An Iterative Optimization-Simulation Approach to Identify Risk Parameters for Scheduling under Uncertain Processing Conditions

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ABSTRACT. Batch processes are preferred to continuous processes in many branches of process industry because of their ability to respond to frequently changing market conditions and their easy controllability. However, the equipment and resources should be efficiently managed through proper scheduling in order to maximize productivity. The optimal planning and scheduling of batch production operations is a complex problem. The complexity does not have only deterministic reasons such as the large variety of processing equipment with different operation and cost characteristics, but also probabilistic reasons which are due to the uncertainty in operation and setup times and production volumes. Although the planning and scheduling of batch processes has been studied extensively, only very few of the works deal with uncertainty in operations. Normally, the risk level is assumed to be constant for all operations on all equipment. As a result the overall schedule is considered as reliable at that fixed confidence level. However, this approach usually yields much higher reliable overall schedule and hence poor utilization of the resources. In this work, different risk level can be assigned to different operations. The optimal schedule is then tested with a BATCHES simulation model. The simulation model in turn provides a measure of how accurate the risk levels for the operations are. An iterative simulation-optimization procedure can be used to converge to the risk levels and to the desired optimal schedule. This approach is illustrated using Baker's Yeast Production, which is highly uncertain due to the fermentation stage. This approach shows that the production schedules can be improved to increase the plant utilization keeping the overall schedule confidence level at the desired target by identifying the critical risk levels at each operation.

Keywords: Scheduling, Simulation, Batch Processes, Uncertainty, Chance Constraint Programming, MILP

I. INTRODUCTION

In batch processing plants the time spent on a chemical processing operation is expected to be more random compared to time spent on purely mechanical operations, such as metal cutting. In general, operation time has two major elements: setup time and processing time. Unlike purely mechanical operations, preparation of a chemical processing equipment before a new batch operation starts is usually very detailed and needs special expertise, which may also be considered as a separate batch operation. Thus, in chemical industries both of the setup and processing periods may be highly variable. In process operations the variation in time may result from the uncertainty in attaining the desired reaction conversion, the required separation purity, etc. In the equipment setup operations the variations may be because of the difficulties in obtaining the stringent chemical and/or biological cleanliness and mechanical readiness of the equipment for the next operation. Both periods, but mostly the setup period between batches, could be highly variable as compared to the duration of mechanical operations. Thus, in most of the real world batch processing applications, operation and setup periods are indeed not deterministic. The planning and scheduling methods should thus be able to handle such uncertain characteristics properly and efficiently to give realistic and applicable solutions.

Scheduling of batch processing plants has been studied widely in the past. However, most of the previous works do not deal with uncertainty. Some of the most recent works attempt to examine the effect of uncertainty on optimal schedules by Monte Carlo simulation (Mignon *et al.,* 1995, Sanmarti *et al.,* 1995) or analyzing the robustness of schedules (Honkomp *et al.,* 1997). Another approach is to use simulation and optimization in a closed loop form to overcome uncertainty in research and development pipeline planning (Subramanian *et al.,* 2001). In this approach, optimization is repeated as it becomes necessary, i.e. when plan deviates significantly from the original conditions due to uncertainty. Hence, this view can be categorized as what if analysis within reactive scheduling policies under simulation-optimization framework to analyze the effect of uncertainty. In other words, it is a variant of Monte Carlo simulation of reactive scheduling policies.

In another series of recent works, it has been shown that the randomness in operation and setup duration can be formulated with probability distributions, and the production planning and scheduling of batch processes can be handled by means of chance constraints (Orcun 1999a, Orcun *et. al*, 2001b). This approach tries to limit the probability of violating constraints, which are exposed to uncertainty, such as operation and setup time constraints within mixed integer linear programming framework. However, it is usually hard to identify the risk (confidence) levels that will be used to obtain deterministic equivalents of the chance constraints, which result in mixed integer linear constraints. Naturally, there is a trade off between reliability and utilization of the plant, the higher the confidence level, the poorer the plant utilization is. Therefore, accurate estimation of risk levels is very important in determining optimum reliable schedules.

