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Increasing the reliability of production schedules in a pharmaceutical packaging department

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ABSTRACT

We study quantitative methods for evaluating the potential benefits of introducing new advanced tracking technologies in manufacturing with special reference to radio frequency identification (RFID). RFID is an effective way for increasing the reliability of production schedules, but there is a lack of scientific research to quantify the return on investment that can be achieved in practice. In this paper we focus on the marginal contribution of RFID to the productivity of the packaging department of a pharmaceutical plant, propose a systematic method for assessing such impact and discuss its implementation on a practical test case. Our results confirm that advanced tracking technologies in combination with effective scheduling procedures deserves a significant potential for improving productivity. Extensions to other production environments are also discussed.

Keywords: RFID, Production Scheduling, Pharmaceutical Manufacturing.

1 Introduction

This paper explores the potential of advanced tracking technologies for increasing the reliability of production schedules in industrial practice and to improve the coordination between planning and scheduling. The latter topic is critical to the successful implementation of planning activities in many industrial settings (Kempf *et al.* 2000) and in particular in the pharmaceutical industry (Pacciarelli *et al.* 2008). We assume that the planning function determines the quantities of products and components to be produced in a given time horizon, while the scheduling function involves the release of work orders to the shop floor, specifying the allocation of shop resources to the different orders over time (Vollmann *et al.* 1997, Voß and Woodruff 2003, Pinedo 2005). Effective planning requires careful forecast of the shop floor production capacity over time, which can be difficult since it depends on the performance achievable by the scheduling function. Following the notation of Kempf *et al.* (2000), a *predictive schedule* describes the designed system behavior over the schedule horizon, while a *historical schedule* specifies the operation start times and resource assignment actually executed on the shop floor.

The difference between the predictive and the historical schedules observed in many production systems, hereinafter called the *scheduling gap*, can be remarkable, in particular when the predictive schedules are produced with computerized scheduling tools. Due to this fact, the practical shop floor performance can be considerably lower than the theoretical one, and many computerized tools for planning and scheduling have had limited success in practice (Pinedo 1995, McKay *et al.* 2002, McKay and Wiers 2003).

Inaccurate models and data are most likely the main reasons for the scheduling gap, besides the stochastic nature of operations. In fact, most production scheduling systems are based on the following two crucial assumptions:

- The scheduling model reflects all the relevant aspects of the practical problem to be investigated and solved;
- Relevant data used by the computerized support system to build the predictive schedule, like processing and setup times, coincide with the actual values provided by the historical schedule.

In practice, none of the two assumptions is exactly met and sometimes both model and data are only rough approximations of the real problem to be solved. According to Vieira *et al.* (2003), many models adopted by computerized systems suffer from excessive simplification and do not incorporate all relevant aspects of the shop floor, while Lee and Özer (2005) point out that relevant data are often derived from rough campaign measures.

The discrepancy between recorded and actual data can be effectively reduced by introducing advanced tracking technologies on the shop floor. A trend towards real-time data collection has been recognized by Hozak and Hill (2009) for best-in-class manufacturers. Radio Frequency Identification (RFID) offers a natural and inexpensive opportunity to this aim, and many authors report on the increased data accuracy achievable through the introduction of RFID systems (Lu *et al.* 2006, Li and Visich 2006, Thiesse and Fleisch 2008, Tajima 2008). Kim *et al.* (2008) propose effective algorithms for data estimation, to be used after that real time information is available.

While the cost of introducing RFID technology in the shop floor can be easily computed, estimating the Return On Investment (ROI) is more difficult (Langer *et al.* 2007).

As pointed out by Lee and Özer (2005) and by Gaukler (2005), there is a lack of scientific studies for evaluating the added value of RFID in industry. Hozak and Hill (2009) point out a lack of research on the evaluation of the overall value of timely information in conjunction with replanning and rescheduling frequencies. Thiesse and Fleisch (2008) identify a clear need for research on the development of more realistic models for evaluating the benefits of RFID in manufacturing. The lack of quantitative methods for assessing such benefits appears today one of the major obstacles to the introduction of RFID. This is confirmed by a recent survey carried out within RFID journal subscribers (*RFID Journal*, July-August 2008) who work for midsize companies that have deployed RFID systems. More than 80% of responders did not achieve or even do not expect to achieve a ROI within two years, and more than 60% are not sure when or if they will get a ROI from the introduction of RFID.

This paper is part of the emerging stream of research on quantitative methods for assessing the added value of RFID in industry. The aim of this paper is manifold.

- We propose a new methodology to quantify the scheduling gap reduction that can be achieved by improving the accuracy of models and data. This advancement is made possible by RFID technology if the information provided by RFID is used to establish a feedback from production activity control to production scheduling.

- We use this methodology to quantify at least a component of the value produced by the introduction of such feedback. Specifically, we concern with the increase of performance of the deliveries that can be achieved on the shop floor through the availability of more reliable production schedules.

- We discuss the application of our methodology to a pharmaceutical packaging department. The pharmaceutical supply chain requires standards of product quality and availability close to 100%. Achieving such standards requires effective tracking and tracing systems to attain excellence in each phase of the planning and scheduling process, as well as at the coordination between these phases. RFID-based tracking and tracing systems have been introduced in the pharmaceutical supply chain mainly for monitoring and counterfeit prevention purposes (Schuster *et al.* 2007, Wyld and Jones 2007). Therefore, extending their use to achieve additional benefits is easier and less expensive than for other production environments.

- We show that the impact of RFID should be analyzed in combination with new production scheduling algorithms, since the availability of more reliable models and data can be better exploited by re-designing the decisional process of building schedules.

The paper is organized as follows. The next three sections present the three main actors of the paper, namely (*i*) production scheduling, (*ii*) RFID technology and (*iii*) the new method we propose to assess the RFID value. Section 5 describes the pharmaceutical supply chain and discusses the application of our methodology to the different production stages. Section 6 deals with the models and algorithms used for the packaging department, which are then compared in Section 7. In Section 8 the potential impact of the proposed methodology on the other departments of the pharmaceutical supply chain, and more in general on different industrial settings, is also discussed. In Section 9 we draw some conclusions on the main findings of our study and its possible application to solve practical problems. We also outline new research directions for developing more realistic models and more effective methods for production scheduling, taking advantage from RFID-based tracking and tracing systems.

