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RÉSUMÉ

La planification durable de la production des biens n'est plus une tendance, mais plutôt un vrai besoin pour notre monde aujourd'hui et la recherche opérationnelle peut (et doit) contribuer à cette tâche importante. Pour se dire durable, un système de planification doit poursuivre autant des objectifs d'efficience économique, qu'énergétique et de responsabilité sociale. À travers l'utilisation de la méthode de la somme pondérée, ce mémoire compare les performances de huit nouvelles formulations pour les ateliers de production flexibles qui optimisent ces trois objectifs simultanément. Les modèles proposés incluent des temps de préparation dépendant de la séquence, différentes vitesses pour les machines, l'allocation et le séquencement des ressources humaines et l'optimisation des choix de fonctionnement de la machine (quand l'allumer, quand l'éteindre ou la mettre inactive). Quatre de ces huit formulations utilisent des contraintes de conservation des flux pour le séquencement des opérations aux espaces de travail et des opérations aux travailleurs. Les quatre autres utilisent un nouveau système de contraintes pour la première fois développé dans ce mémoire, sous le nom de « contraintes de séquence ». De plus, pour la première fois, la relation entre différentes vitesses pour les machines et les travailleurs avec différentes compétences sera étudiée. Le tout est analysé en considérant des instances inspirées des systèmes de production qui traitent trois types d'espace de travail basés sur la ressource goulot (i.e. un atelier automatique, semi-automatique et manuel). Pour comparer les performances de ces nouvelles formulations, le meilleur objectif obtenu, le temps de résolution, le gap et la condition d'arrêt sont compilés pour la résolution de chacune des 30 instances générées aléatoirement et inspirées de systèmes de production réels. La dimension sociale est représentée par un nouvel objectif, inspiré par Karl Marx, appelé la minimisation de l'intensité du travail maximal. Cet objectif a pour but de minimiser l'intensité du travail du travailleur qui a le plus de temps de travail crédité dans l'horaire. Il est proposé que cet objectif prend en considération la vitesse à laquelle le travail est effectué, en créditant plus de temps à un employé qui travaille à un rythme plus soutenu qu'un autre même s'ils ont travaillé pour une durée équivalente. L'analyse comparative des performances des modèles sur les trois objectifs montre que les nouvelles contraintes de séquence ont mieux performées que les contraintes de conservation des flux pour le séquencement des opérations aux ressources et que l'utilisation de variables de temps à deux indices semble mieux performer que trois indices. De plus, les formulations comportant le moins de variables ont, en moyenne, eu un léger avantage au niveau des indicateurs retenus, c'est-à-dire, les formulations ayant le niveau d'intégration le moins élevé. Par contre, ces résultats ne devraient pas décourager les chercheurs d'intégrer davantage de caractéristiques du problème car la différence en termes de temps de résolution pourrait bel et bien être négligeable comparativement aux avantages d'intégrer davantage de caractéristiques du problème lorsque c'est pertinent. Ensuite, une analyse des relations entre les différents objectifs a montré que les trois objectifs étaient en conflit. Une amélioration d'un des objectifs se fera au détriment d'au moins un des autres objectifs du problème. Finalement, la dernière section du mémoire fournit des outils aux gestionnaires pour intégrer de tels outils d'aide à la décision dans la pratique de leurs opérations quotidiennes.

Mots clés : Atelier de production flexible, optimisation multi objective, Pareto front, méthode de la somme pondérée, contraintes de conservation des flux, Programmation linéaire en nombres entiers, intensité du travail, énergie totale dépensée, efficacité énergétique, développement durable.

ABSTRACT

Sustainable development in production systems is no longer only a trend. It has become a real need in today's world. Operational research can (and must) contribute to this new task. To be considered sustainable, a production system must simultaneously consider economic objectives as well as environmental and social objectives. Using the weighted-sum method, this thesis compares the performances of eight new formulations for sustainable flexible job-shops considering all three sustainable types of objectives. These formulations include sequence-dependent set-up times, different machine speeds, workers scheduling as well as when to start, stop or leave machines idle. Four of these following formulations use flow conservation constraints for sequencing operations to workstations and operations to workers. The four other formulations use new sequence linking constraints specifically developed during this thesis. Furthermore, for the first time, the relationship between different machine speeds and workers with different skills will be studied. This analysis is performed considering instances inspired by production systems including three different types of workstations based on the bottleneck resources (automatic, semi-automatic and manual workstations). To compare the performances of those eight formulations, the best objective, resolution time, gap and termination condition will be compiled for all 30 randomly generated instances inspired by real production systems solved. The social dimension of the problem is based on a new objective inspired by Karl Marx called Maximum intensity minimization. This objective seeks to minimize the work intensity of the worker who worked the most considering both, the time spent working and the pace at which that work occurred. Therefore, two workers working for the same amount of time at different pace would not be credited with the same work intensity even if the duration of the work is the same. Comparative analysis of the eight different formulations shows that sequence linking constraints are more efficient than flow conservation constraints to sequence operations to resources. Furthermore, formulations with fewer variables (formulations for which the level of integration is lower) showed better results during the experiment and using 2-index time variables also showed better results during the experiment compared with 3-index time variables. However, those results should not discourage researchers from integrating more features of the problem in future research because the difference in performances might be negligible compared to the advantages of integrating certain features in different business cases. An analysis of the relationship between the three objectives was also performed. It showed that

there is conflict between all objectives for most of the instances solved. This means that an improvement of one of the dimensions of sustainable development will be done at the expense of, at least, one other dimension. Finally, this thesis gives managers tools to integrate decision-making tools like the one presented in this thesis into their day-to-day operations.

Keywords : Flexible job-shop problem, multi-objective optimization, pareto front, pareto optimality, weighted-sum method, flow conservation constraints, mixed-integer linear programming, labor intensity, energy consumption, energy efficiency, makespan, sustainable development.

INTRODUCTION

Our world needs better and greener production systems. The Global Footprint Network (GFN) is a leader in the study of ecological footprint. To determine whether there is an ecological deficit or reserve, the GFN compares two indicators: the ecological footprint and the biocapacity. The world's ecological footprint can be defined as the number of resources that humanity requires over a certain period. In this case, such a period could be defined as a year. The world's biocapacity would then represent what nature can produce over that same period. If the biocapacity is greater than the ecological footprint, it means that nature produces more resources than what humanity consumes. That would result in an ecological reserve. Currently, the world is in a state of ecological deficit instead. It means that the world's ecological footprint is greater than its biocapacity. In this case, the ecological deficit represents when all the resources that are consumed by humanity in a year exceed what nature can produce in that same year. In fact, through the data gathered by the GFN, it is revealed that, from the start of the 21st century, the world's ecological deficit has risen by more than 77%. This is only possible by drawing in from the inventory of resources nature has accumulated over a long period of time. However, this inventory is not eternal and will, eventually, run out (Footprint Data Foundation, York University Ecological Footprint Initiative, and Global Footprint Network, 2023). In fact, the Brundtland report, which acts as a reference in the field, even declares that: "many forms of development erode the environmental resources upon which they must be based, and environmental degradation can undermine economic development. Poverty is a major cause and effect of global environmental problems" (World Commission on Environment and Development, 1987). For instance, when a resource is depleted faster than it can recover, short-term development is prioritized against long-term interests. The depleted resource will show even fewer returns in the future than it would have shown before its depletion. If the GFN's work attempts to assess the negative impact of humanity's economic activity on the environment, and if the words of the Brundtland report hold true, it is only a matter of time before the ripple effect hits and the weakened environment starts having more severe negative impacts on the global economic development.

In the last couple of years, different important organizations have come to a similar conclusion. In 2015, the United Nations agreed upon 17 goals for sustainable development. This initiative was a plea by numerous countries to secure the well-being of humanity. The application of such goals impacts the production systems and industries. Closely related to the day-to-day operations of industries, Goal Nine is concerned with industry innovation and infrastructure. More specifically, one of its targets specifically promotes sustainable industrialization. Also, targets of Goal Seven state a need to work towards affordable and clean energy, prioritizing energy efficiency and energy intensity. On a broader scale, it seeks to guarantee a healthy environment, dignity, equality, the possibility of realization and the end of poverty for everyone. Related to each dimension of sustainable development, this initiative would urge managers to rethink the impact of their business on the environment and people (United Nations Department for Economic and Social Affairs, 2023). Sustainable development is a concept that is highly debated. Nonetheless, the Brundtland report defines it as the ability to fulfill present needs without compromising the ability of future generations to fulfill their own needs. The report also defines sustainable development around three dimensions: environmental, economic, and social. Moreover, discussing all 3 dimensions, the report declared: "These are not separate crises: an environmental crisis, a developmental crisis, an energy crisis. They are all one." (World Commission on Environment and Development, 1987). Such a vision would urge the scientific community to try to escape the compartmentalization of those issues and to think of them simultaneously in their research.

Any production of consumption goods or services relates to each of these three dimensions. It is also the case for any industry. Industries use financial resources, employ people, and consume energy and materials to fulfill their customers' needs. In doing so, their managers make many decisions that have important social, environmental, and economic impacts. Those impacts could be negative such as using chemicals that would pollute the environment, bringing diseases upon their workers and exporting the profits to communities that already are wealthy (World Commission on Environment and Development, 1987). However, industrials also have opportunities to have positive impacts on their communities such as being efficient with the resources they use, offering good working conditions and benefiting local economies. Hence, managers need to have the right tools to make the best decisions and consider their impact in the long, mid, and short term. Although operational decisions have short-term impacts on organizations, compared to strategic and tactical decisions, those still need to be considered thoroughly. In fact, because of their redundancy, operational decisions might, over a long period of time, have more of an impact on the environment, society and economy than some strategic or tactical decisions (Spooner *et al*., 2014).

Job scheduling daily in production systems is an example of a redundant operational decision that has great environmental, social, and economic impacts. The impact of a bad job schedule over a day is not necessarily dramatic on its own, but the application of the wrong decision-making tools will have a sizable impact every day and in the long term. Traditional job scheduling in manufacturing often implies making, at least, two decisions: in what order to process jobs and with which resources (sequencing and resource allocation). In this basic scenario, a set of jobs needs to be completed, meaning that all required operations related to that job must be completed. To do so, one or many resources (also called "machines") might be required for each operation. Moreover, there is a specific order in which operations need to be completed for each job, and this is imposed using precedence constraints, and there are other operational restrictions to consider.