In this work, a two-level approach is used for accurately estimating the confidence levels used in the scheduling model. First, a schedule is generated using estimated confidence levels in the scheduling model based on chance constraint programming. The scheduling model is described briefly in Section II. The baker's yeast production process is described in Section III. This process was chosen because it has high uncertainty due to fermentation steps, which makes the generation of robust schedules a challenging task. The BATCHES simulation model of the yeast process is described in Section IV. The simulation results are used to fine-tune the confidence levels in an iterative loop, which is formalized in Section V. The results of the study and the discussion are given in Section VI. The conclusions and the future research directions are described in Section VII.

II. SCHEDULING MODEL OVERVIEW

In this work operational (modular) approach formalism is used (Orcun *et.al*, 2001a). In the operational approach, the process is divided into batch processing modules called *operations.* An operation can be performed on one or more *operators* in parallel. The timing is established by tracking the batch flowing through the process, i.e. the time batch *j* enters operation *i* and leaves operation *i*. Each operation may have different number of operators. The operators may be machines, equipment, or individual workers performing the given operation. Partitioning the production process into modules makes the grouping of operators with similar characteristics easier during the formulation. This results in constraint blocks that have similar characteristics, namely, if the recipe of a batch, which determines its processing route, requires operation *i*, then it must use one of the operators capable of performing that operation. A direct consequence of the classification of the constraints and variables is the following pseudo description of the model:

```
max profit
subject to
    assignment constraints
    time constraints
    ordering constraints
    continuity constraints
    scheduling period constraints
    assignment coordination constraints
    linearization constraints
    Optional constraints (e.g. production volume constraints)

    production planning and scheduling variables are binary
    time variables are non-negative real
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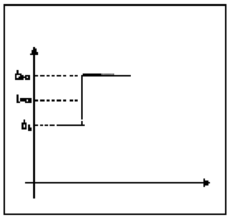
In short, the operational approach enables the mathematical modeling of operation modules by similar type of equations, and it is a unifying modeling strategy for single-product, multi-product and multi-purpose batch processing plants.

In some aspect, operational approach is similar to the state task network (Kondili *et. al*, 1993) commonly used in modeling batch processing plants, where each task corresponds to an operation. However, in the operational approach the batches do not change states. On the contrary they flow through the operators. The operational approach views the batches as flowing entities through the operators able to perform the operations of its production recipe. Hence, the flow shop characteristics of batch process, such as parallel production schemes and equipment sharing among different products can be modeled by this representation, which cannot be accomplished with state task network formalism. Furthermore, in the operational approach, assignment of batches to operations constructs a schedule. Thus, time is viewed as an attribute of a batch in a sense. This eliminates the assignment of time slots or periods to batches and operator, which makes the approach capable of modeling with continuous time. Furthermore, viewing a batch as a flowing entity constructs a natural bridge to simulation models. This is very rare in the literature.

TABLE 1. Uncertainty Models.