2 Production scheduling

Production scheduling involves the release of work orders to the shop floor, specifying the allocation of shop resources to the different orders over time. A considerable distance still exists between the solution methods that can be found in the scheduling literature and those adopted in practice (see, e.g. Ruiz *et al.* (2008)). While scheduling theory is mainly dedicated to the development of sophisticated algorithms for computing optimal solutions to simplified problems, scheduling practice faces all the complexity of the real-world problems by computing sub-optimal solutions with algorithms whose degree of sophistication is in most cases at the level of simple priority dispatching rules.

In the last decade, there is a clear trend in the scheduling literature to reduce the gap between theory and practice by incorporating a larger number of realistic constraints in the models and by developing algorithms able to cope with such constraints (Pacciarelli 2002, Pacciarelli and Pranzo 2004). At the same time, an increasing number of successful applications of sophisticated algorithms can be found in the scheduling practice (Olson and Schniederjans 2000, Bertel and Billaut 2004). Despite this fact, many computerized schedulers have had limited practical success (Portugal and Robb 2000).

When comparing predictive schedules produced by hand and by computer, it is often the case that the latter outperforms the former. However, when implementing the computerized schedule in practice, the performance of the resulting historical schedule can be considerably worse with respect to the predictive one. Therefore, human schedulers do not frequently recognize as good the solutions provided by the computerized tools. Possible reasons include the lack of flexibility of computerized planning and scheduling systems (Mc Kay *et al.* 2002), as well as the mismatch between the key aspects of the scheduling problem to be solved and the system implemented in practice, which tends to reflect more the perceived than the real scheduling problem. For example, simplified models can be adopted because collecting all information necessary for a detailed model would be impossible or too expensive. In addition, the data used by the computer to produce predictive schedules can be unreliable or not updated, in particular for the processing times and setup times of each operation. In fact, the typical procedure used to collect information consists of performing a campaign of measurement when the scheduling system is put to work and then updating the values occasionally, on the basis of historical data. However, besides the stochastic nature of operations, things may change rapidly on the shop floor, so that the values measured at a certain time may be incorrect after a period of time. Moreover, the same operation may require a different processing time if performed by different workstations or by different operators, and even by the same operator in different periods of his/her career. Therefore, the average computed over all workstations and operators may not describe precisely the time required by a specific machine and operator. In other words, most scheduling systems can be viewed as part of an open loop control chain with several sources of error, as in Figure 1.

Error ϕ_1 in Figure 1 is a real-time error representing unpredicted events occurring during operations, ϕ_2 and ϕ_3 represent errors introduced off-line in the data and in the

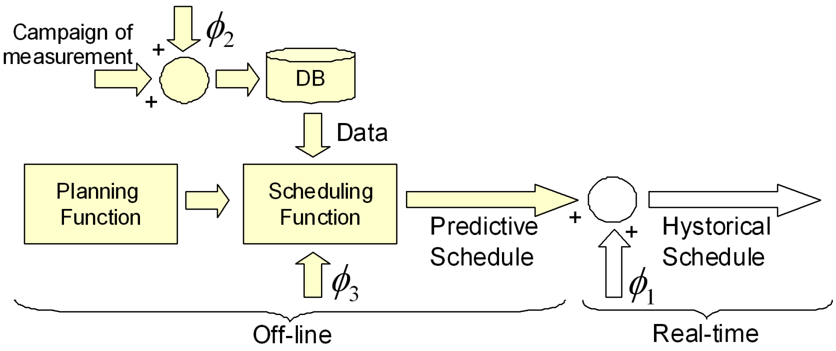

Figure 1: Open loop production scheduling

model, respectively. While ϕ_1 is inherently stochastic in nature and can only be reduced by modifying some characteristics of the production process, ϕ_2 and ϕ_3 can be reduced through careful data estimation and model revision.

The main consequence of designing predictive schedules on the basis of inaccurate models and data is that the schedule implemented in practice becomes frequently infeasible (i.e., materials, workers or machines are not available when they are supposed to be) even when no disruptions or exogenous events occur. This fact forces the manager to frequently update the schedule as soon as it is clear that the predictive schedule will become ineffective in the near future. Such frequent update deteriorates the performance of the shop floor since the hystorical schedule differs more and more from the predictive one.

The need for adjusting the predictive schedule may be drastically reduced by advanced tracking technologies, which make possible to detect any discrepancy between the recorded and the actual data, as well as between the model and the real system behavior. With such technologies the control system would be similar to the closed loop control chain of Figure 2, in which the collection of reliable information allows to capture all the relevant aspects of the practical scheduling problem and, in principle, to reduce ϕ_2 and ϕ_3 down to zero.

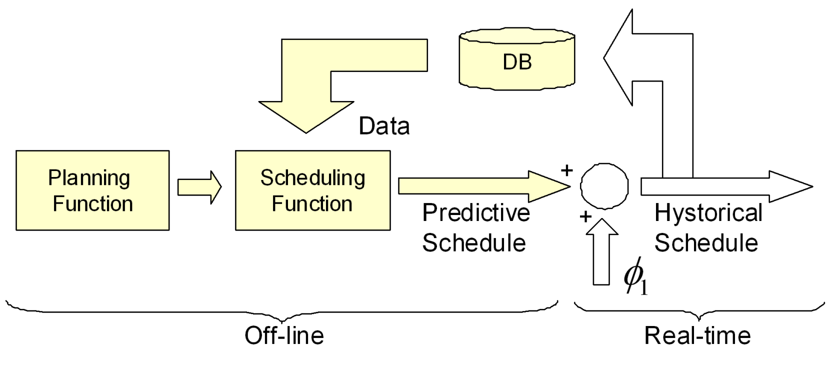

Figure 2: Closed loop production scheduling

A closed loop control chain should incorporate the procedure for data collection as an essential component of the overall control system, linked to the scheduling procedure as well as to the procedure for detecting and correcting model inconsistencies. In the next section we show that RFID technology may provide reliable real-time information on the location and the characteristics of every object circulating on the shop floor, which is equipped with an RFID tag and wirelessly scanned. To close the control loop, tracing information should be used to frequently update the data on the basis of which the predictive schedules are produced. Note that this control loop differs from the common rescheduling procedure used in real-time to update the predictive schedule when it becomes ineffective. Once the data are guaranteed to be reliable, the information can still be used to check whether the predictive schedules violate some practical constraints. Such violation should lead to identify at least one relevant aspect of the real production environment that is not incorporated in the scheduling model and to update the scheduling algorithms consequently.