Although the sequence and resource allocation decisions are the most common decisions, depending on the specific aspects of each shop, managers today should consider more complex questions that favor sustainability. For instance, from an energetic standpoint, should one turn off the machines between operations? Should one include the transportation time of a job between workstations? Hence, with different possible combinations of resource allocation and use, as well as sequence in a job scheduling problem, the number of possible combinations increases rapidly. Considering all objectives, parameters, decisions, constraints and solution possibilities, job scheduling is a complex problem that is not easily solved (Maccarthy & Liu, 1993). It is in this context that Operational Research (OR) becomes a powerful tool for decision-makers.

1.1 Operational Research in the Job Scheduling Problem

OR is defined as the study of quantitative methods for decision-making. It seeks to develop and study tools that provide either optimal or good enough feasible solutions depending on the requirements of the business case and the time allowed to solve the problem (Carter & Rabadi, 2018). This thesis focuses on the use of Mathematical Programming to model and solve a Job Scheduling Problem, seeking to help managers make better decisions in two possible ways. On one side, if the optimal solution of the model is found, it guarantees managers the best outcome possible for the studied problem. If this is not the case, one can provide, on the other side, a good feasible solution. This will help managers find good-quality solutions in a short time and it can reduce the variability between the resulting decisions of more skilled managers and less experienced ones.

As presented before, in complex business cases such as production planning today, it is necessary to consider multiple objectives in the same problem. Indeed, a solution (a schedule) that minimizes makespan might have a poor performance in energy consumption. Hence, the two objectives need to be included explicitly in the mathematical model. However, in a multi-objective problem, it is not always clear what can be the optimal solution. There are solutions that might perform better than others regarding one objective, but that edge might come at a cost in objectives two or three. This challenge gets even more relevant the more there is conflict between two or more of the objectives. The OR community has already made some progress in that field and has concluded that, although it may be impossible to identify a solution that trumps all others, it is possible to disqualify solutions that are dominated. It can hence be defined that the pareto front is the set of non-dominated solutions for an instance of a problem. A solution is non-dominated if no other feasible solution has a better performance in one or many of the problem's objectives while staying at least as efficient in all other objectives (Bui & Alam, 2008). For managers, having access to the set of non-dominated solutions has many advantages. It can allow them to only consider the solutions that either are the best for one objective or a great compromise between the objectives. It also lets the managers choose which objective to prioritize without suggesting to the model that a given objective is more desirable than others.

Traditionally, OR tools that focused on job scheduling were mainly interested in minimizing makespan which is the completion time of the last job processed. Nowadays, sensitivity towards new challenges has risen. It is not sufficient anymore to only consider the economic aspect of operations. It is required to also pay attention to environmental and social impacts. Operations in shops consume energy and materials. Manufacturers also generate waste. In short, shops have ecological footprints. Many shops also employ workers. The conditions in which the labor occurs in a shop have many consequences for the workers. From exhaustion to frustration, workers might be unsatisfied with their job. It might even have an impact on turnover which would be a challenge from a human resource standpoint. On the other hand, technology has greatly improved over the last decade. It is now easier than ever to solve bigger problems in an adequate amount of time.

With better technologies and the requirement to take into consideration more challenges, it is now, more than ever, relevant to develop sustainable decision-making tools for job scheduling.

Therefore, the objective of this thesis is to provide managers with a new sustainable decision-making tool that includes each of the three dimensions of sustainable development while considering most of the relevant features of job scheduling. The intent is to develop a mathematical model that includes most of the relevant features found in the literature and provides a high-quality formulation for the problem.

1.2 Objectives of the thesis and structure of the document

The thesis proposes a flexible job shop problem to help managers decide in a single model the resource allocation, the processing order with starting and completion time of each operation of each job, the workers scheduling, and the resources used (time spent idle or off between operations at each workstation) to optimize all three dimensions of sustainable development: economic, environmental, and social impact. More precisely, it seeks to incorporate explicitly in the formulation three sustainable objectives: 1) to minimize makespan (i.e. economic efficiency), 2) to minimize energy consumption and reduce the environmental impact of operations, and 3) to minimize the maximal work intensity among workers. For the last objective, we propose a novel definition of work intensity and seek to better split the labor burden among workers. The model is formulated and solved using a weighted-sum method. A total of eight equivalent variants of the formulation are proposed for this problem.

Beyond the contribution of the formulation, this thesis presents extensive numerical experimentation to compare each formulation variant and its performance, as well as two key aspects for managers. The computational study of the thesis first compares the variants over 30 randomly generated instances inspired by three small-scale real production systems. It first compares their resolution time, the best objective value, and the optimization gap, to analyze the "strongest" formulation of our problem. Moreover, to help managers compare different solutions to this multi-objective problem, and to study how well pareto fronts can be generated through the weighted-sum method, this paper presents approximations of the pareto front of the 30 randomly generated instances. Finally, the thesis provides decision-makers with tools to choose from a set of non-dominated solutions as well as a presentation of Gantt's charts as a communication tool for dispatching a team.

The rest of the thesis is structured in the following sections: Chapter 2 will focus on the literature review and explain this paper's contribution to the current state of knowledge. Chapter 3 will focus on the problem description. Chapter 4 will focus on the generation of random instances, the performance analysis of the resolution of the 30 randomly generated instances for the eight different formulations and the analysis of the approximated pareto fronts and the relationship between objectives. Finally, Chapter 5 will present managers with tools to choose between multiple pareto optimal solutions among a pareto set and will show how to illustrate the solutions through a Gantt chart for an easy-to-understand presentation of the results.

CHAPTER 2
LITTERATURE REVIEW

The study of job scheduling in the literature can be traced back as far as the 1950s. As an example, Johnson S. M. (1953) studied an algorithm that produced optimal solutions for job scheduling with two machines. Garey *et al*. (1976) proved that Flow-Shop Scheduling problems (FSSPs) with three or more machines were NP-complete problems. Although job scheduling has been studied throughout the last century, it is only since the turning of the 21st century that the “green” variant of job scheduling really started flourishing. He *et al*. (2005) were the first to consider both an energy-related objective and makespan in the same job-shop scheduling problem.

Research on job scheduling is divided into two categories. The first category is represented by papers on Flow-Shop Scheduling Problems (FSSPs). FSSPs represent job scheduling problems in which every job follows the same sequence of resources, having only one resource available per operation. Usually, FSSPs are used to plan the production of highly standardized products that all require similar work. An example of that would be an assembly line. In the literature, there are also papers that focus on considering energy in FSSPs. For instance, Li X. et al. (2018) proposed a model for minimizing the makespan and the total energy consumption in a welding shop in which all jobs follow the same process route. FSSPs also have a flexible variant. On the other side, the Flexible Flow-Shop Scheduling Problems (FFSSPs) feature problems in which all jobs follow the same sequence of resources but there are sets of multiple machines available for each operation. Such a requirement could be represented by a constraint that would specify that, for each job, all j-th operations must be processed by a machine in the j-th set. Such a constraint would meet the requirement that, for a specific operation, all jobs are restricted to the same set of machines. For instance, Liu et al. (2018) studied a flexible flow-shop formulation for recycling businesses. In their formulation, sets of machines were represented by stages of parallel machines for the two stages required in recycling: pre-processing and actual recycling. For the purposes of this paper, however, FSSPs and their variants were not selected. The formulation studied in this paper has the intent of being versatile. It means being able to solve the most complex problems as well as the simpler ones. Therefore, a formulation that can work on the schedule of highly standardized products as well as completely custom products is preferred. That is why the formulation selected is a variant of the next category.

The second category is composed of papers on Job-Shop Scheduling Problems (JSSPs). JSSPs represent problems in which each job follows an original sequence of resources. That means each operation of each job might require a different resource and the *j-th* operation of two different jobs might require different resources. Usually, Formulations of JSSPs are used to model the production of custom products that have little standardization. A workshop for custom-made guitars would be a faithful example of JSSP. A JSSP formulation could also be applied to the scheduling of highly standardized jobs without any modification of the formulation by considering the same required process for each specific job. To produce a fully standardized product, it would mean the set of jobs I is made up of identical operations. However, this paper is focused on an extension of JSSP that is named the Flexible Job-Shop Scheduling Problem (FJSSP). FJSSP formulations are characterized by the fact that each operation of each job can be processed by a set of qualified resources for the operation instead of a specific one. An example of FJSSP could be a shop of custom goods with general-purpose machinery. This section presents the results of an extensive revision of the contributions of the JSSP and FJSSP that are close to the contribution of this thesis. Section 2.1 presents the process of selecting the papers for the review and Section 2.2. the result and analysis of this work.

2.1 Paper selection criteria

To generate the list of relevant papers, the snowball method was applied to the seminal paper of João *et al*. (2022) and papers found afterward. For a paper to be considered relevant, it must 1) study either a job-shop scheduling problem or a flexible job-shop scheduling problem, 2) model it through a mathematical formulation, and 3) the formulation must include at least two objectives and one of them must be related to energy. Therefore, studies that included energy through constraints are excluded from this review. For instance, in their study, Lei et al. (2019) limited the total energy consumption to a maximum threshold with a constraint. Although interesting, such an approach has new challenges. How to set the maximum threshold must be thoroughly thought out. If not cautious enough, this approach is prescriptive and has the disadvantage of enforcing a view of what should be the maximum energy consumption through a restrictive constraint.

The list of relevant papers was generated using Google Scholar as the preferred research tool. The following keywords were applied: energy, green, job-shop scheduling problem, and flexible job-shop scheduling problem. From the search results, papers were filtered by title, abstract and keywords. In case of doubt, the model section was screened. Only the papers available in the library of the University of Quebec were retained. A list of 142 papers that fit the requirements were selected. The literature review made by João et al. (2022) is current and relevant in the case of this thesis. Its use allowed for a faster review of what is available in that field of study.

