An Approach of Preventive Maintenance for Dynamic Systems under Uncertainty

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Abstract – *The paper is aimed to identify robust predictive schedules able to face the effects driving the operation of set processes with operation time variability. It is an initial attempt to formalize the short-term scheduling problem with operational uncertainties. The use of stochastic programming as the modeling system is adopted, and a multi-objective stochastic formulation is first developed and extended to manage the risk of poor performances. The effectiveness of the approach as a decision-support tool is presented in a case study.*

Keywords: *Uncertain system, predictive schedule, optimal approach .*

I. INTRODUCTION

Numerous sources of uncertainty are identified with a direct effect on short-term decisions. Time deviations as a consequence of processing time variations and/or machine breakdowns appear as the most common and costly effects of disruptions encountered in this stage, making difficult the prediction of exact production times and rates in industrial processes. The degree of variability is a function of the process itself, but deviations from 5% upward of the estimated processing times are usual. The sources of uncertainty are considered process time variations; machine break-downs; transport time variations; and demand variations.

The approach to minimize the effects of processing times uncertainty consists of introducing intermediate storage devices before the bottleneck processing units to maintain reserve material for downstream processing. This allows decoupling the operation of the processing units, avoiding the propagation of unexpected events, and allowing the execution of the predictive schedule without modifications. However, the production of reserve material is often expensive, inefficient, and/or technically difficult to maintain, and dedicated storage units could be required for each product or intermediate with an additional cost. Furthermore, if materials leaving a processing unit are unstable, and therefore consecutive operations must be performed under a zero wait (ZW) transfer policy, intermediate storage is not a viable solution. These approaches use trough estimates or simply averages of the processing times observed in previous runs.

2. LITERATURE REVIEW

Relatively few works incorporate information about uncertain operation times proactively in the decision stage. [2] described a mathematical programming framework and solution procedures for robust discrete optimization problems, and defined alternative min-max criteria to differentiate the robustness of various solutions over a given set of potential scenarios. Based on this framework, [3] focused on a single-machine scheduling environment with uncertain processing times represented using the scenario-based approach, and used the flow time as a performance criterion; exact branch-and-bound as well as heuristic algorithms were implemented to solve the problem. A similar proactive scheduling approach was developed in [4] for a two-machine flow shop environment, where the scenario-based and intervals representations of processing times were discussed, and the start to finish time was adopted as the performance measure. [5] presented a two-space genetic algorithm as a general technique for solving robust discrete optimization problems using a min-max criterion; the algorithm was applied to identify a schedule with the minimum worst-case start to finish time for a parallel machine scheduling plant with uncertain processing times. [6] developed a mathematical programming model to determine robust predictive schedules in a project scheduling environment with uncertain operation times represented with discrete scenarios; the robustness measure to be minimized was defined as the expected weighted deviation of the actual from the predicted start times, when only the disruption of one operation time was anticipated; three additional heuristics related to existing algorithms were also presented and compared with the proposed model. Using the same robustness criterion in the same scheduling environment, [7] developed and validated heuristic and metaheuristic procedures to allocate time buffers and generate a robust predictive schedule with acceptable start to finish time; the heuristic algorithms inserted the slack time in a deterministic predictive schedule with minimum start to finish time, keeping the assignment of resources fixed; a tabu search algorithm and an improvement heuristic were also developed to search for the best insertion of time by exploiting the neighborhood solutions. In general, the proactive scheduling approaches proposed so far pursue the identification of predictive schedules with optimal expected performances, or schedules that guarantee a minimum performance with a certain probability. Simple production models are usually assumed (e.g., flow shop, single stage) and/or the main effects of the uncertainty are not considered in the modeling system. Therefore, critical situations that can arise during the execution of a predictive schedule due to deviations from the estimated operation times are not explicitly addressed, not even analyzed. For example, with the generation of considerable wait times the quality of sensitive or unstable materials can decrease and become even unacceptable, thus forcing the rejection of batches with the consequent increase of operating costs. Furthermore, completion times larger than those expected can lead to delays in the promised delivery dates, and hence to customer dissatisfaction.

This chapter focuses on general multipurpose multi-stage batch plants with uncertain operation times, and presents a proactive scheduling approach based on a stochastic programming formulation. The underlying idea is to improve the robustness of the predictive schedule by taking into account, in the reasoning procedure itself, wait times and idle times that may eventually occur at execution time as a consequence of the uncertainty.