3 RFID technology

RFID technology allows automatic identification of physical tags passing at reading distance from an antenna. Since identification uses radio waves, no physical contact and material positioning are required, and therefore no human intervention is normally needed. Thus, scanning is generally faster and more accurate with respect other technologies, such as bar codes, that are more sensitive to human errors.

An increasing scientific effort has been dedicated in the last decade to study how RFID technology should be integrated in the industrial practice from technical to business related issues (Ngai *et al.* 2008). It is a common opinion of the experts that RFID technology offers the possibility to develop reliable and rather inexpensive real-time advanced measurement systems (see e.g. Bottani and Rizzi (2008) and de Kok *et al.* (2008) for cost-related analysis of tradeoffs in allocating resources and operations management). By suitably locating antennas on the shop floor is then possible to monitor production in real-time, with a probability that the information flow coincides with the production flow close to 100% (*RFID Journal* October 2002 and August 2008).

As pointed out by Lee and Özer (2005) and by Hozak and Hill (2009), among others, information itself does not represent value for the company. On the other hand, if used properly, the information obtained from RFID can increase production efficiency and quickly respond to the change of manufacturing environment (Lu *et al.* 2006). In fact, the potential of RFID is not yet fully known (Ngai *et al.* 2007).

For the purposes of this paper, it is particularly relevant that RFID systems may play a key role in producing better estimates of process data, by suitably processing real-time data. However, since the cost of setting up a system for real-time tracking and further elaboration of the collected data is not negligible, it is important to have a clear procedure for estimating the ROI of such system.

In general, the problem of quantifying the RFID value appears to be an important open issue in the RFID literature (see e.g. Lee and Özer (2005), Thiesse and Fleisch (2008)). In the next section, we describe a procedure for computing at least one component of this value, namely the value of information reliability. We discuss the expected performance that can be achieved in a manufacturing plant when production schedules are generated by using data affected by a different degree of reliability. The value of reliability is then the increase of performance achievable when passing from less to more reliable data.

4 Research methodology

This section describes our innovative procedure for estimating the value of RFID in production scheduling. The basic idea behind the procedure is that the discrepancy between predictive and historical schedules is only in minor part due to the inherent stochastic nature of operations. Major differences are due to the mismatch between the model and data used to build the predictive schedule and the practical system that produces the historical schedule. Let $p_i = f_i + v_i$ be the processing time of a job J_i, where f_i is the fixed (deterministic) part and v_i a stochastic variable. The fixed part f_i is the desired value for designing a predictive schedule. For example, the mean value of p_i or a value achieved with probability ψ (i.e., such that the probability of the event $p_i \leq f_i$ is ψ).

In different production environments the variance of v_i can be large or small with respect to f_i. For example, the variance of automated operations is typically smaller than in case of manual operations. However, in practice most computerized scheduling systems work with a deterministic estimate p_i^1 of each processing time p_i and ignore the stochastic part v_i. The aim of the system designer is to replace p_i with f_i, but this is not always the case and we call *discrepancy* the quantity $\delta_i = p_i^1 - f_i$. If p_i^1 is a rough estimate of p_i, then $|\delta_i|$ can be much larger than the variance of v_i.

Collecting more reliable information may help to produce a better estimate p_i^2 of p_i, i.e., an estimate such that $|p_i^2 - f_i| << |p_i^1 - f_i|$. The value of such information is related to the improved performance of the system that would have been achieved if the predictive schedule was built by using the more reliable p_i^2 instead of p_i^1. Since the discrepancy between estimated and real data may vary over the different jobs to be scheduled, we introduce an aggregated value ε that we call the *unreliability* of the data set. Possible aggregations are the mean value of the discrepancies over all the n jobs to be processed, $\varepsilon = \frac{1}{n}\sum_{i=1}^{n} \delta_i$, or the square mean value $\varepsilon = \frac{1}{n}\sum_{i=1}^{n} d_i^2$, or any other aggregated representative of all data discrepancies.

Our procedure computes the value of information with reference to a *given* scheduling algorithm $\mathcal{A}$. It requires the production of several predictive schedules with $\mathcal{A}$ for varying the unreliability ε of the data set. Given the data set and a value for the unreliability ε, we let $\sigma^p(\varepsilon)$ be the predictive schedule obtained with $\mathcal{A}$ on such data set, $\sigma^h(\varepsilon)$ be the associated historical schedule, obtained by using the same sequence as in $\sigma^p(\varepsilon)$ and the real data p_i instead of p_i^1. Since the values p_i are stochastic, also the performance of $\sigma^h(\varepsilon)$ is a stochastic variable. We let $\pi(\varepsilon)$ be the mean value of the performance achieved by $\sigma^h(\varepsilon)$for a given ε. Applying the same procedure for varying ε, we get a curve $\pi(\varepsilon)$ associated to the scheduling procedure $\mathcal{A}$ being used. If using a certain type of RFID technology one can decrease the information unreliability from the previous value ε_2 to $\varepsilon_1 < \varepsilon_2$, the performance improvement is $\pi(\varepsilon_1) - \pi(\varepsilon_2)$, like shown by the curves of Figure 3.

In this paper, we focus on computing the relation between data reliability and process productivity. We do not address the exact computation of the probabilistic uncertainty of the information before and after the introduction of RFID technology, which is very much related to the technology and the specific industrial setting, and it is the subject of more technology oriented RFID studies. However, it appears from the literature that in many cases RFID technology makes possible to reduce the unreliability ε nearly to zero (*RFID Journal* October 2002 and August 2008).