2.2 Distribution of selected papers according to their relevant attributes

Once the papers were selected, a detailed revision was done over the full text. Papers were analyzed and categorized according to three main aspects: the problem variant, the objective classification and the features included in the problem studied. The problem variant indicates if the paper studies a flexible job-shop or a job-shop problem. Then, the objectives modeled by each paper were analyzed. In the case of this study, a formulation will be considered sustainable only by including all 3 dimensions of sustainable development. Objectives will be classified as economic, environmental, or social according to the classification in Akbar and Irohara (2018). Although it is a given that all 142 studies include the environmental dimension because of their energy-related objective, it does not mean all studies include both economic and social dimensions as well.

Objectives related to the economic dimensions are as follows: Total weighted tardiness, Makespan, Total completion time, Reliability, Machine workload, Total tardiness, Production cost, Labour cost, Quality, Mean Machine workload, Total tardiness and earliness, Maximum machine workload, Total tardiness cost, Mean total tardiness, mean flow time, Number of late jobs, Total set-up time, Mean set-up time, Machine utilization, Fault prevention, Work in progress and Total travel distance.

Objectives related to the environmental dimension are as follows: Energy consumption, Energy cost, Number of restarts, Total carbon emission, Recycling rate, Raw material consumption, Peak power consumption, Idle time and Utilization rate.

Objectives related to the social dimension are as follows: Noise, Safety, Vibrations, customer satisfaction, ergonomic risk, and maximal labor intensity.

Finally, for each article, the specific features included were compiled. A feature can be defined as an additional attribute included in a formulation that is not part of the basic formulation of the problem by default. Features present in the literature are as follows: Machine speeds, turning machines on/off between operations, batch scheduling, sequence-dependent set-up times, transportation times, maintenance scheduling, workers scheduling, layout optimization, inventory, distributed manufacturing scheduling and job process planning.

Table 2.1 lists all job-shop papers selected for this review and shows the categorization of each one. Table 2.2 does the same thing for flexible job-shop papers. In addition to the features presented before, Table 2.2 details, for all FJSSP formulations, which are the closest to our variant of the problem, the modelization approach to manage sequencing variables. Seven categories are defined:

The first group of papers named "No Precedence Variables" (NOPV) did not have precedence variables at all. Many papers in this category could do so because their resolution method used encoding and decoding of the solutions of the problem into DNA that can include sequences in its structure. Therefore, the order of operation by a specific resource is no longer a constraint to be verified but a feature of the DNA. The second group of papers named "Disjunctive Constraints" (DISJ) used disjunctive constraints similar to the basic formulation from Manne (1960). Using this method, for all operations at machine k variable z_{ijhgk} will take a value of one if operation j of job i is before operation g of job h or a value of zero if it is the opposite. This means that, for all operations at machine k $z_{ijhgk} = 1 - z_{hgijk}$ and z_{ijijk} must not exist or the constraints must not verify for that variable because an operation cannot be before and after itself. These constraints verify that all operations are either before or after one another if allocated to the same resource thereby being disjunctive constraints. The third group of papers named "Time-Indexed Variables" (TIME) used time-indexed variables. In those, the schedule is seen as discrete because, for each unit of time, an operation is processed at a specific resource or is not. In those papers, w_{ijku} equals to 1 if operation j of job i is processed at machine k during period u and 0 otherwise. This approach may multiply the number of variables very quickly if it is used to solve problems with many periods. The fourth group of papers named "Priority-Indexed Variables" (PRIOR) used formulations in which the processing order for each resource is determined through a priority index. The lower the priority, the sooner the operation is getting processed. The resulting variable is x_{ijkl} :

which is equal to 1 if operation j of job i is done at machine k in priority l and 0 otherwise. This approach multiplies the number of allocation variables by the number of priorities by adding a priority index. The fifth group of papers named “Encoding Constrain Precedence Variables” (ENCODE) present precedence variables but do not force these variables to take a value using a constraint. Instead, it is managed in the encoding and decoding of the solution DNA in the resolution method. Once the precedence variable has a value, it is used in various constraints to verify the merit of a solution with a heuristic. For instance, many genetic algorithms used precedence variables in constraints but did not have any listed constraints that could explain why the precedence variable is not always equal to zero. The way precedence variables are used in these papers is to verify other constraints once the value of the precedence variables has been established after decoding the solution. The more a solution infringes constraints, the less efficient it is and the less likely it is to reproduce. To present an original contribution to the formulation of the studied problem, the sixth and seventh groups are only composed of this paper and use novel formulations never studied before in the literature for sequencing operations in FJSSP. The sixth group is named “Flow Conservation Constraints” (FCC) and uses flow conservation constraints to make sure that there is a next operation for each real previous operation. The seventh group is named “Sequence Linking Constraints” (SLC) and uses new sequence linking constraints never studied before. Using the allocation variables, this method forces the sum of all precedence variables to be exactly equal to the sum of allocated operations at a specific resource minus one. This is because the precedence variables work in pairs of immediately consecutive operations. This explains the name of sequence linking constraints representing the number of links in a sequence. Moreover, all operations must have a next operation except the last one. It sums up exactly how many links of operation pairs there should be in a sequence of operations at a specific resource based on the allocation variable. This type will be explained in more detail in Chapter 3.

Table 2.1 : Reviewed literature on Job-Shop Scheduling Problems

Article	Variant	Dimension			Features
		Economic	Env.	Social	
Abedi M., Chiong R., Noman N., Zhang R. (2020)	JSSP	TWT	E	-	MS, MAINS
Afsar, S., Palacios, J. J., Puente, J., Vela, C. R., & González-Rodríguez, I. (2022)	JSSP	CMAX	E	-	-
Amelian, SS; Sajadi, SM; Nayabakhsh, M; Esmaelian, M (2022)	JSSP	TTE, REL	EC	-	MS, MAINS
Cai, L; Li, WF; Luo, Y; He, LJ (2022)	JSSP	-	E, UR	CS	-
Dai M., Zhang Z., Giret A., Salido M.A. (2019)	JSSP	CMAX	E	-	TTIMES
Dalila B.M.M. Fontes, Seyed Mahdi Homayouni & João Chaves Fernandes (2023)	JSSP	CMAX	E	-	MS, TTIMES
Escamilla J., Salido M.A. (2018)	JSSP	CMAX	E	-	MS
Escamilla J., Salido M.A., Giret A., Barber F. (2016)	JSSP	CMAX	E	-	MS
Giglio D., Paolucci M., Roshani A. (2017)	JSSP	PC	EC	-	MS, BS, SDST, I
Gondran M., Kemmoe S., Lamy D., Tchernev N. (2020)	JSSP	CMAX	PPC	-	-
Gong G., Chiong R., Deng Q., Han W., Zhang L., Huang D. (2021)	JSSP	CMAX	E, NS	-	I/O, MAINS
Gonzalez M.-A., Oddi A., Rasconi R. (2019)	JSSP	TWT	E	-	I/O
González-Rodríguez I., Puente J., Palacios J.J., Vela C.R. (2020)	JSSP	TWT	E	-	-
Gupta S., Jain A. (2021)	JSSP	CMAX, MFT, MTT, NLJ, TST, MST	E	-	SDST, MAINS
Hassani Z.I.M., El Barkany A., El Abbassi I., Jabri A., Darcherif A.M. (2019)	JSSP	PC	EC	-	-
He L., Chiong R., Li W., Dhakal S., Cao Y., Zhang Y. (2021)	JSSP	CMAX, TT	E	-	MS, SDST
He Y., Liu F., Cao H.-J., Li C.-B. (2005)	JSSP	CMAX	E	-	Unknown
Ichoua S., Pechmann A. (2014)	JSSP	CMAX, TWTE	PPC	-	-
Jiang E.-D., Wang L., Peng Z.-P. (2020)	JSSP	CMAX	E	-	MS
Jiang T., Zhang C., Sun Q.-M. (2019)	JSSP	PC	EC	-	MS
Jiang T., Zhang C., Zhu H., Deng G. (2018)	JSSP	TT	EC	-	-
Kawaguchi S., Fukuyama Y. (2020)	JSSP	CMAX	E	-	-
Kurniawan B., Song W., Weng W., Fujimura S. (2021)	JSSP	TWT	EC	-	-
Li W., He L., Cao Y. (2022)	JSSP	CMAX, TT, LC	E, IT	-	MS, SDST, WS
Liao W., Wang T. (2018)	JSSP	PC, TCT	TCE	-	-
Liao W., Wang T. (2019)	JSSP	PC	EC	CS	TTIMES
Lin W., Wang L., Zhou R., Zhang Y., Zhang C. (2018)	JSSP	CMAX	E	-	-

Liu Y., Dong H., Lohse N., Petrovic S. (2016)	JSSP	TWT	E	-	I/O
Liu Y., Dong H., Lohse N., Petrovic S., Gindy N. (2014)	JSSP	TWT	E	-	I/O
Lu C., Zhang B., Gao L., Yi J., Mou J. (2021)	JSSP	CMAX	E	-	MS
Lu Y., Jiang T. (2019)	JSSP	PC	EC	-	MS
Luo J., El Baz D., Xue R., Hu J. (2020)	JSSP	TT, SD	EC	-	MS
Majdoub Hassani Z.I.M., El Barkany A., Jabri A., Abbassi I.E.L., Darcherif A.M. (2021)	JSSP	PC	EC	-	-
May G., Stahl B., Taisch M., Prabhu V. (2015)	JSSP	CMAX	E	-	I/O
Ning T., Wang Z., Zhang P., Gou T. (2020)	JSSP	CMAX, PC, TWTE	TCE	-	-
Piroozfard H., Wong K.W., Tiwari M.K. (2018)	JSSP	TT	TCE	-	-
Raileanu S., Anton F., Iatan A., Borangiu T., Anton S., Morariu O. (2017)	JSSP	CMAX	E	-	MS
Ren J., Ye C., Li Y. (2020)	JSSP	CMAX, TT	E	-	TTIMES
Salido M.A., Escamilla J., Barber F., Giret A. (2017)	JSSP	CMAX	E	-	MS
Salido M.A., Escamilla J., Barber F., Giret A., Tang D., Dai M. (2016)	JSSP	CMAX	E	-	MS
Salido M.A., Escamilla J., Giret A., Barber F. (2016)	JSSP	CMAX	E	-	MS
Wei H., Li S., Quan H., Liu D., Rao S., Li C., Hu J. (2021)	JSSP	CMAX, TWTE	E	-	I/O
Xu J., Wang L. (2017)	JSSP	CMAX	E	-	TTIMES
Yin L., Li X., Gao L., Lu C., Zhang Z. (2017)	JSSP	CMAX	E	N	MS
Zhang L., Li X., Gao L., Zhang G. (2016)	JSSP	CMAX, TWT	E	-	-
Zhang R., Chiong R. (2016)	JSSP	TWT	E	-	MS
Zhou B., Lei Y. (2021)	JSSP	CMAX	E	-	TTIMES
Zhu H., Jiang T., Wang Y., Deng G. (2021)	JSSP	CMAX	E	-	MS
Zhu S., Zhang H., Jiang Z., Hon B. (2020)	JSSP	CMAX	TCE	-	-