2 PROBLEM FORMULATIONS

The short-term scheduling problem is addressed for multipurpose multi-stage systems with uncertain operation times. The process-stage-operation hierarchy is used to model the data, each order has associated a production process, i.e., a set of activities or stages required to transform the input materials into products. Furthermore, each stage involves an ordered set of operations that must be executed one immediately after another and assigned to the same equipment unit. Based on this structured information, given are the set of production orders to be fulfilled, the set of processing stages required in each order, a set of units where they can be processed, the operations required in each stage, and the processing time of each operation represented by a probability distribution.

The objective of the paper is to identify a robust predictive schedule. The robustness criterion for the underlying problem is formally defined as the expected value of a weighted combination of start to finish time and wait times generated during the execution of a predictive schedule. This measure balances the trade off between the need for high plant efficiency, evaluated in terms of start to finish time, and the low wait times, which account for the eventual effects arising due to the uncertainty. To avoid the generation of wait times is particularly important with unstable intermediate products, and when ZW transfer policies are applied. In addition, the reduction of idle times to keep reasonable plant utilization is implicitly considered with the minimization of the start to finish time.

Due to the uncertain operation times, there is no sense in determining detailed start and end processing times for each operation in the predictive schedule, but only the minimum information required to start the production in the plant, i.e., the sequence, the assignment of units to stages, and the initial processing time of each process or batch.

The following assumptions are made:

- from the predictive schedule, the lower control level only requires as a guidance information related to the sequence, the assignment of units to stages, and the processes start times. Then production proceeds according to the control recipe, without rescheduling considerations beyond a simple right-shift of eventual altered operations.
- the non-intermediate storage policy (NIS) between stages is assumed, that is, an intermediate product remains in the processing unit after its production until the unit assigned to the next stage is available.
- Within a stage, all the operations must be executed without interruption.
- three sorts of links are differentiated to describe temporal constraints between operations within a process: simultaneous, instant, and sequential.

Simultaneity accounts for those operations from different stages that have to start and end at the same time. Instant requirements are defined between those operations that have to be produced one immediately after the other. Sequential links establish a relationship between the end time of an operation and the start time of another operation, i.e., they are defined between operations that have to be performed consecutively without immediacy requirements.

To simulate the execution of a predictive schedule when operation times are uncertain, wait times are introduced at the end of a processing stage, or before a transfer operation, if the next unit is not available. To account for the generation of these wait times, sequential links are established in each process between the last operation of a stage (if it is not a transfer operation) and the first operation of the following stage, and between a transfer operation and the preceding one in the same stage.

If an equipment unit is available before the time determined for the next batch, and idle time appears, i.e., processes cannot start before their start time in the predictive schedule

For modeling purposes, a distinction is made between wait times between stages ($w_{ts\,s}$) due to the blockage or unavailability of a unit, and start wait times (w_{to}) due to delays on the predicted processes start times.

3 MODELING APPROACH

An equation-based modeling system is considered in this study for the development of the proactive scheduling approach. Particularly, a multi-objective two-stage stochastic programming model is formulated to describe the features of the problem. This rigorous optimization approach is appropriate since decisions related to the production sequence, assignment, and start times of each process must be taken to start production, before the actual values of operations times are revealed, whereas the eventual effects of the uncertainty and the efficiency of the system are not disclosed until the execution of the predictive schedule. With a two-stage stochastic modeling, scenarios of possible operation times are anticipated to take into account different outcome at the time of scheduling.

A stochastic formulation is first presented using the robustness criterion defined as objective function. The model is next extended to explicitly manage the risk of obtaining highly suboptimal schedule performances. Uncertainty associated with operation times is represented indistinctly by discrete or continuous probability distributions. Monte Carlo sampling is then applied over the probability space to generate a finite set of representative scenarios and approximate the expectation of the objective function

A two-stage stochastic mixed-integer linear programming (MILP) formulation is developed based on the concept of precedence relationship between stages introduced [8]. Decision variables related to the production sequence, the assignment of units to stages, and the processes start times are modeled as first-stage decisions to be taken here-and-now, independently of the realization of the uncertainty. With the predictive schedule fixed in the first-stage, a detailed executed schedule, with the start to finish time and wait times generated due to deviations from the nominal operation times, is computed in a second stage and for each anticipated scenario, i.e., for each realization of processing times. As assumed the processes start times in the predictive schedule act as lower bounds in the executed schedules, i.e., the start time of each process in each scenario is constrained to be at least the start time in the predictive schedule. Material balances, as well as features such as batch mixing and splitting, can also be contemplated in the model, but have been excluded from the scope of this research in order to focus on the problem of the uncertainty, and to avoid additional computational complexities arising from the discrete or continuous -time representation.

$$\min \sum_k \left[\omega_k (\rho_1 \cdot mk_k + (\sum_i \sum_{j \in J_i} \sum_{o \in O_j} \omega t^s_{oik} + \sum_i \omega t^0_{ik}) \right] \quad (1)$$

$$\sum_{u \in U_{ij}} Y_{iju} = 1, \quad \forall i, j \in J_i \quad (2)$$

Where:

ω_k is wait time

ω^s_{oik} wait time between stages (after operation o of process i in scenario k)

ω^s_{oik} start wait time or delay of process i in scenario k

mk_k is makespan value, start to finish time value

To identify a robust predictive schedule the expectation function to be minimized is written as a sum of the weighted combination of makespan (mk) and wait times for each scenario k (eq. 1).

