A Multiobjective Approach for Scheduling a Quenching and Tempering Production Line

Ana Cristina Lima Gomes
Graduate Program in Electrical Engineering - Federal University of Minas Gerais
Av. Antônio Carlos 6627, 31270-901, Belo Horizonte, MG, Brazil
gomes.aclg@gmail.com

Eduardo Gontijo Carrano
Department of Electrical Engineering - Federal University of Minas Gerais
Av. Antônio Carlos 6627, 31270-901, Belo Horizonte, MG, Brazil
egcarrano@ufmg.br

RESUMO

Este trabalho investiga um problema real de sequenciamento de tarefas em uma linha de têmpera de uma indústria siderúrgica. O objetivo é encontrar um conjunto de soluções que minimizem o custo total por consumo de energia e o tempo total de atraso e adiantamento. O problema de sequenciamento de máquinas é de natureza combinatória e bem difundida na literatura como um problema do tipo NP-difícil. Devido a esta característica, um grande número de metaheurísticas foram aplicadas para sua resolução. Neste trabalho, uma abordagem multiobjetivo do algoritmo *Variable Neighborhood Descent* é proposto. Experimentos computacionais com dados reais foram realizados para verificar o desempenho do método e os resultados tem se mostrado valiosos para futuras pesquisas no assunto.

PALAVRAS CHAVE. Têmpera. Sequenciamento de No-Wait Flow Shop. Otimização Multiobjetivo.

Tópicos: PO na Indústria

ABSTRACT

This paper investigates a real scheduling problem in a steel factory for a quenching and tempering line. The goal is to find solutions for this particular no-wait flow shop case, with sequence-dependent setup times, that minimizes the production total energy costs and total weighted earliness and tardiness. Machine scheduling problems are of combinatorial nature and known in literature as NP-hard, therefore, a great number of metaheuristics have been applied for their resolutions. In this paper, a multiobjective approach of a Variable Neighborhood Descent algorithm is proposed. Computational experiments with real data have been carried out to verify the effectiveness of the method and the results are useful for future research in the topic.

KEYWORDS. Quenching and Tempering. No-Wait Flow Shop Scheduling. Multiobjective Optimization.

Paper topics: OR in Industry

1. Introduction

Production scheduling plays an important role in industry and can be a key tool to promote an efficient use of manufacturing resources. It is not easy to find the optimal allocation of people, equipments, stocks and/or tasks over time. The combinatorial nature of these problems includes an extensive search through possible solutions that, depending on the problem size, cannot be done in feasible time, even with the use of computer algorithms. Therefore, optimization techniques have been applied in many real scheduling problems. In this paper, we study a real scheduling case in a steel quenching and tempering line.

Quenching and tempering (QT) are types of heat treatment processes applied in metals or alloys in order to improve the material strength and hardness properties [Dosset and Boyer, 2006]. In a steel mill, they are also responsible for relieving the stress boosted in the metal during the previous rolling stage. They are tightly controlled operations, in which the materials are heated and cooled at specific rates, providing products with different properties for different applications, such as construction, transportation, and oil/gas exploration.

The steel pieces in the QT line are heated in combustion furnaces powered by natural gas. This fuel represents the bigger parcel of changeable costs in this manufacturing line and minimization of its consumption can increase the company competitiveness and reduce their environmental impacts. According to Zhang and Chiong [2016], investment on new equipment and hardware can contribute to industrial energy saving, but it is often very expensive. On the other hand, the use of techniques such as scheduling optimization can also promote energy saving at no additional cost to the industry. One of the goals of this paper is to find scheduling solutions for the heat treatment line to minimize the total energy costs.

In this study case, the definition of the day of the week that the products are going to be treated is done manually and the main objective is to attend the clients delivery dates. Delays can lead to contractual fines and generate more costs, but precedence can also impact the production, because it increases the stocks between the quenching and tempering line and the next manufacturing stages. Therefore, minimization of the total weighted tardiness and earliness is also an interesting objective of this scheduling optimization problem.