E : Energy Consumption, EC : Energy Cost, NS : Number of Starts, TCE : Total Carbon Emissions, RR : Recycling Rate, RMC : Raw Material Consumption, PPC : Peak Power Consumption, IT : Idle Time, UR : Utilization Rate, TWT : Total Weighted Tardiness, CMAX : Makespan, TCT : Total Completion Time, REL : Reliability, MWL : Machine Workload, TT : Total Tardiness, PC : Production Cost, LC : Labour Cost, Q : Quality, MMWL : Mean Machine Workload, TTE : Total Tardiness and Earliness, SD : Scheduling Disruptions, MT : Maximal Tardiness, TWTE : Total Weighted Tardiness and Earliness, MWLMAX : Maximum Machine Workload, TTC : Total Tardiness Cost, MTT : Mean Total Tardiness, MFT : Mean Flow Time, NLJ : Number of Late Jobs, TST : Total Set-up Time, MST : Mean Set-up Time, MU : Machine Utilization, FP : Fault Prevention, WP : Work in Progress, TTD : Total Travel Distance, N : Noise, S : Safety, V : Vibrations, CS : Customer Satisfaction, ER : Ergonomic Risk, INTMAX : Maximum Labor Intensity, MS : Machine Speed, I/O : Turning Machines ON/OFF, BS : Batch Scheduling, SDST : Sequence-Dependent Set-up Times, TTIMES : Transportation Times, MAINS : Maintenance Scheduling, WS : Workers Scheduling, LO : Layout Optimization, I : INVENTORY, DMS : Distributed Manufacturing Scheduling, JPP : Job Process Planning

Table 2.2 : Reviewed literature on Flexible Job-Shop Scheduling Problems

Article	Variant	Dimension			Features	Type
		Economic	Env.	Social		
An Y., Chen X., Zhang J., Li Y. (2020)	FJSSP	CMAX, TT, PC	E	-	TTIMES	NOPV
Ayyoubzadeh B., Ebrahimnejad S., Bashiri M., Baradaran V., Hosseini S.M.H. (2021)	FJSSP	TTC	EC	-	-	DISJ
Barak S., Moghdani R., Maghsoudlou H. (2021)	FJSSP	PC	E, EC	-	TTIMES	TIME
Caldeira R.H., Gnanavelbabu A., Vaidyanathan T. (2020)	FJSSP	CMAX, SD	E	-	I/O	PRIOR
Chen, X. L., Li, J. Q., Han, Y. Y., & Sang, H. Y. (2020)	FJSSP	CMAX	E	-	TTIMES	DISJ
Chou Y.-C., Cao H., Cheng H.H. (2013)	FJSSP	CMAX	E	-	-	NOPV
Coca G., Castrillón O.D., Ruiz S., Mateo-Sanz J.M., Jiménez L. (2019)	FJSSP	TCT	TCE	N, V	-	DISJ
Dai M., Tang D., Giret A., Salido M.A. (2019)	FJSSP	CMAX	E	-	TTIMES	PRIOR
Dai M., Tang D., Xu Y., Li W. (2015)	FJSSP	CMAX	E	-	JPP	DISJ
Du Y., Li J.-Q., Luo C., Meng L.-L. (2021)	FJSSP	CMAX	E	-	TTIMES, MS	PRIOR
Duan J., Wang J. (2021)	FJSSP	CMAX	E	-	MS, I/O	DISJ
Ebrahimi A., Jeon H.W., Lee S., Wang C. (2020)	FJSSP	TTC	EC	-	TTIMES	PRIOR
El Amine Meziane M., Taghezout N. (2018)	FJSSP	CMAX	E	-	-	NOPV
Gong G., Deng Q., Gong X., Liu W., Ren Q. (2018)	FJSSP	CMAX, LC	E, RR	N, S	WS	DISJ
Gong X., De Pessemier T., Martens L., Joseph W. (2019)	FJSSP	CMAX, LC, MWL	EC	-	I/O, SDST, WS	NOPV
Gu X. (2021)	FJSSP	CMAX, MWL	TCE	-	-	NOPV
Guo J. (2019)	FJSSP	TCT	E	N, V	TTIMES	NOPV
Guo J., Lei D., Li M. (2021)	FJSSP	CMAX, TT	E	-	MS	TIME
Han Y., Chen X., Xu M., An Y., Gu F., Ball A.D. (2021)	FJSSP	CMAX, PC	E	-	TTIMES	DISJ
He Y., Li Y., Wu T., Sutherland J.W. (2015)	FJSSP	CMAX	E	-	-	DISJ
Hemmati Far M., Haleh H., Saghaei A. (2018)	FJSSP	PC, Q	EC	-	TTIMES	NOPV
Hemmati Far M., Haleh H., Saghaei A. (2019)	FJSSP	PC, TT	EC	-	TTIMES, WS	NOPV
Hongyu L., Xiuli W. (2021)	FJSSP	CMAX	E	ER	WS	NOPV
Huo D.X., Xiao X.J., Pan Y.J. (2020)	FJSSP	CMAX	TCE	-	TTIMES	NOPV

Jiang Z., Zuo L., Mingcheng E. (2014)	FJSSP	CMAX, PC, Q	E	-	-	NOPV
Karim Ahangar, NK; Khalili, M; Tayebi, H (2021)	FJSSP	CMAX, MT	E	-	MS	DISJ
Lei D., Guo X. (2015)	FJSSP	CMAX	TCE	-	WS	NOPV
Lei D., Zheng Y., Guo X. (2017)	FJSSP	MWL	E	-	MS	NOPV
Li J.-Q., Deng J.-W., Li C.-Y., Han Y.-Y., Tian J., Zhang B., Wang C.-G. (2020)	FJSSP	CMAX	E	-	-	PRIOR
Li J., Du Y., Gao K., Duan P., Gong D., Pan Q., Suganthan P.N. (2021)	FJSSP	CMAX	E	-	TTIMES	ENCODE
Li M., Lei D. (2021)	FJSSP	CMAX, TT	E	-	MS, SDST, TTIMES	TIME
Li M., Lei D., Xiong H. (2019)	FJSSP	MT, CMAX, MWL	E	-	-	TIME
Li Y., Gu W., Yuan M., Tang Y. (2022)	FJSSP	CMAX	E	-	TTIMES	TIME
Li Y., He Y., Wang Y., Tao F., Sutherland J.W. (2020)	FJSSP	CMAX	E	-	I/O	TIME
Li Y., Huang W., Wu R., Guo K. (2020)	FJSSP	CMAX, MMWL	TCE	-	MS, I/O	ENCODE
Li, HC; Duan, JG; Zhang, QL (2021)	FJSSP	CMAX	E	-	TTIMES, LO	ENCODE
Liang X., Chen J., Gu X., Huang M. (2021)	FJSSP	CMAX, MWL	TCE	-	-	ENCODE
Liu Q., Gui Z., Xiong S., Zhan M. (2021)	FJSSP	PC, CMAX, TTE	TCE	-	SDST, TTIMES, DMS	NOPV
Liu Q., Tian Y., Wang C., Chekem F.O., Sutherland J.W. (2018)	FJSSP	CMAX, MU	TCE	-	TTIMES	PRIOR
Liu Q., Zhan M., Chekem F.O., Shao X., Ying B., Sutherland J.W. (2017)	FJSSP	CMAX	TCE	-	TTIMES	NOPV
Liu Z., Guo S., Wang L. (2019)	FJSSP	CMAX	E	-	TTIMES	ENCODE
Liu, J. et al. (2021)	FJSSP	CMAX	E	-	MS	NOPV
Lu Y., Lu J., Jiang T. (2019)	FJSSP	CMAX	EC	-	-	DISJ
Luan F., Cai Z., Wu S., Liu S.Q., He Y. (2019)	FJSSP	PC	E	-	-	ENCODE
Luo Q., Deng Q., Gong G., Zhang L., Han W., Li K. (2020)	FJSSP	CMAX, MWLMAX	E	-	TTIMES, MS	ENCODE
Luo S., Zhang L., Fan Y. (2019)	FJSSP	CMAX	E	-	MS	DISJ
Lv Y., Li C., Tang Y., Kou Y. (2021)	FJSSP	CMAX	E	-	-	ENCODE
Mokhtari H., Hasani A. (2017)	FJSSP	TCT, REL	EC	-	MAINS	PRIOR
Myoung-Ju Parka, Andy Ham (2022)	FJSSP	CMAX	EC	-	-	TIME
Naimi, R; Nouiri, M; Cardin, O (2021)	FJSSP	CMAX	E	-	-	NOPV
Ning T., Huang Y. (2021)	FJSSP	CMAX, PC	TCE	-	-	NOPV
Ning T., Wang Z., Duan X., Liu X. (2021)	FJSSP	CMAX	TCE	-	MS	NOPV