Equation 2 is a first-stage constraint that establishes the assignment of one of the alternative equipment units u to each processing stage j for every process i. The binary variable Y_{iju} is used for this purpose, which takes the value of 1 if stage j of process i is assigned to unit u, or 0 otherwise.

The formalism of robustness used in the previous stochastic model is based on the expected value of start to finish time and wait times over the set of anticipated scenarios. To avoid the identification of predictive schedules with highly suboptimal performances in some of the scenarios, criteria based on the worst-case scenario, and defined in general terms as absolute robustness, robust deviation and relative robustness criteria [8], are assessed and optimized.

The absolute robustness criterion (ZAR) is a minimax criterion that attempts to determine the predictive schedule with simply the best of the worst performance over all the scenarios. The robust deviation (ZDR) and relative robustness (ZRR) criteria are concerned with how the actual system performance compares with the optimal performance that could have been achieved if certain information about the scenario realization had been available at scheduling time. These criteria allow, respectively, the identification of the schedule with the best worst-case deviation or the best worst-case percentage deviation from optimality over all the scenarios.

4. CASE STUDY

For the problem under consideration, and based on the concept of schedule robustness used so far in terms of start to finish time accounting for the efficiency of the system and wait times measuring the effects of the uncertainty, the worst-case scenario implies the scenario with a maximum combination of start to finish time and wait times. Therefore, given a predictive schedule, the absolute robustness measure is formally defined as the maximum sum of start to finish time and wait times over all the anticipated scenarios, expressed according to equation (3)

$$Z_{AR} = \max_k [\rho_1 \cdot mk_k + \rho_2 (\sum_i \sum_{j \in J_i} \sum_{o \in O_j} \omega t^s_{oik} + \sum_i \omega t^0_{ik})] \quad (3)$$

Similarly, the robust deviation and the relative robustness criteria are formalized as the maximum difference or ratio, respectively, over all the scenarios between the start to finish time and wait times generated in the realized scenario, and the start to finish time and wait times of the optimal schedule to be executed if the scenario had already been known at decision time (OF^*_k). These criteria are formalized as stated in equations (4) and (5), respectively.

$$Z_{DR} = \max_k [\rho_1 \cdot mk_k + \rho_2 (\sum_i \sum_{j \in J_i} \sum_{o \in O_j} \omega t^s_{oik} + \sum_i \omega t^0_{ik}) - OF^*_k] \quad (4)$$

$$Z_{RR} = \max_k [\rho_1 \cdot mk_k + \rho_2 (\sum_i \sum_{j \in J_i} \sum_{o \in O_j} \omega t^s_{oik} + \sum_i \omega t^0_{ik}) / OF^*_k] \quad (5)$$

Both robust deviation and relative criteria require the computation of the optimal performance in each scenario

(OF_k^*), and hence a deterministic problem for each realization of processing times is to be solved. This deterministic model derives simply from the stochastic model (SCHED1) considering only one scenario with the corresponding operation times. When the actual scenario is already known at the time of scheduling, no delays in the processes start times are expected during the execution of the schedule. The minimum absolute robustness $Z_{AR}^{\min}$ robust deviation $Z_{DR}^{\min}$ and relative robustness values $Z_{RR}^{\min}$ can be evaluated by solving the SCHED1 model, but minimizing one of the alternate minimizing one of the alternate measures (eqs. 4, 5) instead of equation 1.

For modeling environments that do not support minimax functions, the definition of these metrics is handled by inequality constraints. A predictive schedule with a minimum worst-case is identified, but some degree of flexibility to fix the temporal decisions exists in the second stage for the evaluation of those executed schedules that show a lower performance than the worst-case. Therefore, to be able to compute the proper executed schedules in the second stage of the solution algorithm, model SCHED1 is extended with the incorporation of two additional constraints: the worst-case formalism in terms of absolute robustness (eq. 3), robust deviation (eq. 4), or relative robustness (eq. 5). A robust predictive schedule is then determined, with a maximum expected combination of start to finish time and wait times (eq. 1), and a minimum worst-case defined in terms of absolute robustness, robust deviation, or relative robustness.