Chance Constraints	*Operation Times* $P\{t_{ij}^{1}+\sum_{r\in R}\sum_{k\in K_i} x_{ijk}y_{jr}d_{ikr}+\sum_{r\in R}\sum_{k\in K_i}\sum_{o\in K_p} x_{ijk}x_{pjo}y_{jr}\theta_{ikrpo}\leq t_{ij}^{2}\}\geq 1-\sum_{r\in R}\sum_{k\in K_i} x_{ijk}y_{jr}\alpha_{ikr}$ $i\in I,\ j\in J$ *Setup Times* $P\{t_{il}^{1}u_{ijlk}-2u_{ijlk}t_{ij}^{2}+t_{ij}^{2}\geq\sum_{r\in R}s_{ikr}y_{jr}x_{ijk}+x_{ijk}\sum_{p\in I}\sum_{o\in K_p}\sum_{r\in R}\sigma_{ikrpo}y_{jr}x_{pjo}\}$ $\leq 1-\sum_{r\in R}\sum_{k\in K_i}x_{ijk}y_{jr}\alpha_{ikr}$ $i\in I,\ k\in K_i,\ (j,l)\in PP$ *Production Volumes* $P\{\sum_{j\in J}\sum_{r\in PS_o}V_r y_{jr}\leqslant W_p^x\}\leq 1-\sum_{r\in R}\sum_{k\in K_i}x_{ijk}y_{jr}\alpha_{ikr}$ $PS_p\in PS$
Deterministic Equivalents of Chance Constraints for Log-Normal Distribution	*Operation Times* $t_{ij}^{2}-t_{ij}^{1}-\sum_{r\in R}\sum_{k\in K_i}\mu_{ikr}\geq\sum_{r\in R}\sum_{k\in K_i}\sigma_{ikr}e^{z_{1-\alpha_{ikr}}}x_{ijk}y_{jr}$ $i\in I,\ j\in J$ *Setup Times* $t_{il}^{1}u_{ijlk}-2u_{ijlk}t_{ij}^{2}+t_{ij}^{2}\geq\sum_{r\in R}x_{ijk}y_{jr}\sigma_{ikr}e^{z_{1-\alpha_{ikr}}}+\sum_{r\in R}\mu_{ikr}$ $i\in I,\ k\in K_i,\ (j,l)\in PP$ *Production Volumes* $\sum_{j\in J}\sum_{r\in PS_p}y_{jr}(\mu_r+\alpha_r e^{z_{1-\alpha}})\leqslant W_p^x$ $PS_p\in PS$
Deterministic Equivalents of Chance Constraints for a Discrete Distribution	 *Auxiliary Constraints* $\sum_{l=1}^{L-1}q_l=1$ $l=1,\ldots,L-1$ $b_l q_l\leq 1-\alpha$ $l=1,\ldots,L-1$ $b_{l+1}\geq(1-\alpha)q_l$ $l=1,\ldots,L-1$ *Operation Times* $t_{ij}^{2}-t_{ij}^{1}\geq\sum_{r\in R}\sum_{k\in K_i}\sum_{l=1}^{L-1}q_{likr}a_{likr}x_{ijk}y_{jr}$ $i\in I,\ j\in J$ *Setup Times* $t_{il}^{1}u_{ijlk}-2u_{ijlk}t_{ij}^{2}+t_{ij}^{2}\geq\sum_{r\in R}\sum_{l=1}^{L-1}x_{ijk}y_{jrjr}q_{likr}a_{likr}$ $i\in I,\ k\in K_i,\ (j,l)\in PP$ *Production Volumes* $\sum_{j\in J}\sum_{r\in PS_p}\sum_{l=1}^{L-1}y_{jr}q_{lr}a_{lr}\leqslant W_p^x$ $PS_p\in PS$

When operation durations are random, an operation can be accomplished within a specified time only with certain probability. Therefore, the probability that an operation exceeds a specified time is no more than certain risk level, or a confidence level. This can be modeled with a chance constraint (Charnes and Cooper, 1963), whose deterministic equivalent can be obtained by using quantile rules (Vajda, 1972). For any operator of any operation,

$$P\{\text{Ending time of batch } j \text{ - Starting time of batch } j > \text{operation time of batch } j\} \le \text{risk level}$$

namely, the probability of a delay in operation duration is less than a risk level. Which, implies

$$P\{t^{1}_{ij} + \Sigma_{k}\Sigma_{r}\, d_{ikr}\, x_{ijk}\, y_{jr} \le t^{2}_{ij}\} \ge 1-\Sigma\Sigma\, \alpha_{ikr}\, x_{ijk}\, y_{jr} \qquad i \in I,\ j \in J \qquad (1)$$

Here α_{ijk} is the risk level of operation i when operated by operator k according to recipe r. Risk factors can be either given, or left as decision variables.