Nouiri M., Bekrar A., Trentesaux D. (2020)	FJSSP	CMAX	E	-	-	NOPV
Pach C., Berger T., Sallez Y., Bonte T., Adam E., Trentesaux D. (2014)	FJSSP	CMAX	E	-	I/O	TIME
Pan, ZX; Lei, DM; Wang, L (2022)	FJSSP	CMAX, TT	E	-	-	PRIOR
Peng Z., Zhang H., Tang H., Feng Y., Yin W. (2021)	FJSSP	CMAX	E	N	TTIMES, WS	DISJ
Phanden R.K., Sindhwani R., Sharma L. (2021)	FJSSP	CMAX, PC	E	-	-	ENCODE
Piroozfard H., Wong K.Y., Wong W.P. (2018)	FJSSP	TT	TCE	-	-	PRIOR
Plitsos S., Repoussis P.P., Mourtos I., Tarantilis C.D. (2017)	FJSSP	CMAX, MWL	E, IT	-	-	NOPV
Qu, MH; Zuo, Y; Xiang, F; Tao, F (2022)	FJSSP	CMAX, PC	E	-	-	PRIOR
Ren W., Wen J., Yan Y., Hu Y., Guan Y., Li J. (2021)	FJSSP	CMAX	E	-	-	ENCODE
Seng D.W., Li J.W., Fang X.J., Zhang X.F., Chen J. (2018)	FJSSP	CMAX	TCE	-	MS	DISJ
Shi D.L., Zhang B.B., Li Y. (2020)	FJSSP	CMAX	E	CS	-	ENCODE
Sui Z., Li X., Yang J., Liu J. (2021)	FJSSP	CMAX, FP	E	-	-	NOPV
Sun, XP; Wang, Y; Kang, HW; Shen, Y; Chen, QY; Wang, D (2021)	FJSSP	CMAX, MWL	TCE	-	-	NOPV
Vallejos-Cifuentes P., Ramirez-Gomez C., Escudero-Atehortua A., Rodriguez Velasquez E. (2019)	FJSSP	CMAX	E	-	MS	NOPV
Wang H. (2019)	FJSSP	CMAX, PC, Q	E	-	-	DISJ
Wang H., Jiang Z., Wang Y., Zhang H., Wang Y. (2018)	FJSSP	PC	E	-	-	NOPV
Wang H., Sheng B., Lu Q., Yin X., Zhao F., Lu X., Luo R., Fu G. (2021)	FJSSP	CMAX	E	-	TTIMES	ENCODE
Wang J., Liu Y., Ren S., Wang C., Wang W. (2021)	FJSSP	CMAX, MWLMAX	E	-	DMS	NOPV
Wang J., Yang J., Zhang Y., Ren S., Liu Y. (2020)	FJSSP	CMAX, MWL	E	-	JPP	NOPV
Wang J., Zhang Y., Liu Y., Wu N. (2019)	FJSSP	CMAX, MWL	E	-	-	NOPV
Wei Z., Liao W., Zhang L. (2022)	FJSSP	CMAX	E	-	MS	NOPV
Wen X.-Y., Wang K.H., Li H., Sun H.-Q., Wang H.Q., Jin, L.-L. (2021)	FJSSP	CMAX, TT	TCE	-	JPP	PRIOR
Wu X., Li J., Shen X., Zhao N. (2020)	FJSSP	CMAX, SD	E	-	-	DISJ
Wu X., Shen X., Li C. (2019)	FJSSP	CMAX	E	-	-	DISJ
Wu X., Sun Y. (2018)	FJSSP	CMAX	E, NS	-	MS, I/O	DISJ
Wu, ML; Yang, DS; Zhou, BW; Yang, ZL; Liu, TY; Li, LG; Wang, ZF; Hu, KY (2021)	FJSSP	CMAX	E	-	-	PRIOR
Xu B., Mei Y., Wang Y., Ji Z., Zhang M. (2021)	FJSSP	MTT	E	-	-	PRIOR
Xu W., Hu Y., Luo W., Wang L., Wu R. (2021)	FJSSP	CMAX, PC, Q	TCE	-	TTIMES, MS	NOPV

Xu W., Shao L., Yao B., Zhou Z., Pham D.T. (2016)	FJSSP	CMAX, PC, Q	E, RMC	-	-	NOPV
Yang X., Zeng Z., Wang R., Sun X. (2016)	FJSSP	CMAX	E	-	-	PRIOR
Yin L., Li X., Gao L., Lu C., Zhang Z. (2017)	FJSSP	CMAX	E	N	MS	DISJ
Yong Wang, Wange Peng, Chao Lu *and Huan Xia (2022)	FJSSP	CMAX	E	-	-	NOPV
Zhang C., Gu P., Jiang P. (2015)	FJSSP	CMAX, MWL, WP	TCE	-	TTIMES	PRIOR
Zhang H., Dai Z., Zhang W., Zhang S., Wang Y., Liu R. (2017)	FJSSP	CMAX	EC	-	MS	TIME
Zhang H., Ge H., Pan R., Wu Y. (2018)	FJSSP	CMAX,TTD	E	-	TTIMES, LO	NOPV
Zhang H., Xu G., Pan R., Ge H. (2021)	FJSSP	CMAX	E	-	TTIMES	PRECEDE
Zhang S., Zhong J., Yang H., Li Z., Liu G. (2019)	FJSSP	TWT	EC	-	-	DISJ
Zhang Y., Wang J., Liu Y. (2017)	FJSSP	CMAX, MWL	E	-	SDST	NOPV
Zhang Z., Wu L., Peng T., Jia S. (2019)	FJSSP	CMAX	E	-	I/O	DISJ
Zhou G., Chen Z., Zhang C., Chang F. (2022)	FJSSP	CMAX, SD	TCE	-	-	NOPV
Zhu H., Deng Q., Zhang L., Hu X., Lin W. (2020)	FJSSP	CMAX, LC	TCE	-	WS	DISJ
This paper (2023)	**FJSSP**	**CMAX**	**E**	**INTMAX**	**MS, I/O, SDST, WS**	**FCC/SLC**
E : Energy Consumption, EC : Energy Cost, NS : Number of Starts, TCE : Total Carbon Emissions, RR : Recycling Rate, RMC : Raw Material Consumption, PPC : Peak Power Consumption, IT : Idle Time, UR : Utilization Rate, TWT : Total Weighted Tardiness, CMAX : Makespan, TCT : Total Completion Time, REL : Reliability, MWL : Machine Workload, TT : Total Tardiness, PC : Production Cost, LC : Labour Cost, Q : Quality, MMWL : Mean Machine Workload, TTE : Total Tardiness and Earliness, SD : Scheduling Disruptions, MT : Maximal Tardiness, TWTE : Total Weighted Tardiness and Earliness, MWLMAX : Maximum Machine Workload, TTC : Total Tardiness Cost, MTT : Mean Total Tardiness, MFT : Mean Flow Time, NLJ : Number of Late Jobs, TST : Total Set-up Time, MST : Mean Set-up Time, MU : Machine Utilization, FP : Fault Prevention, WP : Work in Progress, TTD : Total Travel Distance, N : Noise, S : Safety, V : Vibrations, CS : Customer Satisfaction, ER : Ergonomic Risk, INTMAX : Maximum Labor Intensity, MS : Machine Speed, I/O : Turning Machines ON/OFF, BS : Batch Scheduling, SDST : Sequence-Dependent Set-up Times, TTIMES : Transportation Times, MAINS : Maintenance Scheduling, WS : Workers Scheduling, LO : Layout Optimization, I : INVENTORY, DMS : Distributed Manufacturing Scheduling, JPP : Job Process Planning, NOPV : No Precedence Variables, DISJ : Disjunction Variables, TIME : Time-Indexed Variables, PRIOR : Priority Indexed Variables, ENCODE : Encoding Constrain Precedence Variables Value, FCC : Flow Conservation Constraints, SLC : Sequence Linking Constraints						

From the 142 selected papers, 49 study a JSSP formulation and 93 study an FJSSP formulation. Historically, makespan has always been one of the most studied objectives in job scheduling. It still holds true for this literature review. 109 papers out of 142 include makespan as an objective. 79 of the 93 FJSSP studies and 30 of the 49 JSSP studies include makespan which is a majority in both cases.

Regarding the objectives included in this research, only a minority of the 142 studies could be considered sustainable (less than 10% of the reviewed papers). Indeed, only 11 studies feature an objective related to the social dimension. Only ten of those studies could be considered sustainable according to the definition given earlier because Cai et al. (2022) does not include an economic objective. Only four of those ten papers feature an objective representing employees' interests. None of them include an objective related to labor intensity. In the present review, there are 14 studies that consider workload balance. However, all of those consider the workload balance of machines instead of the workload balance of employees. This is why the objective of workload balance of machines had to be placed in the economic dimension rather than the social one. In the literature, however, there are formulations that consider workload balance between employees. Although it would not comply with the previously mentioned requirements because it does not include an objective related to energy or even to the environmental dimension, the formulation in Luo et al. (2023) includes an objective that seeks to minimize the maximum workload for workers. As previously discussed, their objective varies positively with time but not with effort, so it does not include the pace of work in the calculation of workload.

Among the features analyzed, some of the features are present in the literature as little as one time. For instance, only one paper features inventory and batch scheduling in their problem. Some other features were included less than ten times with seven papers including sequence-dependent set-up times, five including maintenance, six including workers scheduling, two including layout optimization, six including distributed manufacturing scheduling and three including job process planning. Among the most studied features, one finds machine speeds being present in 35 papers and transportation times being identified in 31 papers. However, one can see that, not all combinations have been studied simultaneously.

One could argue that some combinations are of low interest. However, it will be argued that workers scheduling, and different machine speeds have an important interaction together that has never been studied to its fullest extent. In fact, only one paper features both different machine speeds and workers scheduling in the same formulation. This is the case of Li et al. (2022) in which authors considered, in the same formulation, sequence-dependent set-up times, different machine speeds and worker scheduling. However, the authors did not consider the possibility of turning machines on or off during operations. Moreover, they do not consider any objectives that could be attributed to the social dimension. Therefore, their study would not meet the requirements to be considered sustainable. Finally, considering only CNC machines did not allow them to analyze that between workers with different skills and machines with different speeds, there are many possible interactions in a shop.