This new model (SCHED2) can be regarded as a robust optimization approach with preference for risk-averse decisions. The stochastic model SCHED1 is extended with the incorporation of the absolute robustness, the robust deviation, or the relative robustness as a measure of the risk of obtaining highly poor performances.

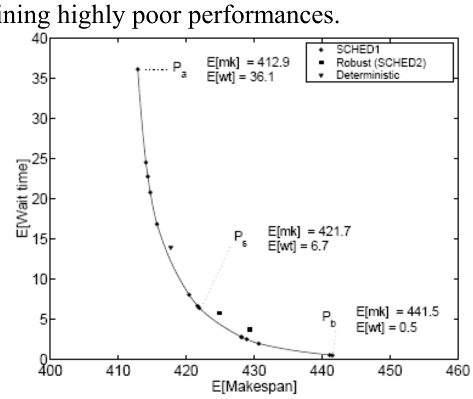

Figure 1: Pareto curve between the expected wait times and expected makespan values

The results obtained related to the expected sum of makespan and wait times, expected makespan, expected wait times values for the predictive schedules determined with the different modeling systems are presented in table 1. The makespan and wait time values of the executed schedule in the nominal scenario according to each predictive schedule are also included (mk_{nom} and wt_{nom} in the table). The decisions made using the deterministic formulation with nominal processing times poorly face the uncertainty, and overestimate the performance of the system.

	Determi-nistic approach	Schedule 1	Schedule 2 with:		
			absolute robustness (AR)	robust deviation (DR)	relative robustnes s (RR)
E[$mk + wt$]	120.4	116.2	119.3	119.2	120.5
E[mk]	105.7	106.9	112.8	107.8	115.7
E[wt]	14.7	9.3	6.5	11.5	4.8
mknom	101.0	107.0	111.3	107.0	115.8
wtnom	0.0	4.0	1.0	6.5	0.8

Although the makespan and wait time values of the predictive schedule obtained are optimal in the nominal scenario, when the deterministic decisions are used to face the uncertainty, the expected makespan raises nearly 5% from the optimum one (from 101 to 105.7 TU), and the generation of significant wait times is expected (14.7 TU). On the other hand, the stochastic modeling with weight values fixed at 1 for both criteria in the objective function allows the identificationof a predictive schedule with expected wait times reduced nearly 37% (from 14.7 to 9.3 TU), and with acceptable expected makespan (106.9 TU).

Using the robust optimization approach with the minimax criteria, alternative predictive schedules are identified with reduced risk of poor performances, while still maintaining improved robustness with respect to the deterministic approach. Using the absolute robustness measure (AR), for example, a predictive schedule is determined with a worst-case performance reduced by 14% (from 152.0 to 131.6 TU), and with an expected wait time value about 56% lower with respect to the deterministic schedule (6.5 vs. 14.7 TU). The reduction in expected wait times is even higher with the predictive schedule identified considering the relative robustness metric (nearly 67 %), despite the increase in the expected makespan and the poor performance in the nominal scenario.

The predictive schedules determined using deterministic models for the nominal and the random scenarios show poorer robustness features than the predictive schedule identified with the proactive approach.

5. CONCLUSIONS

The variable and unpredictable operation times appear as one of the most common sources of operational uncertainty, which has usually been faced through reactive scheduling mechanisms without taking into account any information available at the time of reasoning. Instead, a proactive scheduling approach is developed in this study to account for this uncertainty in general multipurpose multi-stage batch plants, considering in the decision stage itself the main consequences driving the execution process. The proactive approach consists of an optimization model based on a multi-objective two-stage stochastic formulation.

More robust predictive schedules are identified, with significantly reduced expected wait times and acceptable line occupation. The use of the expected makespan as the formalism for schedule robustness is also assessed by evaluating the predictive schedule thus derived. The analysis shows that ignoring the eventual effects arising at execution time is not realistic, and leads to a significant increase in the expected wait times and/or plant under-utilization. Additionally, criteria based on the concepts of absolute, robust deviation and relative robustness are used as control measures to manage the risk of poor performances. This robust optimization approach imposes the worst-case value of these measures as an upper bound, i.e., the predictive schedule determined will perform with a sum of makespan and wait times lower than the worst-case in all the scenarios. The method could be further extended by incorporating these metrics in the objective function, along with the expected criterion, and analyzing the trade of between them. he results of the paper aimed at the formalization of the scheduling problem with operational uncertainties, highlight the importance of managing the uncertainty, as well as its consequences in decision making to perform effectively in an uncertain environment. However, a single source of uncertainty has been considered up to this point, and further research is required to improve the performance of stochastic programming models for applications of industrial size and complexity.

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