determine a value that represents if not more closely, a real world phenomenon using the expression below first by Aytug et al.,[14]:

\[
\overline{DI} = \frac{1}{n} \sum_{j \in Z} \left| t_2 - t_1 \right| + \frac{k}{\sqrt{t_1 - T}} \quad (2)
\]

where:

- \( t_1 \) is the predicted start time of job \( j \) in the current schedule,
- \( t_2 \) is the predicted start time job \( j \) in the successive schedule,
- \( Z \) is the total number of jobs that are not processed from the initial schedule (jobs to be reconsidered during the next rescheduling point),
- \( \left| t_2 - t_1 \right| > 0 \) and \( \left| t_1 - T \right| > 0 \) - this is the case for a disrupted system. A figure below zero imply that manufacturing operations activities started before their actual planned start times,
- \( n \) is the number of elements in \( Z \),
- \( T \) is the current time, a point in time when rescheduling activities are performed, and
- \( k \) is the scaling factor for a penalty function.

Expression (2) is employed to demonstrate the calculation of the given penalty values for a single operation after rescheduling. For demonstration purposes, consider the following as deterministic parameters:

- Current time (T) when rescheduling action take place is assumed to be 28, and
- Scaling factor (k) constantly at 10.

Two disruption factors are considered to illustrate the applicability of the above expressions, for the reason that a dynamic production system may be subject to a wide variety of random disruptions. Case 1 - present stability fluctuations following a machine breakdown. Case 2 - present an idle system due to raw materials shortage (as depicted in figure 2 above). Disruption indices are shown in table 1 below as DI1 and DI2, which are 37.2 for machine breakdown and only 8 following a system disruption by raw material shortage. However, the start time deviation for machine breakdown is higher than raw material shortage, 15 and 3 respectively, and the resulted penalty function shows a less critical modification in the schedule of the operation for raw material shortage. Penalty values are 52.2 and 11 respectively.
Table 1: Stability measures per disruptive factor

<table>
<thead>
<tr>
<th>Disruption Type</th>
<th>Start Time Deviations</th>
<th>Disruption Index/ Penalty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine Breakdown</td>
<td>15</td>
<td>37.2</td>
</tr>
<tr>
<td>Raw Material Shortage</td>
<td>3</td>
<td>8</td>
</tr>
</tbody>
</table>

These results may be interpreted as follows:

**Case 1:** This can be related to machinery/resources damages that are being repaired: unplanned maintenance occurring at maximal rate. This may be due to machines approaching the last phase of their life cycle, where breakdowns just occur randomly and unplanned. In this case, machine breakdowns are recorded to be a more costly disruption factor than its counterpart.

![Figure 3: Machine life cycle (not drawn to scale)](image)

We analyzed three companies to determine the universal solution and the results show that unplanned machine breakdowns are frequently the case where machines are in the last phase of their life cycle. Company “A” shows a correlation to the scenario described above, with machines being old and deteriorated performance. The productivity measure deteriorated from the optimal rating. Company “B”’s machines experienced not so frequent
outages/downtimes. This is due to frequent planned maintenance and machines are still new, which yields optimal performance. Company “C” recorded more downtime than Company “A”, with the machines beyond the planned life cycle. The performance rate is lower than that of the original settings, which affected the entire plant’s performance. Costs associated with maintenance are high as compared to that recorded for the other companies.

Case 2: In this case, the inventory of raw material supplies is getting depleted as time progresses. This can also be because suppliers are experiencing problems in keeping up with total customer demand, failing to deliver products on time, and/or employed resources by the suppliers are at the very last phase of their life cycle hence minimal production performance or it may be due to suppliers overloaded with customer orders and unable to keep up with current demand trends.

4.2 Simulation-based Case Study

In this section a simulation-based evaluation is presented for different settings. The focus is on the relationship between disruptions (namely; machine breakdown & raw material shortages), threshold and stability as well as efficiency under different circumstances. As in the above sections two disruptive factors are considered, namely; random machine breakdown and dynamic raw material arrivals.

Three different rescheduling problems are considered, denoted as \( a_0, a_1 \) and \( a_2 \). Setting \( a_0 \) represents a classical rescheduling problem where each job must be processed on each machine only once (machines interchangeability is not permitted). Case \( a_1 \) and \( a_2 \) represent a situation where operations can be processed on different machines. The number of alternative machines is set to 2 and 3 for case \( a_1 \) and \( a_2 \) respectively, [15].