It is worthwhile to mention that, very likely, different scheduling algorithms may have

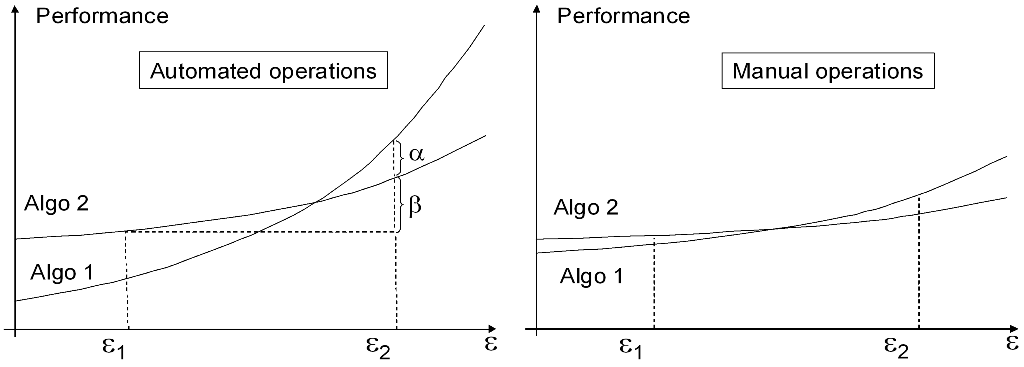

Figure 3: Performance for varying the unreliability

different degrees of sensitivity to process data information. Therefore, when designing the RFID system, it can also be profitable to develop novel scheduling algorithms that will better use more reliable information. Figure 3 shows the case of two algorithms (Algo2 is more robust, Algo1 is less robust but more performing for reliable data) and two production environments, automated and manual operations, in which Algo2 is better than Algo1 for highly unreliable data. It is likely that before the implementation of an RFID tracking system (for $\varepsilon = \varepsilon_2$) Algo2 is more effective, while Algo1 becomes the best choice after the introduction of RFID (for $\varepsilon = \varepsilon_1$). In other words, it is worthwhile to assess the impact of RFID in combination with different (simple and advanced) production scheduling algorithms. Introducing the RFID-based tracking system in combination with Algo2 produces the benefit β in Figure 3. If the scheduling algorithm is replaced with Algo1 there is the additional benefit α. It is worth paying the cost of implementing the RFID-based tracking system and the new algorithm Algo1 only if they generate sufficient ROI.

In case of automated operations the processing times have smaller variance, i.e., smaller values v_i. In this case, scheduling the production with more reliable data (i.e., smaller ε) is expected to reduce drastically the difference between predicted and historical schedules. On the other hand, in case of manual operations the inherent variance of processing times leaves margins of uncertainty even when the unreliability ε becomes close to zero. In such case the performance improvement for reduced ε is expected to be smaller, in case of both Algo1 and Algo2.

5 Pharmaceutical supply chain

This section describes the main characteristics of the pharmaceutical supply chain, which is leading the adoption of RFID technology worldwide (Wyld and Jones 2007). The pharmaceutical production process must satisfy severe requirements of chemical composition and operations execution to guarantee the quality of final products. A typical pharmaceutical supply chain, shown in Figure 4, contains two manufacturing stages: primary and secondary (Cole 1998, Shah 2004). In the former stage active ingredients are produced through complex chemical and biochemical processes. In the latter stage active ingredients are mixed with other components to produce tablets and other drugs, followed by the packaging of final products.

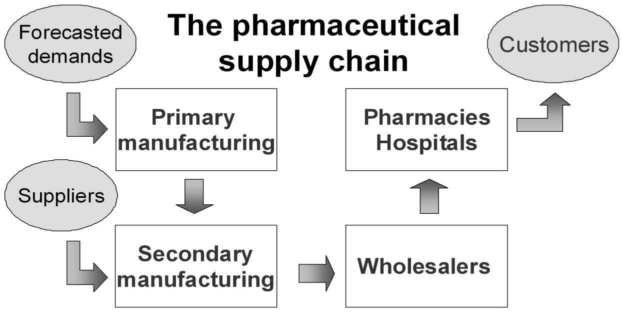

Figure 4: Material flow in a pharmaceutical supply chain

Primary manufacturing is typically organized as a *push* process in which production is driven by forecast demand, while secondary manufacturing is organized as a *pull* process, driven by wholesaler orders. The two stages are then decoupled by relatively large stocks of materials. Primary manufacturing is therefore not very sensitive to short-term demand fluctuation. Here, the main issues are quality assurance and careful lot sizing to avoid shortages of active ingredients. As a consequence, the scheduling function does not play a significant role to increase throughput and RFID are expected to impact more on quality assurance than on throughput improvement.

Secondary production is typically very sensitive to market demand, and therefore effective tracking and tracing are critical issues to ensure schedule reliability as well as to improve the coordination between planning and scheduling, and finally to guarantee 100% availability of final products.

We next focus on secondary manufacturing systems, that are usually organized in multi-purpose plants producing a variety of intermediate and finished products. Production is frequently organized into four main departments, as in Figure 5, which to a certain extent can operate independently from each other. In the *dispensing* department raw materials are handled, weighed according to the drug recipes and stored in sealed bins. In the *manufacturing* department materials are taken from the bins and processed to produce tablets, powdered or liquid drugs, which are again stored in sealed bins. In the *counting* department packaging materials are prepared according to different orders and market places. Finally, in the *packaging* department drugs and packages are transferred to the packaging lines and processed. Large plants may have several dispensing or manufacturing departments to make products with different production requirements, e.g. human and veterinary medicine.

Drugs and other materials moving from a department to the other, or even from a machine to another of the same department, are stored in sealed bins, in order to avoid cross-contamination. The whole process is particularly suitable for tracking purposes by means of RFID systems since the tags can be associated to the bins and re-used several times. The presence of a large warehouse to store the bins waiting for processing at each department makes possible, at a certain extent, to schedule the activities at the various departments independently from each other.