In many real scheduling applications more than one objective must be achieved simultaneously. Once they represent a trade-off, a multiobjective optimization can be applied. The advantage of using this approach is to present to the decision makers a set of compromise solutions from which they can choose the more appropriate one [Silva et al., 2004].

The bi-objective scheduling of the QT production line can be modeled as a no-wait flow shop problem. In a flow shop, a set of n jobs are processed in m machines in the same order. The no-wait constraint occurs when the job operations must be treated continuously without interruptions on and between the machines. This kind of scenario is frequent in metallurgical processes and in other practical environments like chemical industries [Nagano and Miyata, 2016]. Quenching and tempering must follow one another immediately to avoid the degradation of the materials and rework. These types of problem have been addressed by Bertolissi [2000] and Sapkal and Laha [2013] and were used as base for the applied mathematical model.

Another characteristic of this study case, that were also considered in modeling, are the sequence-dependent setup times. The setup times are needed to change the furnaces temperatures between two products and they have an impact in both job completion times and energy consumption. The first papers addressing scheduling problems have appeared in literature in mid-1950s, but only in mid-1960s setup times were explicitly considered, mainly motivated by industrial and service applications [Allahverdi, 2015].

No-wait flow shop scheduling problems have been proved to be non-deterministic polynomial time hard (NP-hard) in a strong sense [Nagano and Miyata, 2016][Hall and Sriskandarajah, 1996]. It justifies the recent increase on metaheuristic proposals for solving both single and multiobjective applications. Even thought these techniques do not guarantee the discovery of exact solutions, good results can be found within reasonable computational cost. Blum and Roli [2003], in their review of metaheuristics for combinatorial optimization, enumerate some algorithms that can be used for solving scheduling problems, such as Simulated Annealing, Tabu Search (TS), GRASP, Iterated Local Search (ILS), Variable Neighborhood Search (VNS) and Genetic Algorithms (GA). An ILS algorithm is proposed by Naderi et al. [2012] for the solution of a multiobjective no-wait flow shop problem with a mixed integer programming model. Hybrid GA were used by Zhang and Chiong [2016] and Dai et al. [2013] in multiobjective scheduling problems to minimize total energy consumption. Choobineh et al. [2006] uses a TS to solve a tree objective single machine scheduling problem with sequence-dependent setup times.

A multiobjective approach of a Variable Neighborhood Descent (VND) algorithm is proposed to solve the quench and tempering scheduling problem. This method is a variant of VNS and it deserves attention for being used as a local search routine for other metaheuristics. Vanchipura et al. [2014] used VND to improve a constructive heuristics in the solution of a flow shop with sequence-dependent setup times. Gao et al. [2008] implemented a hybrid genetic and Variable Neighborhood Descent algorithm to optimize a three objective job shop scheduling problem and Fleszar et al. [2012] applied a hybrid VND and Mathematical Programming in parallel machines with sequence-dependent setup times.

The remainder of this paper is organized as follows: in Section 2, a detailed description of the QT scheduling problem is presented together with the applied mathematical model; Section 3 introduces the proposed multiobjective VND algorithm; Section 4 presents the performed computational experiments and discusses the results, and; finally, in Section 5, the final considerations and directions for future researches are given.

2. The Quenching and Tempering Scheduling Problem

The layout of the quenching and tempering production line is shown in Figure 1. The process begins in the hardening furnace (HF), where the material is heated above the steel transformation temperature [Dosset and Boyer, 2006]. Immediately after heating, each steel piece goes into a water cooling system where they will be rapidly cooled to obtain the appropriate product hardness property, part of the quenching procedure. After the water immersion, the material goes through a cooling bed (CB) and it enters the tempering furnace (TF), primarily to increase ductility and toughness. Temperature in this furnace is below the hardening one and cooling is then performed by still air in the subsequent cooling bed [Dosset and Boyer, 2006].