The scope for the problem presented can be considered as a \( 5 \times 8 \) (or simply \( 5^8 \)) scheduling problem. The problem consists of 5 machines \( (m) \) and 8 jobs \( (j) \): the number of operations per job is \( n_j = m \). Efficiency measure per schedule is makespan and is given by \( C_{max} = \max[c_1, c_2, c_3, \ldots, c_n] \), where \( n \) represents the number of jobs. The total number of jobs to be rescheduled is eight (8). Resulted best makespan values calculated by not taking into account any disruptions, are 42, 30 and 21 time units, for \( a_0, a_1 \) and \( a_2 \) respectively.

In the presented experiments end-time monitoring theory (as first presented by [15]) is employed to monitor the performance of respective production schedules during execution.

\[
\frac{1}{n} \sum_{j=1}^{n} |c_{j,\text{sim}} - c_{j,\text{plan}}| > \partial
\]  

(4)

where:

- \( n \) is the number of operations completed,
- \( c_{j,\text{sim}} \) is the simulated end time of operations \( j \), and
- \( c_{j,\text{plan}} \) is the anticipated/planned end time of operation \( j \).
Expression (4) above calculates the mean absolute tardiness for all operations involved and compared to the rescheduling threshold ($\vartheta$) following operations completeness. Following a logic presented in section 3.1, once a threshold is exceeded, a new schedule is generated. Regarding schedule creation; for the current problem the disruption indices are calculated by using scaling factor $k = 10$.

4.3 Results

In this section results are outlined. Illustration of the impact of both material shortage and machine breakdown is given, and also how these disruption factors affect “schedule stability” in the presence of threshold.

The results may be interpreted as follows:

**Figure 4a:** Effect of the duration of machine breakdown (dt) on efficiency

**Figure 4b:** Effect of the duration of raw material shortage (dt) on efficiency

The results may be interpreted as follows:

**Figure 4a:** The disruption due to machine breakdown is more dependent on the status of the machines' life cycle, i.e. how old a machine is. The older the machine, the more likely it is to breakdown, and the newer and well-serviced the machine, the more likely it is to realize...
optimal uptime and performances. Figure 3 illustrates poor performance following breakdown of a machine from the initial rescheduling point. Machines are acknowledged as the heart of the production system, and must be maintained at all cost possible.

Figure 4b: Point “A” refers to a first rescheduling point following disruption due to material shortage. In this case the manufacturing system comes to a standstill until a material is delivered to the system. It is proven that material shortage affects efficiency and/or productivity factors overtime. Efficiency performance is more dependent on the ability of suppliers to deliver materials on time. This measure can be ameliorated by ensuring suppliers deliver products timely by putting a “penalty” measure in place following suppliers’ “failure” to deliver on-time. Penalty indices are calculated based on how early or late an order is. Late delivery should be more costly than early delivery. Points “B” represent a second rescheduling point, whereas from “B-C” denote downtime that may include activities such as set-up times, loading times, etc.

Concluding remarks on the observations for the two above cases: Machine breakdowns have more impact in terms of both efficiency and monetary measures than its counterpart (material shortage) overtime with an assumption that “suppliers” get penalised for late deliveries beyond acceptable values. This way, a system can still be profitable even if it’s idle as the supplier will absorb the costs of failing to deliver.

5 CONCLUSION

It can be concluded that the effectiveness of rescheduling methods in the case of machine breakdown depends more on the “stage” of the scheduling horizon at which disruption occurs, i.e. if a disruption occurs right after reschedule creation or in the middle of the rescheduling horizon it is obvious to apply the proposed strategy. The selection of the required threshold \( \delta \) depends on the required level of stability.

Following the simulation results, it can further be concluded that investigated rescheduling parameters (rescheduling threshold) and disruption generated into the system had considerable impact on the number of rescheduling actions and the timing of these actions and also on the stability of the schedule execution. Finding the appropriate rescheduling threshold for each given rescheduling situation may result in a compromise between stable schedule execution and schedule quality.

It is proven scientifically that performing rescheduling process with a threshold value is below acceptable impact for rescheduling as discussed in this paper; the systems’ deviation in terms of productivity measure becomes immense. It is less costly when a system is left to recover from performance deviation due to disruptions, as opposed to rescheduling.Schedulers should use the “threshold” as a starting point to decide whether to reschedule or not.

In conclusion, machine breakdown has high degree of impact on the manufacturing system than raw materials shortage considered in this study. It can also be concluded that frequent
Rescheduling of operations also increases production costs, and as such is not promoted. The extension of these experiments could be future work by applying different methods to further understand how various disruptions affect manufacturing systems in terms of monetary value, i.e. how these disruptions affect the economical standing of the South African economy.

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7 REFERENCES


