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Approach to Integrate the Learning and Fatigue Effect Into the Flowshop Scheduling Problem

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1 Introduction

Scheduling problems have gained attention since the 1950's. The classical theory has worked on the basic hypothesis that job processing time are constant, or that uncertainty can be dealt using *stochastic* or *fuzzy* approaches. These approaches are far from reality, especially when the resources are humans. Therefore, in recent years, the consideration of humans as a flexible and complex resource has gained importance. It is true that production systems have been transformed with the arrival of technology, but humans continue to be the most common resource in several areas because of their cognitive and physical skills that machines cannot yet emulate economically [8].

In the case of manual operations, job processing times may change because of the learning or deterioration effects [3]. Recently, scheduling

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problems with learning effect have attracted attention, in particular the study of the single machine system [7]. However, the flowshop scheduling problem (FSSP) is attractive in industrial contexts, as it is a common configuration in real manufacturing systems such as textile, footwear, automotive, picking process, or luxury industries, etc., where the worker’s performance has a direct effect on productivity levels. In this type of scenario, it is evident that the way jobs are sequenced can directly reinforce or weaken the learning or deteriorating process (for example, fatigue in humans). Consequently, obtaining a suitable job scheduling becomes relevant.

The FSSP with learning and deterioration effects, belongs to the family of scheduling problems with time-changing effects, for which the search for a solution requires a hard computational effort [1, 5]; the problem is known to be NP-hard [10]. This has motivated studies focusing mainly on the analysis of the problem complexity and the design of algorithms to resolve it, rather than the integration of human characteristics into the problem. The latter requires interdisciplinary work to develop accurate modelling of human factors, allowing the Operational Research community to integrate human phenomena into production systems [2, 8].

The objective of this work is twofold. On one hand, we first describe a real problem and how approaching it as a dynamic scheduling helps us understand and find ways to solve it. On another hand, once we identify theoretical approaches for modelling the effect of learning and fatigue, we try to find the right model for the case study and use the human factors tools to derive the parameters. The case study is based on a picking line, where each picking zone represents a workstation (such as in the flowshop configuration). Further details are given in Section 2.1.

The rest of this document is organized as follows. Section 2 describes the methodology and proposes the case study. The early results are presented in Section 3. Finally, the ongoing work is mentioned in Section 4.

2 Methodology

This section presents each phase of the proposed methodology to integrate the learning and fatigue effects into the FSSP. For a better contextualization, it starts with the presentation of the case study.

2.1 Case study

The problem takes place in a picking line of a Colombian dry food company. This line has 14 picking zones linked by a conveyor. All orders have the same routing. This type of picking system involves two main elements: the first is the worker who is in each picking zone, while the second is a container that follows the routing, visiting all picking zones and filling all the SKUs (Stock Keeping Units) that belong to its order. The company has more than 1000 SKUs, and the processing time for each container in each picking zone varies depending on the SKUs needed in the order. For the purposes of this study, orders shall be referred to as jobs. The company aims to obtain the sequencing of jobs and the breaks regime, balancing economic objectives (i.e., makespan) and social objectives (i.e., maximal difference of accumulated fatigue level among operators).

2.2 FSSP

Formally speaking, the process under study can be modelled as a FSSP where a set of N independent jobs must be processed by a set of M resources (workers), in order to minimize the makespan. Each worker can process one job at a given time, all resources process jobs in the same sequence and preemption of a job is not allowed. Let \bar{p}_{ij} be the normal (baseline) processing time of job j by the i -th resource. All workers are available in their workstation at the beginning and have a 100% productivity rate. The scheduling is performed through the jobs permutation sequence.

2.3 Learning model

A total of 12 workers signed an informed consent and participated in this phase (4 women and 8 men). Half of them have internal working experience of less than 6 months, while the others have an experience of more than 6 months. To check if the picking worker is impacted by a learning effect (mainly related to the SKUs position), an experimental test was designed. It was conducted in the training laboratory for the picking operations of the company under study (which has similar characteristics to the real operation). The test consists in processing a typical order (with 21 SKUs), repeating this operation 6 times per worker.

To calculate the Learning Rate of each worker, the Two Intervals Method was used [9]. In the framework of scheduling problem, the autonomous learning or learning-by-doing is defined for several models. In this study, from the models referenced by Paredes et al. [6], the most

accepted and commonly used models were selected to fit the experimental data.

2.4 Fatigue model

A total of 14 picking workers (one per each picking zone) participated in this phase. The subjects (7 women and 7 men) were between 18 and 34 years old ($26.21y.o. \pm 5.23$). Participants agreed to take part in the study by signing an informed consent. Muscular activity was registered with eight (8) Surface Electromyography Sensors (SX230, BioMetrics Ltd., Uk). Sensors were placed in 8 muscles involved in the picking operation for 40 minutes of real work. We adapted from Glock et al. [4] the Fatigue - Recovery model to define the accumulated fatigue level per worker. Similarly, a Rest Allowance (*RA*) model is adopted for determining the location and length of breaks.