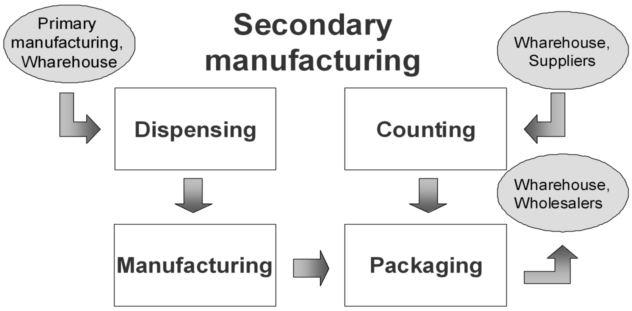

Figure 5: Secondary pharmaceutical manufacturing plant

6 Packaging department

The packaging department studied in this paper contains three packaging lines working in parallel. Each line performs the entire process of assembly packages, blisters, tablets and package inserts (see Figure 6), and monitors the process to achieve a standard of product quality close to 100%.

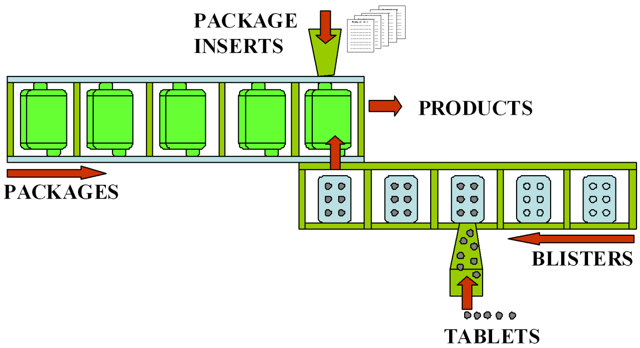

Figure 6: A sketch of the main packaging operations

In our formulation, each line acts as a single machine which can process at most one job at a time. A set of n production orders, called jobs $\mathcal{J} = \{\infty, \in, ..., \backslash\}$, has to be scheduled on a set of m machines $\mathcal{M} = \{\infty, \in, ..., \Updownarrow\}$. Each job must be processed entirely on the same machine. To process job j, a machine must be equipped with a fixed number b of operators, which is the same for each production line, and with a tool T_j that defines the size of the blister. Let $\mathcal{T} = \{\infty, \in, ..., \sqcup\}$ be the set of tools available. Each job j has a release time r_i, a processing time p_j, a due date d_i and a hard deadline D_i that is defined for urgent orders when there is a risk of stock-out at the final customers. A given removal time τ_{ij} is required between two jobs i and j processed consecutively on the same machine, in order to clean and calibrate the machine and to remove the tool T_i if i and j use different tools. If $T_i \neq T_j$ an additional setup time σ_{ij} is required after τ_{ij} to set up the new tool T_j.

The scheduling problem is characterized by different timing constraints. Job release times are determined by the scheduled completion times at the earlier manufacturing departments. Human resources availability is constant within a shift, but it can vary from one shift to another, the night shift being typically less supervised. Machines can be unavailable in given periods for preventive maintenance operations. Modeling the practical scheduling problem requires to consider a number of constraints and the incorporation of several details into the model. Tools are shared among families of similar products and available in a limited number of copies, in most cases there is a single copy of each tool. Cleaning operations, mechanical configurations and job processing require a given amount of work for human operators, therefore machines cannot process jobs nor execute setups or removals without the presence of human resources. In order to reduce the risk of cross-contaminations, the plant policy is to assign each operator to a specific machine during the whole shift. Setups and removals cannot be preempted. On the other hand, the processing of a job on a machine can be interrupted and resumed later on the same machine if the machine becomes unavailable for planned maintenance or if the number of operators in the subsequent shift is not sufficient to process the job.

The problem can be described with the three-fields classification scheme of Graham *et al.* (1979) as follows:

$$OSMPM|r_i, d_i, D_i, R_{sd}, S_{sd}, u_j|Lex(C_{max}, T_{max}).$$

The first field contains the shop environment and $OSMPM$ stands for *Open Shop Multi-Purpose Machines*. The choice of the open shop environment is motivated by the fact that the jobs using the same tool or the same machine must be sequenced and any processing order is acceptable. The problem structure is therefore similar to an open shop scheduling problem. The second field contains the constraints of the problem. Here, R_{sd} and S_{sd} indicate sequence-dependent removal times and sequence-dependent setup times, respectively. Notation u_j indicates that there are predefined periods of time during which some resource (machines and/or operators) are not available. Job processing is resumable, i.e., can be interrupted when the machines or the operators become unavailable and resumed later, even if no other job can be processed in between. Setups and removals are not preemptive, i.e., they cannot be started if unavailability arises before completion. The third field contains two performance indicators to be optimized in lexicographic order: C_{max} is the makespan minimization while T_{max} is the maximum tardiness minimization.

The above problem is a particularly difficult NP-hard problem, which can be solved by the simple rules or sophisticated tabu search algorithms described in Venditti *et al.* (2009). Specifically, the greedy algorithm of Figure 7 is described by the authors as a good surrogate of the human scheduler behavior.

In this paper we assess two versions of the tabu search algorithm of Venditti *et al.* (2009), denoted in the following as *simple* and *advanced*. Both versions make use of two basic moves. The first one is based on the interchange of a pair of adjacent jobs sequenced on the same machine or on the same tool. The second move is based on removing a job from the sequence of jobs processed on a machine [on a tool] and inserting it in the sequence of another machine [of another tool].

The two versions differ in the following aspects. With the simple version, the algorithm restricts the interchange move to consecutive jobs on a critical path, defined as the classical longest path on a graph representation of the problem. With the advanced version, an extended critical path is introduced, which generalizes the former longest path and enlarges the neighborhood of the current solution. Another difference is in the choice of the method used to evaluate the two objective functions for a neighbor of the current solution. With the simple version, two heuristic values are computed in constant time.