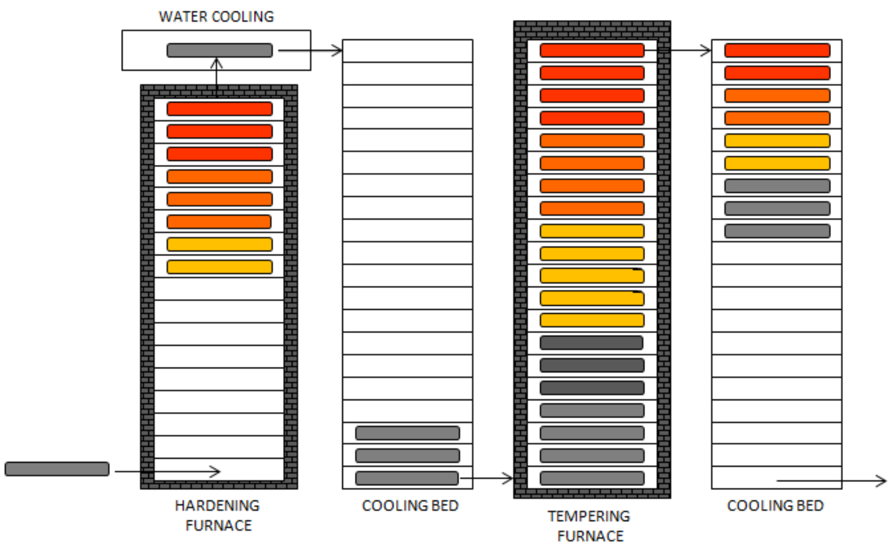

Figura 1: Layout of the quenching and tempering line

The process is continuous and, once a material goes inside the HF, it flows through the equipments, in the same order without interruption (no-wait flow shop), according to the arrows shown in Figure 1. The furnaces and cooling beds were scaled for a high production and they are capable of treating simultaneously more than one steel piece with the same process conditions. Products with different treatment settings requires a line setup. The machines capabilities, represented by the white rectangles of Figure 1, are merely illustrative.

A client request for an amount of a particular product generates a production job with specific process parameters, that are: the production flow rate and the treating temperatures in the HF and TF furnaces. The combination of these parameters establishes the desirable heating and cooling curves of the treated material, as presented in Figure 2. The production flow rate, also known as cycle times, is given in seconds by equipment position. The temperatures are in degrees.

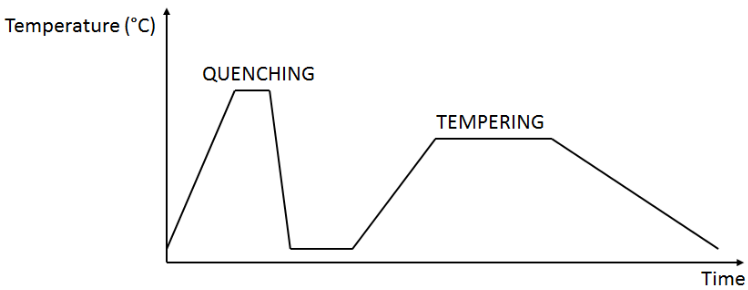

Figura 2: Desired temperature profile for the quenching and tempering processes

2.1. Mathematical Model

In this subsection the suggested mathematical model applied to the QT scheduling optimization problem is presented in details.

A production job i represents a set of q_i pieces requested by a client with certain characteristics. Each job has a planned execution date e_i and a production rate r_i. The furnaces heating temperatures for job i are t_{ik}, where k is the machine index. The cooling bed temperatures are set to zero to eliminate their influence in setup time and energy consumption calculation. The equipments capacities are z_k.

