

# Support information file for manuscript "Multi-objective matheuristic for minimization of total tardiness and energy costs in a steel industry heat treatment line"

## 1. Introduction

This document is divided into two sections. The first one explains how to use the shared dataset and its respective results. The second section presents preliminary tests that supported the definition of the algorithm parameters.

## 2. Computational Experiments

We shared 24 test instances that can be used for validation and future works.

For each instance there is an Excel sheet (format .xlsx) that contains the optimization parameters shown in Table 1. The values of the parameters are in different tabs where we have the parameter description in the first row and then the data with the specific indexes. For the setup times, which are a 3d matrix, we have separated the values per machine also by tabs. In this case, machine 2 (cooling bed) does not appear, because the setup times for it are all zero.

Table 1: Notation for heat treatment scheduling model parameters.

$i, r$	index for job.
$k$	index for machine.
$b$	cost of natural gas [ $\$/Nm^3$ ].
$p_i$	total process time of job $i$ throughout all machines [ $h$ ].
$p'_i$	process time to enter all pieces of job $i$ in first machine [ $h$ ].
$p'_{ik}$	process time of a piece of job $i$ in machine $k$ [ $h$ ].
$s_{irk}$	setup time of job $r$ in machine $k$ , when job $i$ precedes job $r$ [ $h$ ].
$d_{ir}$	minimum delay at start of job $r$ , when job $i$ precedes job $r$ [ $h$ ].
$v_i$	total volume of gas used during execution of job $i$ throughout all machines [ $Nm^3/h$ ].
$v_{ir}$	total volume of gas used to setup all machines for job $r$ , when job $i$ precedes job $r$ [ $Nm^3/h$ ].

The computational experiments presented in the manuscript were all performed with the 24 instances: 30 executions of the proposed matheuristic and 30 executions of the

MOGVNS algorithm initialized with a simple heuristic. We used an 8GB RAM Ubuntu 18.04 LTS server to run the tests.

The raw results from these tests are also shared as CSV data with the filenames as 'instanceX-30exec-15s.csv'. Each row of the file contains the results from one execution of the algorithm. The columns listed are:

- Instance: instance identification;
- RealSolution: the cost functions of the sequence executed in reality. The first value is the total tardiness (TT) followed by a space and the total energy cost (TEC);
- Execution: execution number (from 0 to 29);
- Initial Method: the method used to generate the initial solutions for the MOGVNS algorithm. When the value is "MILP", we are referring to the proposed matheuristic executions and when it is "Heuristics", the only MOGVNS run for comparison;
- NumGroupsTEC (only for MILP initial method): number of jobs considered in the minimization of TEC after applying the grouping strategy;
- TimeTEC (only for MILP initial method): runtime of MILP to minimize TEC in seconds;
- GapTEC (only for MILP initial method): the gap of MILP to minimize TEC (if the solver reached the 1h maximum runtime);
- NumGroupsTT (only for MILP initial method): number of jobs considered in the minimization of TT after applying the grouping strategy;
- TimeTT (only for MILP initial method): runtime of MILP to minimize TT in seconds;
- GapTT (only for MILP initial method): the gap of MILP to minimize TT (if the solver reached the 1h maximum runtime);
- TimeTT\_TEC (only for MILP initial method): runtime of MILP to minimize TEC after TT in seconds;
- GapTT\_TEC (only for MILP initial method): the gap of MILP to minimize TEC after TT (if the solver reached the 1h maximum runtime);
- InitialCostFunctions: cost functions of the initial solutions found by the Initial-Method. The first value is TT followed by a space and TEC;
- Algorithm: this column only identifies the metaheuristic applied, which will always be MOGVNS-FI;
- RunTimeSec: the runtime of the MOGVNS\_FI run in seconds;
- NumParetoSolutions: the number of solutions in the final approximated Pareto front (PF);

- **CostFunctions:** the cost functions of each solution of the final approximated Pareto (used to draw the charts). A pipe "|" separates the values from different solutions, and first, there are the total tardiness and then, separated by a space, the total energy costs. Example for a 3 solutions PF: 'sol1(TT) sol1(TEC) — sol2(TT) sol2(TEC) — sol3(TT) sol3(TEC)';
- **Solutions:** the final sequences given by each solution of the final approximated Pareto front. A pipe "|" separates them, and they are ordered according to the CostFunctions column.