Transportation times seem to have interested a sizeable chunk of the scientific community working in job scheduling. It is featured in 32 out of the 142 articles in the literature compiled for this thesis. However, it is only relevant in shops in which workstations are far enough apart that it makes a sizeable difference. Moreover, in many workshops, layouts are optimized to minimize travel distance between workstations that are often linked together. In addition, travel distance can be incorporated, to some extent, in set-up times. Therefore, one could consider that the transportation time in a smaller workshop is negligible compared to other times such as set-up times that can hardly be optimized through layout. Including transportation times in the formulation also adds another layer of complexity to an already difficult problem. It would add decision variables, parameters, and constraints to an already hard-to-solve problem and increase the resolution time. On top of the three dimensions of sustainability already studied, it would make for a formulation that is much more complex which is out of the scope of this thesis and less interesting than a formulation that can more easily be solved for instances of plausible size in a decent amount of time.

For each paper presenting a FJSSP formulation, a type was assigned to differentiate the different strategies used for sequencing operations. A total of seven strategies were identified to manage precedence variables if those were present in the studied formulation. None of the papers featuring a FJSSP formulation in the relevant literature used sequence linking constraints or flow conservation constraints to manage precedence variables. The use of both these strategies is a novelty in the current literature.

Considering all previous arguments, this thesis has the following contributions:

- It proposes eight different formulation variants of a problem with a combination of objectives and features never studied before in the literature which are minimization of makespan, total energy consumption and labor intensity with sequence-dependent set-up times, processing speeds, turning equipment off and workers scheduling.
- For the first time in an energy-efficient flexible job-shop formulation with more than one objective, it studies an objective related to the labor intensity of employees that cannot be reduced to machine workload.
- It compares a 2-index formulation with a 3-index formulation for starting and completion times of the same problem to determine which one is more efficient.
- It compares formulation variants with flow conservation constraints to a formulation that uses a new constraint never studied before in the literature. This constraint is based on the total amount of allocated jobs to a resource to specify the exact amount of operation sequences in a schedule. Both options will be compared to identify the most efficient between the two types of constraints.
- Through the approximation of the pareto front, it studies the relation between makespan, energy consumption and labor intensity for the first time in a sustainable flexible job-shop formulation that includes sequence-dependent set-up times, different machine speeds, workers scheduling and machines that can be turned off or left idle between operations.

CHAPTER 3
PROBLEM OVERVIEW

This section is dedicated to the presentation of the problem studied and its mathematical formulations. The reader can expect a description of the problem, its principal objectives, and constraints. All necessary assumptions will also be listed. Eight different formulations of the problem are then presented.

3.1 Problem description

In a manufacturing context, several resources are used to warrant the production of one or many products inside a production facility. This thesis proposes a general sustainable flexible job-shop scheduling problem that incorporates several aspects applicable to various production environments and can, therefore, be adapted to different workshop types.

We define (and name) this problem as the Sustainable Flexible Job-Shop Problem with Sequence-Dependent Set-up Times and Workstation Speeds and States with workers scheduling (SFJSSP*). The problem considers a finite and known set of jobs that need to be completed. Each job is completed by the execution of one or more operations. The problem is categorized as a job shop because the sequence of resources (workstations or workers) used to process the operations of a given job is not necessarily the same as the sequence of resources used for the operations of the previous or following job. In this job shop, each operation of each job can be handled by one or several resources. Each resource has one or more possible work speeds for each operation. Those will determine the processing time and processing power of a given operation of a given job at a given resource. It is considered that for each operation of each job, one and only one resource of each type is required (one workstation and one worker), and that neither the workstation nor the worker can handle more than one operation at a time. Each operation of each job has a processing time which may vary according to the workstation where it is processed, the worker performing it and the speed at which it is carried out. This concept allows us to model three different organizational modes: an automatic station, a semi-automatic station and a manual one.

First, in the case of an automatic workstation, most of the labor is done by a machine with little human supervision and the machine speed determines the processing time. An example of that would be a computer numerical control machine (CNC) that executes the work entirely after configuration. Second, in the case of a semi-automatic workstation, part of the labor is executed by the machine and part of the labor by a worker. It means that setting the speed of the machine and the skills of the worker define the processing time. In other words, different workers with different skills will complete the same task with the same machine (adjusted for the same speed) in two different amounts of time. An example of a semi-automatic workstation could be a sewing machine in which knots might be sewn at variable speeds by the machine, but it is the worker who ultimately feeds the sewing machine. An assembly line could also be considered semi-automatic for the following reasons. Although the pace of work is determined by the machine, the worker must be able to perform his tasks at that pace. Therefore, there are workers who can perform such tasks at such pace and other workers who cannot. The consideration of different skills would then exist in the sense that not all workers are able to perform at a workstation at all available speeds. Third, manual workstations should be used to represent workstations in which the speed and processing time are set by the skill and speed of the worker assigned to it. Hence, the only factor that determines the processing speed is the worker. In such a workstation, there might be some tools but most of the work would be done manually. An example would be a workstation used to manually put guitar strings on a guitar. Different workers would then show different performances being able to execute the task in a different amount of time. What is interesting is the fact that, inside one shop, many of these types of interactions between workers and different machine speeds may co-exist. A workstation could be manual, and another workstation in the same job shop might be fully automatic. A formulation that seeks to be closer to reality must be versatile enough to represent automatic workstations as well as manual and semi-automatic ones.

All workstations have three states: processing, idle and off. The processing state is the only state in which a workstation can execute an operation, but it is the state that consumes the most energy. For each workstation, in this state, the energy consumed depends on the operation performed and the speed at which the operation is processed. The off state does not consume any energy at all; however, a starting time is required once the workstation passes from the off to the processing state, which consumes a certain fixed amount of energy per machine. The idle state does not allow any operations to be performed, but it consumes less energy than the processing state while allowing an immediate return to the processing state without any energy consumption. For each workstation, the energy consumed in idle mode is constant, and will vary only according to the time the workstation is held in this state.

In this job shop, the energy consumed is calculated through the following equation: $Energy = power * time$. Processing operations consumes power. The required power to process, to start-up or to maintain a workstation in an idle state is known in advance for all operations, all workstations and all speeds. For the same operation, different workstations and different speeds will consume a different amount of power whereas workers might not influence power consumption, but they influence how long an operation takes on a workstation, so they still influence the total energy consumed through time.

This problem also considers that workers are flexible, i.e., they can change workstations during the shift. Finally, we consider a fixed and known set-up time, which can be defined as the time required to prepare the workstation to perform a given operation. It includes material preparation, workstation setting, adjustment of machines, etc. We consider a sequence-depending set-up time, meaning that the set-up time required between two operations at a given workstation, will depend on the worker that will perform the task, the workstation they are in, as well as the previous operation performed.

The Sustainable Flexible Job-Shop Problem with Sequence-Dependent Set-up Times, and Workstations Speeds and States with Workers Scheduling (SFJSSP*) seeks to help managers with multiple decisions in the operational planning of a shop. First, it decides the resource allocation, deciding which workstation, which worker and which speed are assigned to execute each operation of each job. Second, it helps with workstation sequencing, deciding explicitly the specific order of operations processed at each workstation. Third, the schedule of each worker is determined. This sequencing sets, for each worker, the selected workstation and the order of each operation assigned to them. Finally, it decides the change of states of the workstations and the timing decisions for each state and for the execution of each operation.

To be sustainable, the formulation of the SFJSSP* must consider at least one objective for each of the three dimensions of sustainable development. For the economic dimension, it considers the minimization of the makespan which represents the completion time of the last operation of the last job processed. The environmental dimension is represented by the objective of energy consumption minimization of the job shop, knowing that energy is accounted for when tools are left idle, are turned on, are set up or when operations are processed. Finally, for the social dimension, the problem considers the minimization of the maximum labor intensity which represents the labor of the worker who worked the hardest. Labor intensity is calculated by considering both the pace of work (a value between 0 and 1 considering the relative speed of the work compared to the maximum speed possible) and the duration of work. The product of the two dictates the labor intensity credited to a worker for processing an operation ($pace\ of\ work * duration\ of\ work = labor\ intensity$).

In addition to the aspects explained above, the following assumptions are made:

(1) The processing speed cannot be changed once an operation has started.
(2) Transportation times between workstations are negligible.
(3) The worker who does the set-up and starts the equipment (if necessary) before processing an operation is the one who is assigned to process that operation.
(4) An operation cannot be stopped once started.
(5) Exactly one workstation and one worker are required to process an operation.
(6) Workstations and workers cannot process multiple operations at the same time.
(7) All relevant equipment at workstations starts in an off state from the previous shift and needs to be turned on before executing any work.

3.2 Problem formulation

The SFJSSP* seeks to process a set of jobs I. Each job $i \in I$ has a set of operations J_i required to be completed. Moreover, we define a set of workstations K, and a set of available workers L. As stated before, this problem considers that all operations need to be performed by a given workstation and worker, and a workstation has a set of speeds available at workstation $k \in K$ referred to as V_k.

Before presenting the different formulations, some general sets and parameters are presented. This will lead to the presentation of the baseline formulation. This first and baseline formulation is based on Manne (1960), one of the classical formulations for JSSP, which is adapted and modified to add the details and particularities of the SFJSSP*. Afterward, the section details the other formulations and exposes their differences.

All eight different formulations rely on a precedence variable. It's either w_{ijhgkl} for sequencing operations at workstations or $u_{qrmijkl}$ or u_{qrijl} for sequencing operations with workers. Precedence variables have been extensively studied in the literature. However, no previous studies used flow conservation constraints or sequence linking constraints to manage precedence variables. Therefore, to effectively serve its purpose, a precedence variable needs a set of constraints that forces it to represent the right schedule. This set of constraints must force the precedence variables to take a value and it must maintain the link between the precedence variables and the allocation variables. For instance, sequencing operations means the following operation cannot start before the previous one ends. All formulations with a name starting with F will use flow conservation constraints to manage precedence variables and formulations with a name starting with S will use sequence linking constraints instead. From 1 to 4, the level of integration decreases with each new formulation, but the number of variables also decreases. F1 and S1 are the two formulations closest to the basic formulation from Manne (1960). Then, starting times and completion times will be reduced to 2-index variables instead of 3-index variables in S2 and F2 to match the formulations in the more recent literature. F3 and S3 will not allow off or idle states between operations that do not follow each other. Finally, F4 and S4 are the two formulations that have the fewest variables, but it does not compute from which workstation and to which workstation a worker is moving. This is necessary to compute travel times for workers between operations. Going from 1 to 4, formulations have fewer variables at the cost of being able to integrate fewer considerations for different real production cases.