Figure 3 shows a schedule view of the QT line. The equipments are displayed in the horizontal axis, with a scale band proportional to the machine capacity (merely illustrative), and the production times are in the vertical axis. The grey parallelogram represents two consecutive production jobs.

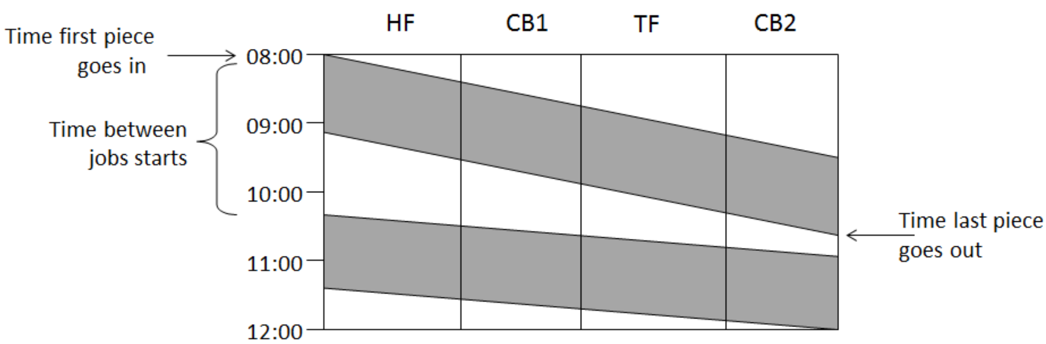

Figura 3: Schedule view of the QT line

The job processing time p_i, which is the time between first steel piece goes into production and the last one goes out, is calculated by (1).

$$p_i = r_i q_i + \sum_{k=1}^{m} r_i z_k, \tag{1}$$

in which the first part of the equation represents the total time to enter all q_i pieces from the job i in the production line (p_i^t) and the second part is the sum of the last piece processing time in each equipment (p_{ik}^t). Parameter m is the total number of machines.

The total time between the start of jobs i and j on the first machine, when job j directly follows job i in scheduling, is the sum of the necessary line setup time and minimum delay to render the production no-wait constrains. The setup time (s_{ij}) is required to change the HF and TF furnaces temperatures from job i to job j. Each furnace has its own setup time (s_{ijk}) depending on its cooling and heating rates and the difference in treatment temperatures. The total setup is given by the maximum value between the furnaces, such as calculated by (2).

$$s_{ij} = \max_{k \in \{1,\ldots,m\}} s_{ijk} \tag{2}$$

Production jobs with different process conditions (cycle times and temperatures) cannot be treated simultaneously in the furnaces. The minimum delay term (d_{ij}) guarantees that the first steel piece of job j does not arrive in the machines until they have completely processed job i, otherwise, production will be interrupted. The calculation of d_{ij} was adapted from the paper of Bertolissi [2000], such as shown in (3).

$$d_{ij} = p_i^t + p_{i1}^t + \max_{k \in \{2,\ldots,m\}} \left(\sum_{q=2}^{k} p_{iq}^t - \sum_{q=1}^{k-1} p_{jq}^t, 0 \right) \tag{3}$$

Given a set of n jobs and the variable vector $\vec{\sigma} = [\sigma_1, \sigma_2, \ldots, \sigma_n]^T$, which is the sequence they will be processed on the m machines, the completion date (c_i) of each job can be calculated using (1), (2), and (3). For $i \in \{1, 2, \ldots, n\}$ and $k = \{1, 2, \ldots, m\}$, we have:

$$c_{\sigma_1} = p_{\sigma_1}, \tag{4}$$

$$c_{\sigma_i} = \sum_{j=2}^{i} \left(d_{\sigma_{j-1}\sigma_j} + s_{\sigma_{j-1}\sigma_j} \right) + p_{\sigma_i}. \tag{5}$$