There is an R script ("results\_analysis.R" - R version 3.6.3) attached to the results data that can be executed to generate the tables and statistical analysis from the CSV files.

### 3. Algorithm Parametrization

Two preliminary tests were done to define the MOGVNS algorithm parameters:

1. 30 runs of the multi-objective variable neighborhood descent search algorithm (MOVND-FI) shown in the manuscript to define the best configuration of neighborhoods and see the average execution time.
2. 30 runs of a multi-objective random variable neighborhood search algorithm (Duarte et al., 2015) to define the shaking procedure.

For item 1, three neighborhood configurations were tested:

- 0: SWAP + EXCHANGE + INSERT
- 1: INSERT + EXCHANGE
- 2: EXCHANGE + INSERT

The MOVND-FI algorithm was executed to compare the neighborhood configurations, and the hypervolume of the final approximated Pareto was calculated. Figure 1 shows the results for the three configurations where it can be seen that the average value of configuration 2 is higher than the others.

From the boxplot, it is also possible to see that the MOVND-FI is robust to different neighborhood configurations since the differences in hypervolume are not so high. Figure 2 shows the results of a Tukey's test, based on an analysis of variance (ANOVA) with a 95% level of confidence, that confirms no statistical differences from the neighborhoods configuration. Even though it is not possible to affirm which one is the best, we chose the third one as the final algorithm configuration for its higher average values.

From the MOVND executions, it was possible to check the average runtime for each descent run. These values, presented in Figure 3, were used for the definition of the maximum execution time of the MOGVNS used in the manuscript.

For item 2, four different shaking procedures were compared:

- MORVNS-I: exchange operations with randomly selected jobs;
- MORVNS-II: insert operations with randomly selected jobs;

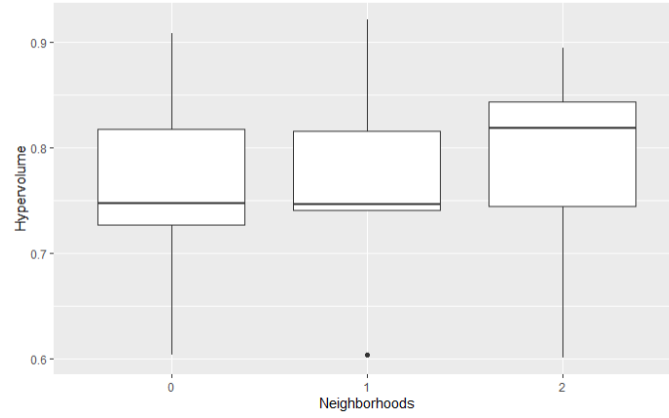


Figure 1: Comparison of the hypervolume mean values of 30 executions of the MOVND-FI with the different neighborhood configurations.

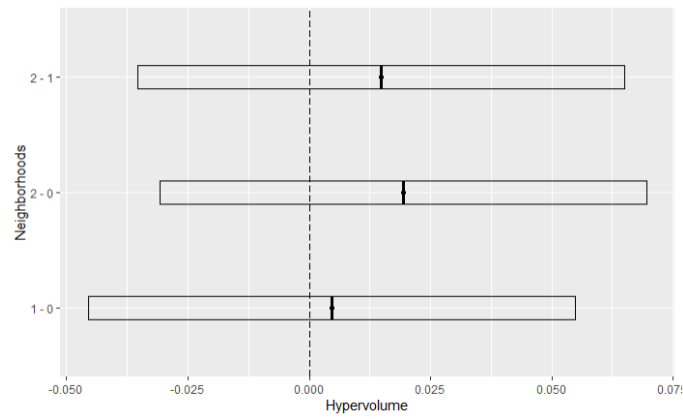


Figure 2: Tukey's test with a statistical comparison of the three neighborhood configurations.