Constraint (1) is the probabilistic version of nonlinear form of production time constraint and implies that the probability of satisfying production time constraint, or the probability that the schedule is in time, is larger than a certain confidence level. The risk is present when operator k has to work on batch j according to recipe r; recipe r has to be assigned to batch j and batch j has to be processed by operator k of operation i according to recipe r, which means $x_{ijk}\, y_{jr} = 1$. If this is not true, the product is zero and the right hand side of (1) becomes one. Also, the expression within the probability statement reduces to $t^{1}_{ij} \le t^{2}_{ij}$, which is always true since the entering time is never larger than the leaving time, and constraint (1) reduces to $1 \ge 1$.

When uncertainty is in the form of normal probability distribution, the deterministic equivalents of chance constraints can be obtained as follows: When Z is a standard normal random variable, the deterministic equivalent of $P\{Z \le z\} \ge 1 - \alpha$ is $z \ge z_{1-\alpha}$. Here $z_{1-\alpha}$ corresponds to the $(1-\alpha)^{th}$ quantile. In other words, $P\{Z \le z\} = 1- \alpha$. Assuming the operation duration D is a normal random variable with mean μ and variance σ^2, the deterministic equivalent of chance constraint $P\{D \le t^1 - t^2\} \ge 1-\alpha$ becomes $(t^1 - t^2 - \mu)/\alpha \ge z_{1-\alpha}$. From which, $t^1 - t^2 - \mu \ge \alpha z_{1-\alpha}$ follows. When Z has a log-normal distribution the probability expression $P\{Z \le z\} \ge 1 - \alpha$ implies $ln(z) \ge z_{1-\alpha}$. Then, the deterministic equivalents of chance constraints for set up times and production volumes can be derived similar to the case with uncertain operation times. The final form of the constraints for the log-normal probability distribution and discrete probability distribution are reported in Table 1. The details of the derivations of the deterministic equivalents of chance constraints for wide variety of probability distribution functions can be found elsewhere (Orcun 1999a, Orcun *et.al*, 2001b).

III. CASE STUDY: BAKER'S YEAST PRODUCTION

Baker's yeast production is one of the main branches of conventional fermentation industry. The production process consists of the rapid multiplication of yeast (microorganisms) in a controlled medium of nutrients. This step is followed by the separation of the product by washing and filtering from fermented wort. Molasses, a by-product in sugar production, is the main nutrient for baker's yeast. The mixture is acidified with sulfuric acid, which coagulates the colloidal compounds. Then, the coagulated solids are separated using centrifuge. Fermented wort is obtained by diluting molasses with water and adjusting the temperature. Molasses is then inoculated with the yeast bacteria that are grown in the laboratories. The microorganisms use the sugar in the molasses as a source of energy and building material, together with the nitrogen and phosphate nutrients. When fermentation is complete, the yeast is washed with water and then centrifuged. The rest of the water is removed in filter presses; the final product having a 25-30 % moisture content is obtained.

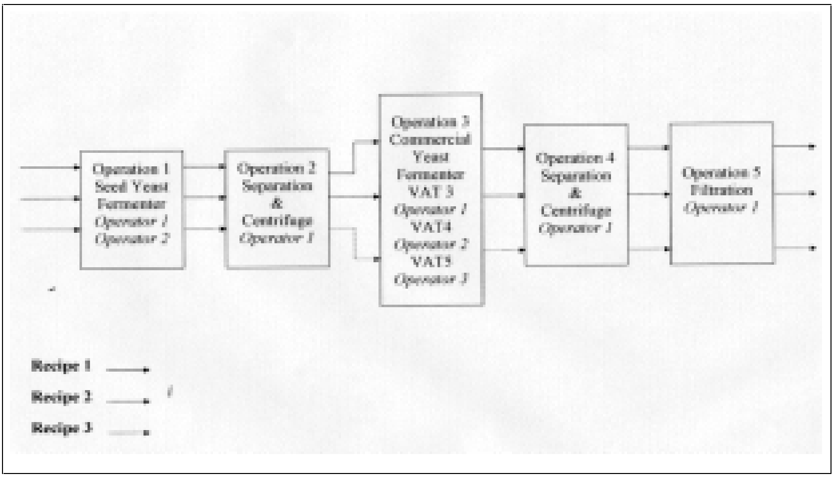


FIGURE 1. Operational Approach: Modules in Baker's Yeast Production.