2.5 FSSP with learning effects

In this phase of the study, fatigue and learning should be incorporated simultaneously, as phenomena that affect the job processing time. The first conceptual models dealing with FSSP with a learning effect for minimization of makespan are proposed. We intend to propose a bi-criteria model, including makespan minimization (economic objective) and minimization of the maximum difference of accumulated fatigue level among workers (social objective). Since the FSSP problem belongs to the NP-Hard class, we will solve it by implementing a constructive heuristic method such as the Nawaz-Enscore-Ham algorithm (NEH), improved by a Simulated Annealing algorithm (SA) and connected with a simulation technique.

3 Preliminary Results

In this section, we present the results obtained up to now in our study.

3.1 FSSP results

In [6] we present the mathematical model, using Mixed-Integer Linear Programming (MILP) of a typical flowshop scheduling problem with makespan minimization. For small problem instances, the Glpk solver allows us to find the optimal solution. This model is the basis for the subsequent incorporation of the effects of learning and fatigue.

3.2 Learning model results

Using the Two Intervals Method [9], it was possible to calculate the Learning Rate (LR) from the experimental data. Our results are similar to the LR reported in the literature, which indicates that for manual labor, the rate is nearly 80%. The experimental data were fitted to nine learning equations collected by Paredes et al. [7]. The performance comparison with the MAPE, showed that in 92% of cases, three models (Equations (1),(2), and (3)) showed a superior fit. They are:

- Position-Based Learning Effect Model (P-LE)

$$p_{ijr} = \bar{p}_{ij} r^\alpha \quad (1)$$

- Sum-of-Processing-Time-Based Learning Effect Model (ST-LE)

$$p_{ijr} = \left(1 + \theta \sum_{k=1}^{r-1} p_{ijk} \right)^\alpha \bar{p}_{ij} \quad (2)$$

- DeJong's Learning Effect Model (DJ-LE)

$$p_{ijr} = (M + (1 - M)r^\alpha) \bar{p}_{ij} \quad (3)$$

Where α is the learning index ($\alpha < 0$), θ is a conversion factor (e.g., 1/60 to convert hours to minutes) and M represents the “factor of incompressibility” ($M = 0.5$ in our case). These findings indicate that the learning effect of workers is not represented by a single model; on the contrary, different models of learning effect may coexist.

3.3 Fatigue model results

During the experimental sessions, we measured muscular activity of 8 muscles during the execution of picking operations. The signals were processed and normalized. We managed to achieve an indicator of fatigue of 26.80% of the total of the 1082 SKUs registered in the warehouse. Due to the SKU rotation and based on the Pareto principle (80/20 rule), it is possible to speak of a representation closer to 80% of the total of picking operation.

3.4 FSSP with learning and fatigue effect results

During the initial phase, the problem was approached conceptually. In [6] mathematical models of FSSP with learning effect, minimizing the makespan were stated. Four models for calculating the learning effect

mentioned in the literature were considered (Equations (1),(2),(4), and (5)). For small problem instances, Glpk and Bonmin solvers were used to solve linear (with Equations (1) and (4)) and non-linear models (with Equations (2) and (5)) respectively. Where β is a control parameter with $0 < \beta < 1$.

- Truncated Position-Based Learning Effect (TP-LE)

$$p_{ijr} = \bar{p}_{ij} \max \{r^\alpha, \beta\} \quad (4)$$

- Truncated Sum-of-Processing-Time-Based Learning Effect (TST-LE)

$$p_{ijr} = \bar{p}_{ij} \max \left\{ \left(1 + \theta \sum_{k=1}^{r-1} p_{ijk} \right)^\alpha, \beta \right\} \quad (5)$$

The results and the literature support the argument that this problem belongs to the class of NP-hard problems, for the case of three or more production resources with makespan minimization. In later contributions, considering large problem instances, the Johnson's Rule (JS) for the problem with 2-resources and the NEH algorithm were applied. In our latest work, we developed a SA algorithm where the initial solution is obtained using the NEH and the Adjacent Pairwise Interchange (API) and Non-Adjacent Pairwise Interchange (NAPI) local search operators were compared.

Computational experiments were performed using benchmark datasets for job processing times, α and β . With a total of 155.520 executions, we concluded that the NEH algorithm achieves outstanding results and that the SA works better for models where the learning rate is fast. In general terms, the SA + API shows improved performance in relation to SA + NAPI.

4 Ongoing Work

Our ongoing work mainly includes statements of the mathematical model of the FSSP with fatigue, minimizing the maximum difference in accumulated fatigue level between workers, as well as to develop an algorithm to solve benchmark and case study instances. Thereafter, we will deal with the FSSP with learning and fatigue effects, considering the minimization of the makespan and the maximum difference of accumulated fatigue level among workers. Here, SA algorithm will be used, and a simulation technique to identify a good solution for both objectives. For the case study, the plan is to provide a breaks pattern for the workers which will enable them to recover physically. With our work, we combine human factor modelling

and operational research in a real-world scenario, enabling the company to maintain productivity standards and improve the well-being of workers.

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