The total weighted earliness and tardiness (TWET) of each job from sequence σ is then given by (6):

$$TWET = \sum_{i=1}^{n} w_i^e T_i^e + \sum_{i=1}^{n} w_i^t T_i^t, \tag{6}$$

in which T_i^e and T_i^t are, respectively, the earliness (calculated using (7)) and tardiness (calculated using (8)) of job i, being w_i^e and w_i^t earliness and tardiness weight parameters.

$$T_i^e = \max[e_i - c_i, 0] \tag{7}$$

$$T_i^t = \max[c_i - e_i, 0] \tag{8}$$

In the course of production, natural gas (NG) is regularly burned up by the furnaces. NG is consumed constantly while the furnace is processing the steel pieces from a job and also when it is empty, preparing itself for the entrance of a new material. The time each furnace k stays idle, between two consecutive jobs i and j, is shown in Figure 4 and is calculated as given in (9).

$$i_{ijk} = d_{ij} + s_{ij} + \sum_{l=2}^{k} p_{jl-1}^t - \left(p_i^t + \sum_{l=1}^{k} p_{il}^t \right) \tag{9}$$

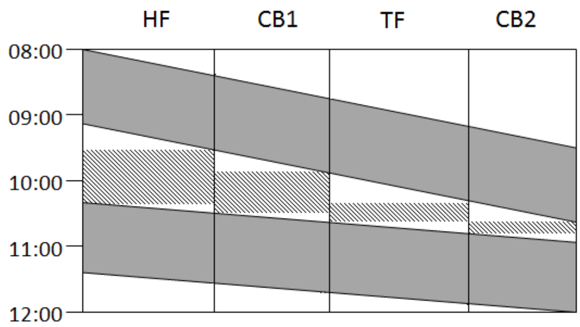

Figura 4: Highlight of the machines empty periods between jobs

The total NG volume consumed by job i is sequence-dependent, and it can be determined as shown in (10).

$$V_{\sigma_i} = \sum_{k=1}^{m} \left(i_{\sigma_{i-1}\sigma_i k} f_{\sigma_{i-1}\sigma_i k} + \left(p^t_{\sigma_i} + p^t_{\sigma_i k} \right) f_{\sigma_i k} \right), \tag{10}$$

in which f_{ik} is the constant NG flow required to keep the furnace at temperature t_{ik} and f_{ijk} is the NG flow required to change the furnace temperature from t_{ik} to t_{jk}.

The cost by volume of natural gas consumed in the furnaces is denoted by b. Therefore, the total energy cost (TEC) of production sequence σ is calculated as described in (11).

$$TEC = \sum_{i=1}^{n} bV_i \tag{11}$$

Equations (6) and (11) expresses the two minimization objectives of the QT scheduling optimization problem. Formulation of this problem can then be presented as:

$$\text{Minimize} \begin{cases} TWET \\ TEC \end{cases} \tag{12}$$

3. Proposed MOVND Algorithm

Variable Neighborhood Descent (VND) is a variant of Variable Neighborhood Search (VNS), a metaheuristic proposed to solve hard optimization problems, such as the quenching and tempering production scheduling. This method relies on systematically changing neighborhoods while searching for solutions in the exploration space. In the particular case of VND, the neighborhood structures are explored in a deterministic way. Its efficiency is based on three factors [Hansen and Mladenovic, 2003]: the local minimum of a neighborhood is not necessarily the local minimum of another; the global minimum is a local minimum of all neighborhoods; in several problems the local minimum between neighborhoods is relatively close.

A neighborhood in the QT case is represented by a set of permutation operations over the n jobs of decision variable σ. Three neighborhoods are examined sequentially in this scheduling problem. The first one consists on swapping two adjacent jobs (i and $i+1$), the second on exchanging two jobs i and j, regardless of their adjacency, and the third on removing job i from its position and inserting it at position j. Figure 5 exemplifies the swap, exchange, and insert operations. The neighborhood cardinalities are $n-1$ for swap, and $n(n-1)/2$ for exchange and insert operations.