In summary, Baker’s yeast production consists of five major operations: seed yeast fermentation, separation and cleaning of the fermented product, commercial yeast fermentation, separation and cleaning of the commercial fermented product and finally filtration of the final product.

Because of the nature of fermentation, the processing times of the seed yeast fermentation and commercial yeast fermentation are highly variable. The data obtained from a real plant suggests that these periods can be modeled by a log-normal probability distribution (Tümsen *et. al*, 1996). In Table 2 the operation times are given as either cumulative distribution profile (as "probability, value" pair) of the discrete probability distributions or log-normal distribution denoted by "LN". Modules of the operational approach, which represent the production site, are shown in Figure 1.

The fermentation operation causes additional complications. Due to the biological nature of fermentation the amount of yeast produced is also variable (see Orcun *et. al*, 1999b). However, in this study the production volumes will be assumed fixed at their mean values. The schedules are generated based on the objective of maximizing the profit (for economics of the plant refer to Orcun *et. al*, 1999b).

TABLE 2. Baker's yeast production plant data.

Recipe 1	**Operation 1**		**Operation 2**	**Operation 3**			**Operation 4**	**Operation 5**
	1	**2**	**1**	**1**	**2**	**3**	**1**	**1**
Operation time (hr)	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.636,1.50 0.909,1.75 1.000,2.00	LN (2.74, 0.063)	-	-	0.25,1.25 0.50,1.50 1.00,1.75	0.1429,2.75 0.2858,3.25 0.4257,3.75 1.0000,4.00
Setup Time (hr)	9	9	7.5	5.5	-	-	5	1
Recipe 2								
Operation time (hr)	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.636,1.50 0.909,1.75 1.000,2.00	-	LN (2.73, 0.055)	-	0.20,1.50 0.40,1.75 1.00,2.25	0.50,4.00 0.75,4.75 1.00,5.25
Setup Time (hr)	9	9	7.5	-	5	-	0.6	1.35
Recipe 3								
Operation time (hr)	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.012,21.5 0.929,22.5 0.988,23.0 1.000,23.5	0.636,1.50 0.909,1.75 1.000,2.00	-	-	LN (2.82, 0.036)	0.167,2.00 0.667,3.25 0.833,3.50 1.000,4.00	0.50,6.50 0.75,7.25 1.00,7.50
Setup Time (hr)	9	9	7.5	-	-	5	0.6	1.35

IV. SIMULATION MODEL OVERVIEW

The structure of the recipe network in BATCHES is very similar to the operational approach used in the optimization formulation. An operation is modeled as a task, and a task is modeled as a series of subtasks. A flow line connecting two subtasks represents the transfer of material between the associated tasks (BATCHES, 2001).

The recipe network YEAST_1, shown in Figure 2, is for the manufacture of **Recipe 1** used in the formulation. The recipe network consists of five tasks, FERM01, CENT02, FERM03, CENT04 and FILT05. The first four characters of a task name indicate the nature of the associated operation while the last two digits indicate the operation identity as used in the formulation. Thus, FERM01 is a fermentation operation, and it is the first operation in the recipe. The three recipes used in the formulation have similar structure, only the subtask level details, such as duration, amount of raw material, are different for each recipe. A list of suitable equipment is specified with each task. The suitable equipment list defines the operators on which the operation can be performed. In this example, all operations have one piece of equipment suitable, except FERM01, which has two suitable pieces of equipment.