Algorithm Greedy

1. Compute an estimate workload for each machine as follows:
   1.1 Compute the minimum workload W_h for machine $h \in \mathcal{M}$ by summing processing time + minimum setup time + minimum removal time of all jobs that can be executed on h only;
   1.2 Compute the quantity $Q(i)$ by summing processing time + minimum setup time + minimum removal time of all jobs that can be executed on h and other i machines in $\mathcal{M}$;
   1.3 Add the quantity $\frac{Q(i)}{i+1}$ to W_h, for $i = 1, \ldots, m-1$.
2. Assign human operators to machines, proportionally to the values W_h.
3. Partition the entire time horizon into L time intervals of given length λ.
4. Schedule the jobs in each time interval $[(l-1)\lambda, l\lambda]$, for $l = 1, \ldots, L$, as follows:
   4.1 Let $\mathcal{J}_{\updownarrow}$ be the set of jobs with deadline or due-date smaller than $l\lambda$;
   4.2 Group the jobs in $\mathcal{J}_{\updownarrow}$ requiring the same tool;
   4.3 Sequence the jobs in each group as for the ERDF (Earliest Release Date First) rule;
   4.4 Sequence the groups one at a time by assigning a block to the next available machine on the basis of the SSTF (Shortest Setup Time First) rule until all groups are scheduled.

Figure 7: Pseudocode of the greedy algorithm

With the advanced version, the exact values of the two objective functions are computed in linear time.

7 Experiments on the packaging department

This section reports on the performance of the greedy algorithm and of the two versions of the tabu search algorithm for varying the reliability of the data set. All the algorithms are coded in C language and run on a PC equipped with a Pentium® 4, 3.0 GHz with 1024 MB Ram. Two different sets of problem instances, described in Venditti *et al.* (2009), are used for the performance assessment. The first set comes from the industrial practice and consists of a real instance plus 16 realistic instances representing the range of possibilities that can arise during operations. The second set of instances consists of 20 randomly generated instances.

Each perturbed instance is obtained by adding a random error uniformly distributed to each processing time p_j, removal time ρ_{ij} and setup time τ_{ij}. In the instances of the first set, for each value $x \in \{p_j, \rho_{ij}, \tau_{ij}\}$, the error is chosen in the range $[-\varepsilon x, +\varepsilon x]$. In the instances of the second set the error is chosen in the range $[0, +\varepsilon x]$. For each instance, we generate 30 perturbed instances for each value of $\varepsilon \in \{0, 0.05, 0.1,\ 0.2, 0.3,\ 0.4, 0.5, 0.6, 0.7,\ 0.8, 0.9\}$. Following the methodology of Section 4, each perturbed instance is first solved by the three algorithms of Section 6 and the performance of each solution is then assessed by replacing the perturbed processing, setup and removal times with their original values. In this section, we limit our study to the makespan, which is the main objective function. The performance of each algorithm on a specific instance and for a given ε is then obtained by computing the average makespan over the 30 perturbations. In what follows, we report on the performance of the three algorithms for each set of instances.

7.1 Results on the first data set

The real instance corresponds to a real production plan for 18 days spanning over three weeks, from Tuesday of the first week to Friday of the third week. In this period of time, a total of 26 production orders are scheduled with no urgent orders. Therefore there are no deadlines in this instance. All the jobs are available from the first day and the due dates are fixed equal to the end of the last Friday. Operators availability in each week allows to activate three blister lines from Monday to Friday for two shifts of seven hours each (from 6:00 a.m. to 8:00 p.m.). From Tuesday to Friday, there is an additional short shift of three hours (from 8:00 p.m. to 11:00 p.m.) in which only two machines can be activated. Figure 8 shows the results for this instance.

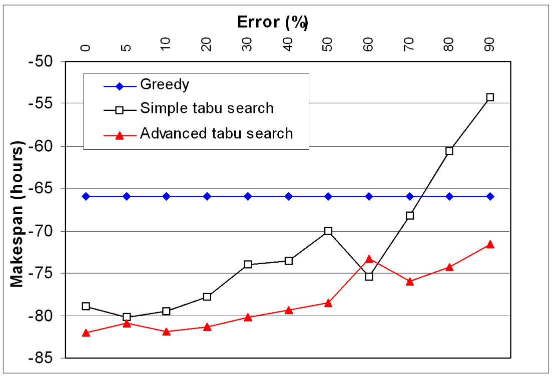

Figure 8: Results for the real instance

Each point in Figure 8 is the average makespan computed over the 30 perturbations. On the horizontal axis we report the error ε and on the vertical axis we report the difference between the actual makespan and the total length of the scheduling period (428 hours from 0:00 a.m. of the first Tuesday to 11:00 p.m. of the last Friday, for a total of 232 working hours). In other words, a negative value on the vertical axis means that all the jobs can be completed within the scheduling period, even if anticipating the completion of all jobs would leave room for increasing the department productivity.

It is interesting to comment the results for the greedy algorithm, since this algorithm is very close to the scheduling practice. Though very inefficient, the greedy is extremely robust to errors in the data set. This algorithm is considered good by the human schedulers since at the end of the three weeks the performance of the historical schedule is similar to that of the predictive one. The same result does not hold for the tabu search algorithms, that are more sensitive to the information reliability. It is quite surprising that even if both versions of the tabu search outperform the greedy for errors up to 70%, they are not considered much reliable by the human schedulers, who tend to prefer the greedy. This is a good indicator that the data set is highly unreliable, and that in the human schedulers experience the actual behavior of the schedules is quite far from the predictive schedules. At the same time, it is clear that there is room for optimization. Reducing the error down to 0 and changing the scheduling algorithm from the current greedy to the advanced tabu search would result in an average reduction of the makespan of 16 hours for a scheduling horizon of two weeks, which corresponds to increasing up to 6.7% the department productivity. It is however important to improve at the same time data reliability and scheduling procedure since the simple implementation of an advanced tracking system would produce no benefit if the production is still scheduled by using the current greedy.