The local search strategy adopted for exploring the neighborhoods in the proposed algorithm is based on first improvement, i.e. once an improved solution is found, it replaces the current solution and a new local search starts. A diagram of the proposed local search routine is shown

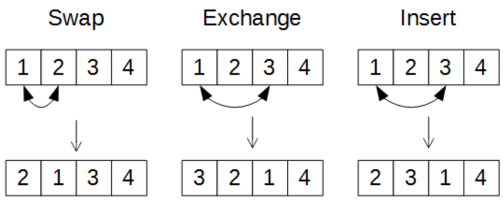

Figura 5: Neighborhoods

in Figure 6. No single solution exists that optimizes simultaneously TWET and TEC objectives. Therefore the goal is to find solutions that are not outperformed[1] by other ones and that present different trade-offs with regard to the two objectives. These are called nondominated Pareto solutions, or efficient solutions, and they form a set of compromised solutions known as the Pareto set. Each successful run of the local search leads to an update of the approximated Pareto set.

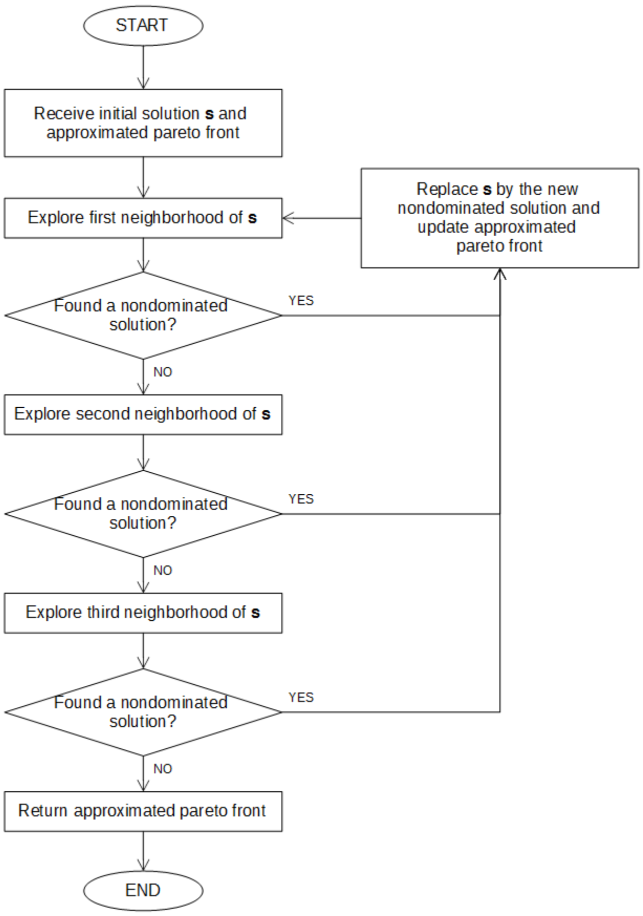

Figura 6: Proposed local search routine

Algorithm 1 describes the multiobjective VND (MOVND) method applied in the QT optimization problem. The procedure starts with the evaluation of an initial solution s that is added to the approximated Pareto front. A local search is then performed over s and the solution is marked as investigated. If the local search is successful, a new random not investigated solution of

[1]It is said that a solution is outperformed (dominated) in multiobjective optimization if there is another solution that is better than it in at least one objective without being worse in the other ones.

the updated Pareto set approximation is chosen and a new local search is rolled. The randomness method was implemented due to the multiobjective structure of the algorithm and it was based on the works of Geiger [2004] and Naverniouk [2005]. The algorithm goes on until all solutions of the Pareto approximation were visited or when ten successive local searches were performed without improvement.