Each task consists of four subtasks. The first subtask, CLEAN, models the initial set-up and cleaning steps before the main processing begins. The duration of the CLEAN subtask of various tasks is recipe dependent. During the FILL subtask either the raw material, in the case of FERM01 operation, or the upstream batch is transferred into the assigned piece of equipment. The transfer of material is assumed to be instantaneous. The actual processing time of an operation is specified as the duration of the subsequent subtask, either CONVERT or CENTRIFUGE subtask, of the corresponding task. The subtask durations of the processing subtasks are either continuous distributions, such as Log Normal, or discrete probability function tables. All recipes use the same raw material, raw material A. However, the amount of raw material is recipe dependent. Similarly, the yield of the finished product is recipe dependent.

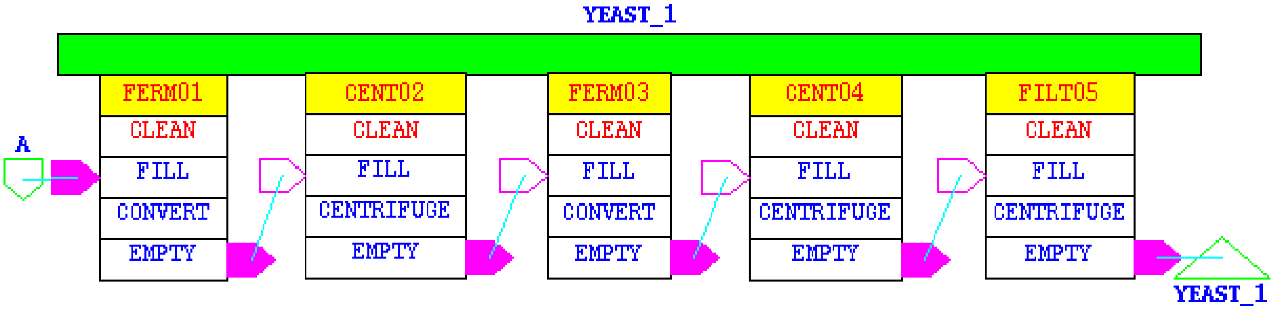


FIGURE 2. BATCHES recipe network for one of the recipes in the Baker's Yeast process.

The schedule generated by the MILP was translated into processing sequences, the BATCHES modeling construct that controls the onset of operations during simulation. Each processing sequence identifies the operation, the expected start time of the associated batch and the name of the equipment in which that batch must be processed. The simulation model consists of the recipe information and the processing sequences.

V. SCHEDULING-SIMULATION BRIDGE

In the real world, processing times almost always have variability due to the uncertain nature of the underlying physical or chemical change which are beyond the control of plant personnel. Therefore, no matter how carefully the schedules are determined, one always experiences deviations from the schedules as a result of these uncertainties. As a result, the operation starts are delayed, and in case of poorly constructed schedules the scheduling horizon is violated. If the scheduling horizon is packed too aggressively, which yields the optimal plant utilization, then one can strongly expect that overall makespan of the schedule will exceed the scheduling horizon when the schedule is executed. This is the natural effect of delays introduced due to uncertainties. There is a trade off between maximizing plant utilization and generating a reliable schedule, which presents an opportunity for finding the best combination. This work is the first systematic approach in finding the best solution so that plant utilization is maximized and the scheduling horizon is not violated. The reliability of a schedule is determined by making several simulation runs with specified statistical distributions and tracking the number of horizon violations, average and maximum earliness and lateness of the makespan, i.e. deviation from the scheduling horizon. Note that, better the schedule is, these values tend to become close to zero. As the number of horizon violations, along with average lateness and maximum lateness increase, the schedule becomes more aggressive and therefore not very robust. If there are no horizon violations coupled with increased earliness and large maximum earliness then the schedule quality decreases from the plant utilization perspective.