We next report on the 16 realistic instances, divided into two groups with 8 instances in each group. The time period for scheduling production spans over two weeks, from Monday to Friday. In each day three machines are available for 14 hours from 6:00 a.m. till 8:00 p.m. and two machines are available for 7 hours from 8:00 p.m. till 3:00 a.m. of the following day. The first group contains easy instances. There are no urgent orders, the release dates [the due dates] coincide with the start of the first week [the end of the second week] for all jobs and the total processing time of all jobs (with the exclusion of removal and setup times) is approximately 50% of the department capacity. The second group contains instances of medium level of difficulty. There are no urgent orders but the release dates and the due dates may vary over the two weeks and the workload is slightly larger.

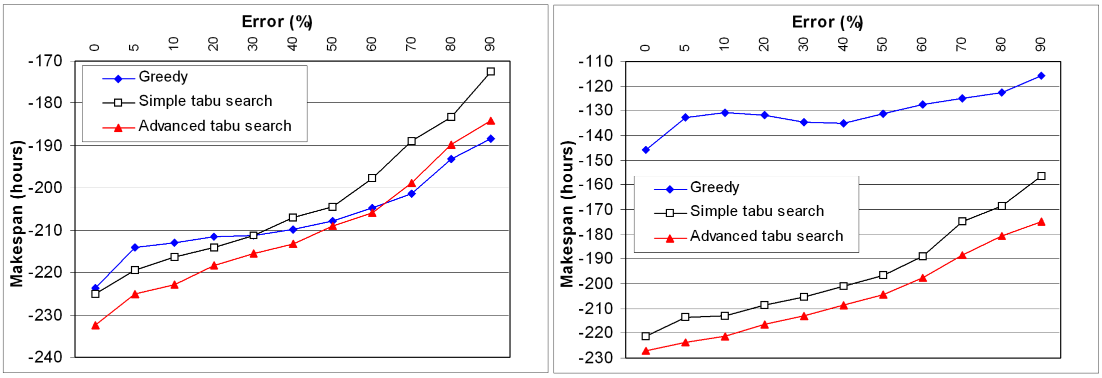

Figure 9: Realistic instances. Easy (left); medium (right)

Figure 9 shows the results for these instances. On the vertical axis we report the difference between the actual makespan and the total length of the scheduling period (291 hours from 0:00 a.m. of the first Monday to 3:00 a.m. of the last Saturday, for a total of 210 working hours).

As far as the easy instances are concerned, we observe that the greedy algorithm performs quite satisfactorily when the data set is unreliable. In fact, for $\varepsilon = 0$ the advanced tabu search outperforms the greedy by almost 9 hours, which corresponds to increasing the department productivity by 3%. However, this improvement reduces for increasing values of the error. For $\varepsilon \geq 0.3$ the greedy outperforms the simple tabu search, and for $\varepsilon \geq 0.7$ the greedy becomes the best algorithm.

For the medium-difficulty group of instances both the tabu search versions outperform the greedy for all values of ε. For $\varepsilon = 0$, the increase of productivity of the advanced tabu search with respect to the greedy is almost 28%.

For both groups of instances all the three algorithms are quite sensitive to errors in the data set. When passing from $\varepsilon = 0.9$ to $\varepsilon = 0$ the makespan for the greedy algorithm decreases by about 30 and 35 hours for the medium and the easy instances, respectively. It corresponds to increasing the department productivity by more than 10% and 12% for the two groups of instances. The productivity increase is even larger for the tabu search. When passing from $\varepsilon = 0.9$ to $\varepsilon = 0$ the makespan for the simple tabu search decreases by more than 64 and 52 hours for the medium and the easy instances, respectively. The productivity increases up to more than 22% for the medium instances. For the advanced tabu search, when passing from $\varepsilon = 0.9$ to $\varepsilon = 0$ the makespan decreases by more than 52 and 48 hours for the medium and the easy instances, respectively.

7.2 Results on the second data set

The second data set consists of 20 random instances, obtained by generating 10 instances with $m = 2$ machines and $n = 20$ jobs and 10 instances with $m = 3$ machines and $n = 60$ jobs. The number t of tools in each instance is set equal to n, each job is compatible with all machines and for each job there is a single tool available.

The duration of a shift is set to seven hours for each shift. Working days range from Monday to Friday, and in each day there are sufficient operators to activate m machines in the first two shifts, from 6:00 a.m. to 8:00 p.m., and $m - 1$ machines in the third shift, from 8:00 p.m. to 3:00 a.m. of the following day. There is therefore one unavailability of seven hours in the third shift compatible with all machines. From 3:00 a.m. to 6:00 a.m., there are three hours in which all the machines are unavailable, due to the lack of personnel. The time horizon available is fixed equal to two weeks, i.e., to 30 shifts for a total of 291 hours and 210 working hours.

A tool is randomly assigned to each job, and therefore in each instance there are tools not used and tools shared among several jobs. For each job J_j, the values r_j, d_j, D_j and p_j are randomly generated. For 50% of jobs, release dates r_j are set equal to the first hour of the time horizon while random values in the first week are assigned to remaining jobs. Similarly for 50% of jobs, due dates d_j are set equal to the last hour of the time horizon. For 40% of remaining jobs, random due dates in the second week are generated. The last 10% of jobs have assigned a random deadline in the second week.

Processing, setup and removal times are randomly generated in order to obtain a minimum workload approximately equal to 90% of the total processing time available on all machines. The number W of hours available for processing on all machines is $W = 7 * 10 * (3 * m - 1) = 210 * m - 70$. We reserve approximately 70% of W to the job processing times by generating, for each job J_j, a processing time p_j in the range $[1, 1.4 * \frac{W}{n}]$. For each pair of jobs (J_i, J_j), the removal time is fixed equal to zero and the setup time is randomly generated in the range $[0.5, 0.4 * \frac{W}{n}]$ for $i \neq j$, and fixed equal to 0.2 for $i = j$. This choice corresponds to reserving approximately 20% of W to the setup times.

Figure 10 shows the results for these instances. The vertical axis shows the difference between the actual makespan and the total length of the scheduling period (291 hours). For both groups of instances the greedy is more robust than the two tabu search versions and becomes the best algorithm for highly unreliable data. However, when the error ε is close to zero the advanced tabu search clearly outperforms the greedy, with an increase of productivity up to more than 9% for the instances with two machines and 20 jobs and more than 7% for the instances with three machines and 60 jobs.