Algorithm 1: MOVND

Input: initial solution
Output: approximated pareto front
begin
  Evaluate initial solution
  Add initial solution to approximated pareto front
  repeat
    Select a not investigated solution **s** from approximated pareto front
    Mark **s** as an investigated solution
    Run local search in **s** and update approximated pareto front
  until *stop condition*;
  Return approximated pareto front
end

4. Computational Experiments

A real instance of the quenching and tempering scheduling problem was tested to analyze the performance of the presented algorithm. This instance represents a set of 100 jobs to be produced in 10 days. The main aspects evaluated in the experiment were: the multiobjective approach ability to find sufficient Pareto solutions, the evenness of the distribution of solutions along the Pareto set, and the method convergence over different runs.

Figure 7 shows the approximated Pareto fronts found in 5 different runs of the MOVND algorithm. The values presented in the chart axis, for both objectives TWET and TEC, were multiplied by a constant to preserve the company data. From the results, it is possible to see that the solutions from different runs all gathered in the same chart region. Even though the optimal Pareto front of the problem is unknown, it can be concluded that the method presents good convergence over different executions, a property appreciated in multiobjective approaches. The diversity of the Pareto set can also be observed in the results. A high density of solutions appears in the highlighted red box of Figure 7 with an even distribution, but some points outside the box presents a discontinuity, which can be a characteristic of the problem or an indication that the MOVND algorithm diversity can be improved. Further studies must be performed to evaluate closely this matter.

The average execution time of a MOVND run, for this 100 jobs scheduling, was of 11 minutes. Although time performance is not a focus in the present analysis, this can be considered an acceptable time for the problem size.

The initial solution adopted in all the runs of the test was the real production sequence planned manually for the jobs set, which is suggested by the company planning sector. Figure 8 presents the values of TWET and TEC for this solution and also the overall nondominated Pareto solutions from the five series displayed in Figure 7. The sequence choices that improve both objectives when compared to the initial solution are highlighted in the red box. This result shows that the application of an optimization technique enhances the actual process of production scheduling. An estimated 3% reduction in the total energy costs can be achieved once we go for the Pareto solution with maximum TEC. If we analyze the other extreme of the Pareto set, the reduction can be of more than 6%.