The above approach can be viewed as black box approximation, where the overall performance of the schedule is rated without looking into the internal dynamics, i.e. individual batch timing violations at all. With respect to these criteria alone, one can achieve a "good" schedule, which yields good makespan measures when executed while violating internal dynamics of the schedule. Recall that internal dynamics of the schedule is determined by equipment assignments and timing for each batch. For this reason, in this work two waiting measures are introduced to evaluate the internal dynamics of the schedule: resource waiting time and queue waiting time. Resource waiting time occurs when the upstream operation takes longer than the scheduled period. In this case, the downstream operation must wait until the material becomes available. The other type of waiting occurs when the batch has to be queued. This can happen due to two reasons. When the previous batch of an operation takes more time than the scheduled duration the next batch of that operation may get delayed, consequently blocking out the upstream operation until the downstream becomes available. The second case arises due to schedule. The upstream operation may be completed earlier than the scheduled time. In this case, to obey to the schedule the batch should be stalled. In both cases, the batch is queued. One can keep track of the total resource waiting time and total queue waiting time in each operation and operator for every recipe. When the schedule is aggressive the resource waiting time will increase. This is because, in a tightly packed schedule any upset in one of the early stages of production will propagate towards the downstream operations. On the other hand, as the slack time introduced due to confidence level increase, the queue waiting time will increase. These two measures can be used to balance the internal dynamics of the schedule. The best schedule will be the one that minimizes and balances the two measures. Thus, for the best schedule the sum of these two times will be minimum and their ratio will be close to 1.0. Note that, the total waiting time can be zero only in the deterministic environment. Additional measures, such as average waiting times, maximum average waiting times among all equipment and recipes may help in tie breaking.

In the next section, an initial attempt to manually bridge simulation and scheduling models using schedule reliability measures explained above will be demonstrated on an industrial case study, which has highly variable operating conditions due to fermentation steps. In this work the focus will be limited to the operation duration variability only.

VI. RESULTS AND DISCUSSION

In the study, the schedule created with mean values of operation times has been used as the basis for comparison. The reason being that the mean operation times are used commonly for generating the deterministic schedules when the scheduling models do not account for uncertainty. To limit the search for best confidence level, a lower limit of 50% confidence is assumed since the schedule generated using mean operation times is at least 50% confident. In the remainder of the text when a confidence level is stated for a schedule, for example 75% confident schedule, it means that the schedule is *at least* 75% confident. This is due to discrete probability distributions. Note that for discrete probabilities the next point that will guarantee the selected confidence level must be used. For example, for operator *1* of operation *1* while generating 50% confident schedule, 22.5 is used as processing time. For 100% confidence the upper bound is used. However, 100% confidence level is not theoretically achievable for continuous probability distributions. Therefore, in this example, for log-normal distributions an arbitrary upper limit for processing time, 24 hours, is imposed. With such a policy, one can achieve 100% confident schedules for practical applications.

TABLE 3. Simulation results for makespan matrices.

Run	Average Makespan (hr)	Horizon Violations (%)	Average Horizon Earliness (hr)	Average Horizon Violation (hr)	Max. Horizon Earliness (hr)	Max. Horizon Violation (hr)	Scheduled Batches for Each Recipe (r1,r2,r3)	Objective Function from MILP: Profit
With means	162.04	0.00	5.96	N/A	6.99	0.00	(0,4,4)	18343701114
With 100% confidence	166.93	0.00	1.08	N/A	1.50	0.00	(0,3,4)	16772424285
With 50% confidence	160.82	0.00	7.18	N/A	8.96	0.00	(0,4,4)	18343700890
With 75% confidence	161.05	0.00	6.95	N/A	8.96	0.00	(0,4,4)	18343671866
With 90% confidence	162.43	0.00	5.57	N/A	6.08	0.00	(0,4,4)	18343648360
With 80% confidence	161.78	0.00	6.22	N/A	6.85	0.00	(0,4,4)	18343679109

Confidence level for the next iteration is determined using interval halving, which is 75%. Table 3 summarizes the makespan measures and Table 4 lists the schedule dynamics matrices. The results were obtained by making 100 simulating runs for each schedule, using a different initial seed in each for generating random numbers. In all of the cases, makespan measures (see Table 3) suggest that the schedules are good. None of them violates the scheduling horizon and the profits are comparable except for 100% confidence, where the plant utilization is traded off to increase the confidence level. However, dynamics matrices differentiate between the cases that seem to be equivalent for black box measures (makespan measures).