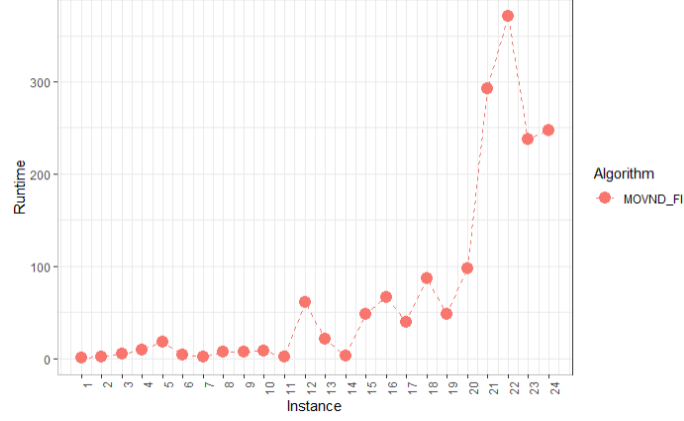


Figure 3: Average runtime in seconds for the MOVND algorithm per instance.

- MORVNS-III: an exchange and then an insert operation with randomly selected jobs;
- MORVNS-IV: randomly chosen exchange or insert operations with randomly selected jobs.

The MORVNS stoppage criteria were the maximum execution time ( $t_{max}$ ). The performance metric used to compare the configurations was the hypervolume, and Figure 4 shows that the MORVNS-IV outcomes the others in terms of its average values.

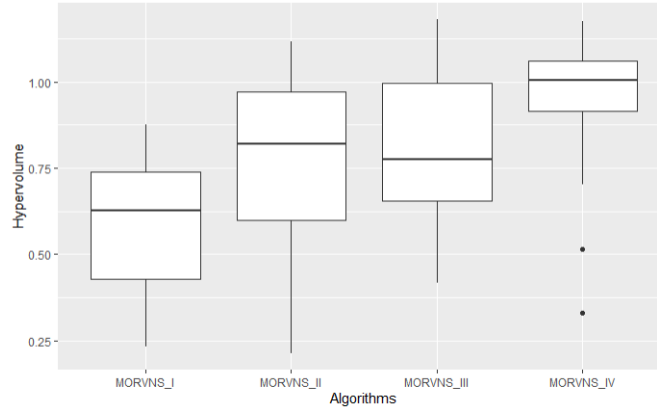


Figure 4: Comparison of the hypervolume mean values of 30 executions of the MORVNS with four different shaking procedures.

In a statistical analysis, using ANOVA and Tukey's test with a 95% level of confidence, MORVNS-IV is also better than the others, as shown in Figure 5. The MORVNS algorithm is more sensitive to these shaking configurations because it only relies on these

random movements. Despite that, it allowed us to verify the efficient of the MORVNS-IV shaking procedure, that was chosen for the final MOGVNS algorithm.

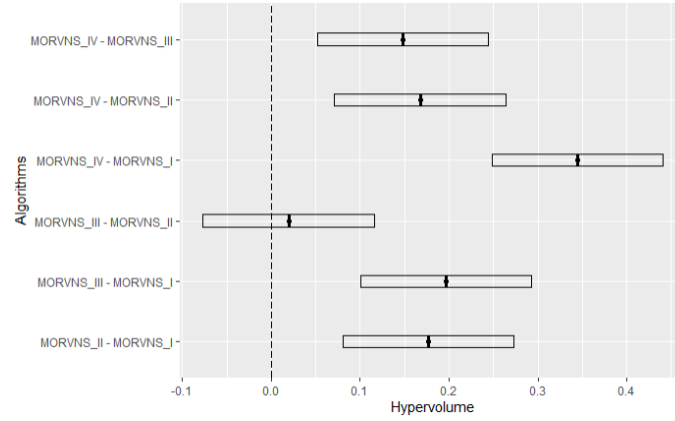


Figure 5: Tukey's test with a statistical comparison of the four shaking procedures.

## References

Duarte, A., Pantrigo, J. J., Pardo, E. G., & Mladenovic, N. (2015). Multi-objective variable neighborhood search: an application to combinatorial optimization problems. *Journal of Global Optimization*, 63, 515–536. <https://doi.org/10.1007/s10898-014-0213-z>.