To identify the different formulations, the index in Table 3.1 will be used:

Table 3.1 : Index of names for all formulations

F	With Flow conservation constraints
S	With Sequence linking constraints
1	3-index formulation for time variables
2	2-index formulation for time variables
3	2-index formulation with interruption times before operations
4	2-index formulation with simplified worker sequence

Letters and numbers combine for naming a formulation variant. For example, formulation F1 refers to the 3-index formulation with flow conservation constraints.

This thesis proposes eight different formulations for the problem proposed. Given enough time, all eight formulations will give the same optimal solution to the problem. The different formulations include two 3-index formulations and six 2-index formulations for time variables. All formulations have their counterpart with sequence linking constraints and flow conservation constraints (4 of each). The first two formulations with 3-index for time variables (S1 and F1) are used to compare with the first two 2-index formulations (S2 and F2) to assess the difference in resolution performance between using 2-index and 3-index variables for accounting time. F3 and S3 explore the difference in resolution performance from reducing interruption time variables. F4 and S4 explore the difference in resolution performance from reducing sequencing variables. Formulations using both flow conservation constraints and sequence linking constraints (F and S) for each formulation variant (1,2,3,4) allow for a broader comparison between all different alternatives. To the best of our knowledge, using flow conservation constraints for sequencing has not been attempted before in job shop-like problems. Sequence linking constraints are also a novelty that has been invented for this experiment and will be tested for the first time. Results can also be analyzed from another point of view. It can be seen as the cost of integration in terms of resolution performance. For instance, comparing the results of S4 and F4 to the results of S3 and F3 allows for analyzing what are the costs in terms of resolution performances to integrate travel times for workers between operations at different workstations.

Common sets, parameters, and variables

Here is the list of sets and parameters that are present in all formulation variants of the problem. Note that to the real set of jobs that need to be executed in the shop, the formulation adds a subset of dummy jobs (with a processing time of zero) to allow the right accountability of time at the beginning and end of the schedule at every resource. The general sets of parameters are as follows:

Sets:

I: Set of jobs to be scheduled (including dummy jobs)
I_{real}: Subset of real jobs from customers (excluding dummy jobs)
I_{start}: Set of dummy jobs to be completed at the start of the schedule
I_{end}: Set of dummy jobs to be completed at the end of the schedule
J_i: Set of operations to be completed for the job i
K: Set of available workstations
L: Set of available workers
V_k: Set of available speeds for the workstation k

Parameters:

p_{ijklv}: Processing time of the operation $j \in J_i$ of the job $i \in I$ at the workstation $k \in K$ at speed $v \in V_k$ by a worker $l \in L$

a_{ijhgkl}: set-up time executed by a worker $l \in L$ and required to pass from the operation $j \in J_i$ of a job $i \in I$ to the operation $g \in J_h$ of a job $h \in I$ at the workstation $k \in K$

d_k: the time required to start the relevant equipment at a workstation $k \in K$, making the workstation pass from off state to processing state

π_{ijkv}: power consumption during the processing time of the operation $j \in J_i$ of a job $i \in I$ at a workstation $k \in K$ at speed $v \in V_k$

α_{ijhgk}: power consumption during the set-up time of a workstation $k \in K$ to be ready to process the operation $g \in J_h$ of a job $h \in I$ after the operation $j \in J_i$ of a job $i \in I$

δ_k: power consumption during the starting time of the relevant equipment at a workstation $k \in K$ (when passing from off to processing state)

β_k: power consumption during idle time at a workstation $k \in K$

φ_{kv}: pace of work at a workstation $k \in K$ at speed $v \in V_k$

M: a big number

Sequence and allocation variables

x_{ijklv}: Jobs allocation variables. Binary decision of executing (or not) the operation $j \in J_i$ of a job $i \in I$ at a workstation $k \in K$ by a worker $l \in L$ at a speed $v \in V_k$

y_{ijhgkl}: On/Off variables. Binary decision variable of having to turn on (or not) a workstation $k \in K$ by a worker $l \in L$ after the operation $j \in J_i$ of a job $i \in I$ and before the operation $g \in J_h$ of a job $h \in I$

w_{ijhgkl}: Sequencing variables at the workstation. Binary decision of executing (or not) the operation $g \in J_h$ of a job $h \in I$ at a workstation $k \in K$ by a worker $l \in L$ after the operation $j \in J_i$ of a job $i \in I$ at the same workstation $k \in K$. This variable set shows the workstation sequence, noting that worker $l \in L$ is not necessarily the one doing operation $j \in J_i$ of job $i \in I$. The same operation $j \in J_i$ of a job $i \in I$ cannot precede itself to the extent that w_{ijijkl} does not exist.

$u_{qrmijkl}$: Worker sequencing variables. Binary decision of having a worker $l \in L$ process the operation $j \in J_i$ of a job $i \in I$ at a workstation $k \in K$ after processing the operation $r \in J_q$ of a job $q \in I$ at a workstation $m \in K$. This allows to model the sequence of operations that are executed by workers around the shop. Notice that the same operation $j \in J_i$ of a job $i \in I$ cannot precede itself to the extent that $u_{ijmijkl}$ does not exist.

Time calculation and workload variables

b_{ijhgk}: Idle Time Variable. Continuous variable to count the idle time spent after the operation $j \in J_i$ of a job $i \in I$ and before the operation $g \in J_h$ of a job $h \in H$ at a workstation $k \in K$

n_{ijhgk}: Off Time Variable. Continuous variable to count the off time spent after the operation $j \in J_i$ of a job $i \in I$ and before the operation $g \in J_h$ of a job $h \in H$ at a workstation $k \in K$

$cmax$: Total completion time. Continuous variable representing the total completion time of the last job $i \in I$ completed. $cmax = \max_{i \in I} c_i$

c_i: Job completion time. Continuous variable representing the completion time of the last operation $j \in J_i$ to be completed for a job $i \in I$

s_{ijk}: Operation start time variable. Continuous variable representing the starting time of the operation $j \in J_i$ of a job $i \in I$ at workstation $k \in K$

c_{ijk}: Operation completion time. Continuous variable representing the completion time of the operation $j \in J_i$ of a job $i \in I$ at workstation $k \in K$

t_l: Worker workload. Continuous variable representing the total amount of work completed by a worker $l \in L$ during the planning horizon.

$intmax$: Intensity variable. Continuous variable representing the maximum workload. It states the total amount of work completed by the worker who worked the most. $intmax = \max_{l \in L} t_l$

3.2.1 3-index with flow conservation constraints (F1)

Using the sets, parameters and variables described in Section 0, the 3-index formulation is defined by the minimization of the three-part objective function (Z1, Z2 and Z3) subject to constraints (1) to (29)

Z1 $$Min\ cmax \tag{Z1}$$

Z2 $$Min\ intmax \tag{Z2}$$

Z3 $$\begin{aligned} Min \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{l \in L} \sum_{v \in V_k} \pi_{ijkv} p_{ijklv} x_{ijklv} \\ + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} \beta_k b_{ijhgk} \\ + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} \sum_{l \in L} \delta_k d_k y_{ijhgkl} \\ + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} \sum_{l \in L} \alpha_{ijhgk} a_{ijhgkl} w_{ijhgkl} \end{aligned} \tag{Z3}$$

Subject to :

$$\sum_{k \in K} \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} = 1 \qquad \forall\, i \in I, j \in J_i \tag{1}$$

$$s_{ijk} + c_{ijk} \le M \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} \qquad \forall\, i \in I, j \in J_i, k \in K \tag{2}$$

$$\sum_{k \in K} s_{ijk} \ge \sum_{k \in K} c_{ij-1k} \qquad \forall\, i \in I, j = 2, \dots, |J_i| \tag{3}$$

$$\begin{aligned} c_{ijk} \ge s_{ijk} + \sum_{l \in L} \sum_{v \in V_k} p_{ijklv} x_{ijklv} - M \Big(1 \\ - \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} \Big) \end{aligned} \qquad \forall\, i \in I, j \in J_i, k \in K \tag{4}$$

$$\begin{aligned} c_{ijk} \le s_{ijk} + \sum_{l \in L} \sum_{v \in V_k} p_{ijklv} x_{ijklv} - M \Big(1 \\ - \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} \Big) \end{aligned} \qquad \forall\, i \in I, j \in J_i, k \in K \tag{5}$$

$$c_{ijk} \leq 0 \qquad \forall\, i \in I_{start}, j \in J_i, k \in K \tag{6}$$

$$s_{hgk} \geq c_{ijk} + b_{ijhgk} + n_{ijhgk} + d_k \sum_{l \in L} y_{ijhgkl} + \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{k \in K} \sum_{l \in L} w_{ijhgkl}\right) \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K \tag{7}$$

$$s_{hgk} \leq c_{ijk} + b_{ijhgk} + n_{ijhgk} + d_k \sum_{l \in L} y_{ijhgkl} + \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{k \in K} \sum_{l \in L} w_{ijhgkl}\right) \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K \tag{8}$$

$$s_{hgk} \geq c_{ijk} - M\left(1 - \sum_{v \in V_k} \sum_{l \in L} x_{ijklv}\right) - M\left(1 - \sum_{v \in V_k} \sum_{l \in L} x_{hgklv}\right) \qquad \forall\, h \in I_{end}, g \in J_h, i \in I, j \in J_i, k \in K \tag{9}$$

$$\sum_{k \in K} s_{hgk} \geq \sum_{k \in K} c_{ijk} - M\left(1 - \sum_{k \in K} \sum_{v \in V_k} x_{ijklv}\right) - M\left(1 - \sum_{k \in K} \sum_{v \in V_k} x_{hgklv}\right) \qquad \forall\, h \in I_{end}, g \in J_h, i \in I, j \in J_i, l \in L \tag{10}$$

$$\sum_{i \in I} \sum_{j \in J_i} w_{ijhgkl} \leq \sum_{v \in V_k} x_{hgklv} \qquad \forall\, h \in I, g \in J_h, k \in K, l \in L \tag{11}$$