As for the sensitivity to unreliable data, for both groups of instances all the three algorithms are quite sensitive to errors in the data set, with the exception of the greedy algorithm and the small size instances. When passing from $\varepsilon = 0.9$ to $\varepsilon = 0$, the productivity increases in Figure 10 (left) [in Figure 10 (right)] is more than 2% [more than 10%] for the greedy algorithm, is more than 16% [more than 20%] for the simple tabu search, and is more than 14% [more than 22%] for the advanced tabu search.

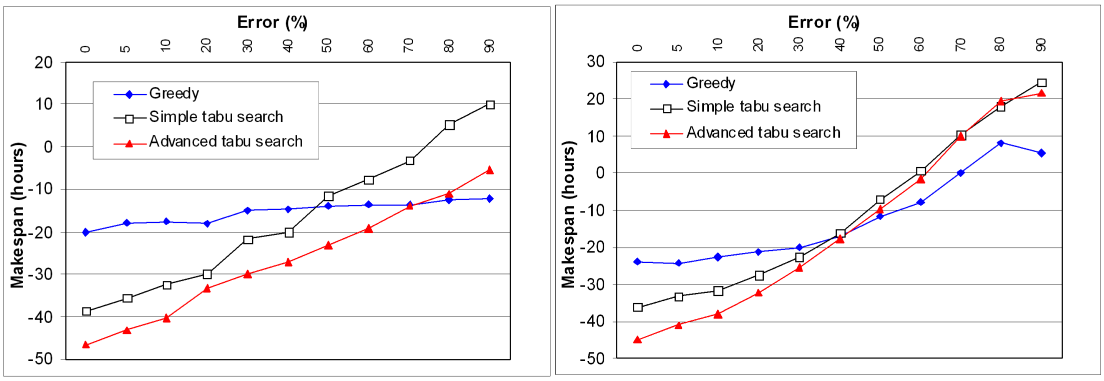

Figure 10: Random. 2 machines, 20 jobs (left); 3 machines, 60 jobs (right).

8 Discussion

The experiments carried out in the packaging department clearly show that using reliable data in combination with advanced scheduling procedures deserve a significant potential for improving productivity. In fact, due to the high level of automation in this department, the inherent variance of processing times is small with respect to other departments with a higher degree of manual operations. Therefore, the difference between predictive and historical schedules should be mainly due to estimation errors of the processing and setup times, at least in absence of unexpected disruptions.

As for the different production stages of the pharmaceutical supply chain, described in Section 5, higher benefit in secondary manufacturing is expected from our method than in primary manufacturing. Within secondary manufacturing, in the dispensing department lower benefit is expected compared to the packaging department, since operations in the dispensing department are mainly manual and the production environment is composed by few parallel machines. Here the stochasticity of operations can be large, so that reducing the estimation error down to zero may not produce much benefit.

The impact on the counting department is expected to be similar to the packaging one, while the potential benefit achievable in the manufacturing department is higher, since this production environment is a complex job shop with a high level of automation. Estimation errors easily propagate to different jobs and machines, thus increasing their negative impact on the performance compared to the other departments.

Most of the discussion above applies to other manufacturing systems as well. Clearly, when the variance of processing times is large, as it occurs frequently in case of manual operations, the adoption of RFID may generate little benefit to productivity since the increased data reliability is masked by the inherent stochasticity of the processing times. On the other hand, we observe that stochasticity is frequently used to represent a lack of knowledge. For example, large variability of processing times can be due to the fact that operators perform differently from each other. This kind of variability can be effectively managed by associating a specific processing time to each pair (operation, operator). Estimating such data can be done at affordable cost by using RFID in combination with suitable information systems, e.g., as proposed by Kim *et al.* (2008). If the processing times variance decreases sufficiently when referred to each specific operator, it can be possible that more advanced algorithms, able to use such information, will further improve the productivity.

For the technique to be successfully applied, it is however necessary that a formal procedure for scheduling operations is available and that the predictive schedule is implemented in practice. Therefore, when the data set is subject to frequent changes or the weekly bucket of work changes everyday, scheduling on a weekly horizon is unlikely to meet company expectations even if processing times are 100% reliable.

9 Conclusions and further research

This paper describes a general methodology to assess a component of the value generated by the introduction of RFID in manufacturing. We discuss the variation of productivity which can be achieved by scheduling production with a given algorithm and by using data affected by different errors. When the error on data decreases nearly to zero, the performance that can be achieved by the production system is limited only by the inherent data stochasticity and by the effectiveness of the adopted scheduling algorithm. In this context, it may be profitable developing sophisticated algorithms in order to take advantage from the availability of more reliable data.

It should be noticed that this paper does not take into account real-time rescheduling. In fact, the availability of reliable real-time information on the status of the shop floor makes possible to face unpredicted events (such as disruptions, but also the inherent data stochasticity) by rescheduling the production on the fly. To this aim, the availability of advanced tracking information and computerized scheduling algorithms may further improve the plant productivity with respect to the thumb rules commonly adopted in these cases. It follows that the overall benefit deriving from closed loop scheduling is expected to be larger than that measured in this paper, and that further research is needed to quantify other components of the RFID value in production activity control.

A number of problems remain that need further research. The coordination between planning and scheduling as well as the interaction between human and automated scheduling systems are critical to the success of planning and scheduling activities. Despite this fact, they have not received enough attention in the literature. Automated planning and scheduling tools offer new opportunities to improve productivity, but the current interaction mechanisms between planning and scheduling do not seem adequate to fully exploit their potential. New concepts are necessary in this field.

Further research should also strive to improve the effectiveness and reliability of models and algorithms. In recent years, there is a clear trend in the academic literature towards richer scheduling models, but practical scheduling problems are still significantly more difficult than the typical academic ones. Simple and general algorithms are useful when prototyping a scheduling system. *Ad hoc* algorithms can obtain better results when dealing with well-established problems. Analysis of heuristic algorithms and new mathematical properties for practical problems will be useful from an academic as well as an industrial point of view.

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