Total waiting time and ratio of resource waiting time to queue waiting time change drastically based upon the confidence level chosen. As the confidence level increases, the queue waiting time increases which is indicative of time slacks introduced to make the schedule confident. Similarly, the resource waiting time increases, as the schedule is made more aggressive. Recall that, the results agree totally with the expectations that were set forward previously. Using waiting time ratio, which is 8.86 for 75% confidence, the direction of the search for the next iteration is inferred. Note that the ratio decreases as the confidence level increases and our target is to make it close to one for a balanced schedule. For this reason, 90% is chosen for next iteration. As it can be noticed, the 90% confidence level satisfies decreased total waiting time and waiting time ratio. However, waiting time ratio is 0.20, which is not really satisfactory. Thus, the next iteration should be on the direction to get this ratio closer to 1.0. This can be established by decreasing the confidence level. Therefore, 80% confidence is chosen for next iteration. As it can be noticed from the results, it satisfies our goals. Namely, it is a balanced schedule with minimized total waiting time, which has also good objective function value. With respect to the final iteration one may choose further continue the search. In this case, direction will be reducing the confidence level. However, since the discrete probability distributions will yield the same processing times as in 80% confidence case within (75%, 80%) confidence region, the search procedure can be stopped here.

TABLE 4. Summary of simulation results and schedule quality measures.

Run	**Total Resource Waiting Time (hr)**	**Total Queue Waiting Time (hr)**	**Total Waiting Time (hr)**	**Waiting Time Ratio (Resource/ Queue)**	**Average Resource Waiting Time (hr)**	**Average Queue Waiting Time (hr)**	**Maximum Average Resource Waiting Time (hr)**	**Maximum Average Queue Waiting Time (hr)**
With means	929.41	386.50	1315.91	2.40	0.57	0.35	0.82	0.99
With 100% confidence	0.00	6833.60	6833.60	0.00	N/A	2.54	0.00	8.67
With 50% confidence	870.75	574.28	1445.03	1.52	0.66	0.84	0.83	1.11
With 75% confidence	3143.00	354.73	3497.73	8.86	1.16	0.51	1.36	0.87
With 90% confidence	250.08	1273.05	1523.13	0.20	0.48	0.76	0.63	1.20
With 80% confidence	354.97	926.60	1281.57	0.38	0.52	0.68	0.64	1.00

VII. CONCLUSION AND FUTURE DIRECTIONS

In this work, an iterative approach using simulation and math programming to develop reliable schedules under uncertain operating conditions was demonstrated. This approach is fundamentally different from others in that the focus is on developing reliable schedules to begin with by using the strengths of simulation and math programming techniques. Two measures, namely, resource and queue waiting times (See Section IV for details) provided the basis for evaluating the reliability of a given schedule. A schedule was generated by solving an MILP formulation whereas the waiting times were generated by implementing the schedule on a simulation model. As demonstrated in this work, minimizing total waiting time and balancing the resource and queue waiting times can be used as a measure to fine-tune the schedule given that the makespan measures are acceptable. A search strategy utilizing interval halving was used to identify the optimal risk parameters to attain a reliable schedule under variable operating conditions.

In this work, the scope was limited to variability in processing times. One possibility for future research direction is to extend this methodology to processes that have production yield variability as well as the setup duration variability. Another possible direction is to study other processing schemes in which the intermediate storage policies are permitted. Recall that, this work is focused on a production facility that has a no intermediate storage policy. As a third direction, this methodology can be extended to fine tune independently the confidence levels of individual operators for every recipe.

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