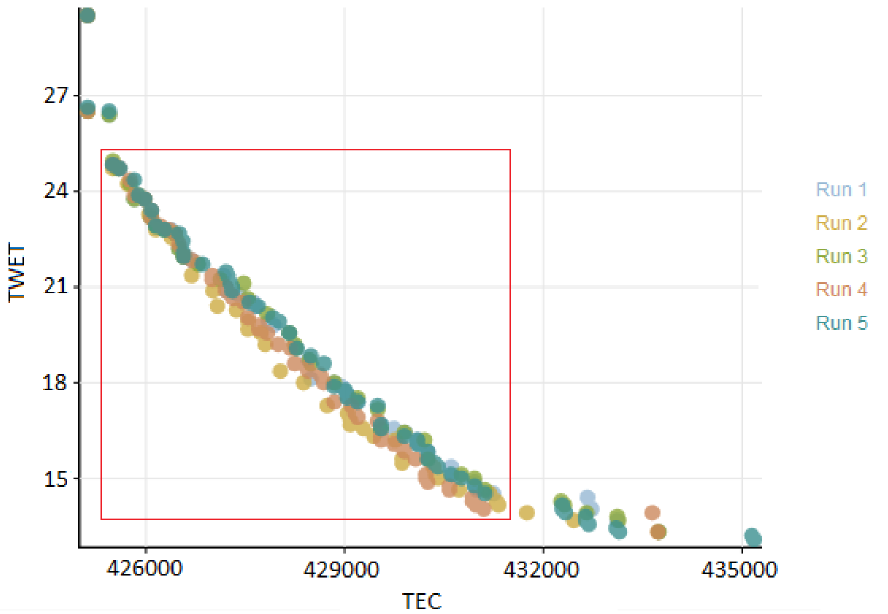

Figura 7: Approximated Pareto Fronts of 5 execuitons of the MOVND algorithm

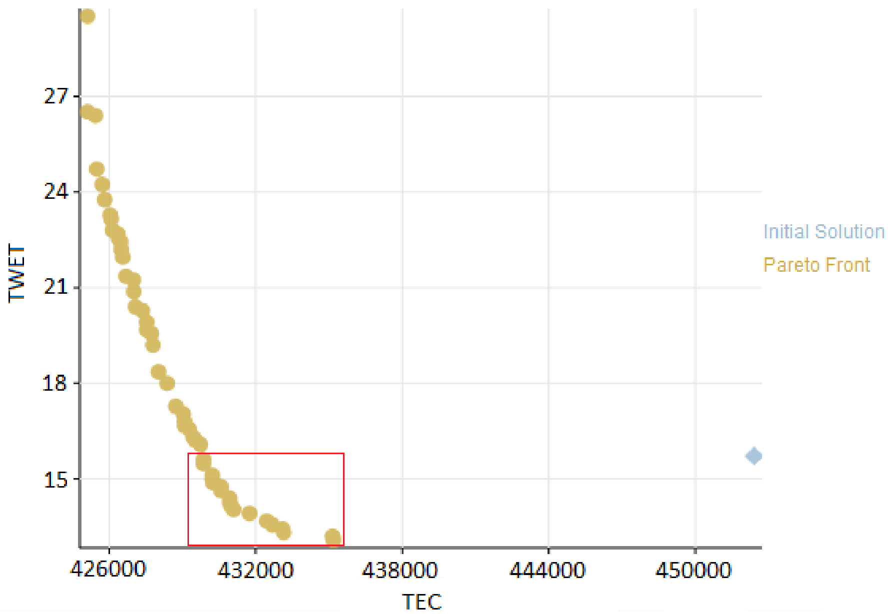

Figura 8: Final Approximated Pareto Front of the MOVND algorithm

5. Conclusion

This paper investigated a real scheduling problem in a steel factory quenching and tempering line concerning the minimization of the production total weighted earliness and tardiness and total energy costs. To solve this issue, a mathematical model was developed based on the manufacturing no-wait flow shop and sequence-dependent setup time characteristics and the result was a generic design applicable to other QT lines with different layouts. It is of no knowledge from the authors the presence of a model applied to such a problem in literature.

A multiobjective approach was used to settle a set of compromised solutions for the scheduling problem. Due to its combinatorial nature and well known NP-hard behavior, a metaheuristic based on the Variable Neighborhood Descent algorithm was proposed. The local search procedure, based on first improvement, was used to explore three classic neighborhoods of permutation problems: swap, exchange, and insert. Real data was used in computational experiments to evaluate the efficiency of the method. The MOVND showed good convergence and diversity in the results within a reasonable execution time for a set of 100 jobs. It can also be observed from the results that an optimized scheduling can decrease the energy costs from 3% up to 6% and improve the delays in closely 50%, when compared to a manual scheduling. These results already justify the use of a multiobjective approach to solve the QT production line scheduling.

This manuscript and its results are part of an initial study of the QT problem. The main goal of this work was to prove the capability and benefits of using an optimization technique to solve the production line scheduling. Future work will still be conducted and the following aspects will be taken into consideration:

- Enhancement of the mathematical model with production windows restrictions. In this paper, if the total completion time of the jobs in a solution overcomes the total production days planned for this set of jobs, it is still considered as a feasible solution. In the QT line the production windows are defined based in mandatory maintenance activities which must be respected by the scheduling.

- Study and comparison of other algorithms, including linear programming. As shown in the introduction section, several metaheuristics and mixed programming methods have been applied for the solution of scheduling problems with the QT characteristics. The focus is to find the more suitable algorithm to optimize the heat treatment bi-objective scheduling. In this step the execution times of the algorithms will be examined in detail.

- Analysis of the impacts of the scheduling solutions over the real production.

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