$$\sum_{h \in I} \sum_{g \in J_h} \sum_{l \in L} w_{ijhgkl} \leq \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} \qquad \forall\, i \in I, j \in J_i, k \in K \tag{12}$$

$$\sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} w_{ijhgkl} = \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} w_{hgijkl} \qquad \forall\, h \in I_{real}, g \in J_h, k \in K \tag{13}$$

$$\sum_{h \in I} \sum_{g \in J_h} \sum_{l \in L} w_{ijhgkl} \geq \sum_{l \in L} \sum_{v \in V_k} x_{ijklv} \qquad \forall\, i \in I_{real}, j \in J_i, k \in K \tag{14}$$

$$s_{hgk} \geq c_{qrm} + d_k \sum_{i \in I} \sum_{j \in J_i} \sum_{l \in L} y_{ijhgkl} + \sum_{i \in I} \sum_{j \in J_i} \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{l \in L} u_{qrmhgkl}\right) \quad \forall\, q \in I, r \in J_q, m \in K, h \in I, g \in J_h, k \in K \tag{15}$$

$$\sum_{q \in I} \sum_{r \in J_q} \sum_{m \in K} u_{qrmijkl} \leq \sum_{v \in V_k} x_{ijklv} \quad \forall\, i \in I, j \in J_i, k \in K, l \in L \tag{16}$$

$$\sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} u_{qrmijkl} \leq \sum_{v \in V_m} x_{qrmlv} \quad \forall\, q \in I, r \in J_i, m \in K, l \in L \tag{17}$$

$$\sum_{q \in I} \sum_{r \in J_q} \sum_{m \in K} \sum_{k \in K} u_{qrmijkl} = \sum_{q \in I} \sum_{r \in J_q} \sum_{m \in K} \sum_{k \in K} u_{ijkqrml} \quad \forall\, i \in I_{real}, j \in J_i, l \in L \tag{18}$$

$$\sum_{i \in I} \sum_{j \in J_h} \sum_{k \in K} u_{qrmijkl} \geq \sum_{v \in V_m} x_{qrmlv} \quad \forall\, q \in I_{real}, r \in J_q, m \in K, l \in L \tag{19}$$

$$b_{ijhgk} + n_{ijhgk} \leq M\left(\sum_{l \in L} w_{ijhgkl}\right) \quad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K \tag{20}$$

$$y_{ijhgkl} \leq w_{ijhgkl} \quad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{21}$$

$$n_{ijhgk} \leq M\left(\sum_{l \in L} y_{ijhgkl}\right) \quad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K \tag{22}$$

$$y_{ijhgkl} = w_{ijhgkl} \quad \forall\, i \in I_{start}, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{23}$$

$$cmax \geq c_i \quad \forall\, i \in I \tag{24}$$

$$intmax \geq t_l \quad \forall\, l \in L \tag{25}$$

$$c_i \geq \sum_{k \in K} c_{ijk} \quad \forall\, i \in I, j \in J_i \tag{26}$$

$$t_l \geq \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{v \in V_k} \varphi_{kv} p_{ijklv} x_{ijklv} + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} d_k y_{ijhgkl} + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} a_{ijhgkl} w_{ijhgkl} \qquad \forall\, l \in L \tag{27}$$

$$c_i \geq 0 \qquad \forall\, i \in I \tag{28}$$

$$t_l \geq 0 \qquad \forall\, l \in L \tag{29}$$

$$s_{ijk}, c_{ijk} \geq 0 \qquad \forall\, i \in I, j \in J_i, k \in K \tag{30}$$

$$n_{ijhgk}, b_{ijhgk} \geq 0 \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K \tag{31}$$

$$x_{ijklv} \in \{0,1\} \qquad \forall\, i \in I, j \in J_i, k \in K, l \in L, v \in V_k \tag{32}$$

$$w_{ijhgkl}, y_{ijhgkl} \in \{0,1\} \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{33}$$

$$u_{qrmijkl} \in \{0,1\} \qquad \forall\, q \in I, r \in J_q, m \in K, i \in I, j \in J_i, k \in K, l \in L \tag{34}$$

Constraints (1) to (6) define resource capacity and core time variables relationship for the entire schedule. Constraint (1) ensures a unique allocation between operations, jobs workstations and workers. It forces that exactly one workstation $k \in K$, one processing speed $v \in V_k$ and one worker $l \in L$ is selected to process each operation $j \in J_i$ of every job $i \in I$. Constraint (2) ensures that the starting time and the completion time of an operation $j \in J_i$ of a job $i \in I$ at a workstation $k \in K$ is equal to zero unless that operation $j \in J_i$ of a job $i \in I$ is scheduled at that workstation $k \in K$. Constraint (3) ensures that, for all operations $j \in J_i$, except the first operation, of each job $i \in I$, because it does not have a previous operation, an operation $j \in J_i$ of a job $i \in I$ can only start after its previous operation $j - 1 \in J_i$ of the same job $i \in I$ is completed.

Constraints (4) and (5) allow the exact calculation of operations starting and completion times. Constraint (4) ensures that, for all operations $j \in J_i$ of every job $i \in I$ at every workstation $k \in K$, if an operation $j \in J_i$ of a job $i \in I$ is to be processed at a workstation $k \in K$, its completion time must be at least as big as its starting time plus its processing time at that workstation $k \in K$. Constraint (5) ensures equality to its starting time plus its processing time at that workstation $k \in K$. When the operation is scheduled at a workstation $k \in K$, its completion time must be exactly equal to its starting time plus its processing time.

Through these two constraints, it is desired to ensure that a workstation is always in a state until the end of its intended work. By always forcing an equality between two operations, even if those are not processed at the same workstation, the model would be unsolvable because the value of the starting and completion time of operations not done at a specific workstation must be zero according to constraint (2). Otherwise, if equality is not enforced, nothing ensures that a state is given to the workstation right after the end of the processing time. The workstation could be in no state at all for a certain period which does not exist and is not logical in the model.

Constraint (6) ensures that, for all operations $j \in J_i$ of every job $i \in I_{start}$ at every workstation $k \in K$, the completion time is less or equal to 0.

Constraints (7) to (14) define the sequencing of jobs for workstations including interruption times and starting times. Constraints (7) ensures that, if two jobs follow one another at a workstation, the difference between the starting time of the preceding operation and the completion time of the next operation at the same workstation is not less than the sum of the time spent idle or off between operations, the set-up time and the starting time if it is necessary.

Constraint (8) ensures that, if two jobs follow one another at a workstation, the difference between the starting time of the next operation and the completion time of the preceding operation is not bigger than the sum of the time spent idle or off between operations, the set-up time and the starting time if it is necessary.

Together, constraints (7) and (8) define an equality but only when two operations are processed immediately successively by the same resources. Forcing this equality on two operations not processed successively or by the same resources would make the problem unsolvable.

Without constraint (8), nothing would force a workstation to be in one of the listed states. In fact, being in a state has a negative impact on the objective because it consumes energy or requires eventually consuming time and energy to restart. Constraint (8) forces the model to declare time in one of the defined states. Otherwise, the model would tend to not declare a state at all during that period to not suffer the negative impact of consuming energy in a processing or idle state or having to spend energy and time to restart equipment.

Constraint (9) ensures that, for all operation $g \in J_h$ of a dummy at the end job $h \in I_{end}$, if it is done at the same workstation $k \in K$ as another operation $j \in J_i$ of a job $i \in I$, then it only starts after the real operation finishes.

Constraint (10) ensures that, for all operation $g \in J_h$of a dummy at the end job $h \in I_{end}$ if it is done by the same worker $l \in L$ as another operation $j \in J_i$ of a job $i \in I$, then it only starts after the real operation finishes.

Constraint (11) ensures, for all next operations $g \in G_h$ of every next job $h \in I$, for all workstations $k \in K$ and for all workers $l \in L$, that: 1) at most as many operations $j \in J_i$ of a job $i \in I$ can be selected as there are next operations $g \in G_h$ of a next job $h \in I$ processed at a workstation $k \in K$ and done by a worker $l \in L$; and 2) a next operation $g \in G_h$ of a next job $h \in I$ processed at a workstation $k \in K$ and done by a worker $l \in L$ can only follow an operation $j \in J_i$ of a job $i \in I$ if it is to be processed at that specific workstation $k \in K$ and to be done by that specific worker $l \in L$.

Constraint (12) ensures, for all operations $j \in J_i$ of every job $i \in I$ at every workstation $k \in K$, that: 1) at most as many next operations $g \in G_h$ of a next job $h \in I$ processed at by a worker $l \in L$ can be selected as there are operations $j \in J_i$ of a job $i \in I$ processed at a workstation $k \in K$; and 2) an operation $j \in J_i$ of a job $i \in I$ processed at a workstation $k \in K$ can only be before a next operation $g \in G_h$ of a next job $h \in I$ processed at by a worker $l \in L$ if it is to be processed at that specific workstation $k \in K$.

Constraint (13) ensures that, for all next operations $g \in J_h$ of a real job $h \in I_{real}$ done at a workstation $k \in K$ by a worker $l \in L$, there exists the same operation $g \in G_h$ of a real job $h \in I_{real}$ done at that same workstation $k \in K$ as a previous operation of another operation done by the same or another worker $l \in L$ at the same workstation $k \in K$. In short, this flow conservation constraint ensures that all operations of a job $i \in I_{real}$ must be both the next operation of another one at workstation $k \in K$ as well as the previous operation of another one at that same workstation $k \in K$.

Constraint (14) ensures that, for all operations $j \in J_i$ of a real job $i \in I_{real}$ processed at a workstation $k \in K$ that same operation $j \in J_i$ of a real job $i \in I_{real}$ done at that same workstation $k \in K$ exists as a previous operation of another one done at that same workstation $k \in K$. In short, if the operation $j \in J_i$ of a real job $i \in I_{real}$ is scheduled at a workstation $k \in K$, then it must be a part of the sequence of operation for workstation $k \in K$ and we ensure that by enforcing that it exists as a previous operation somewhere in the sequence.

Constraints (15) to (19) define the sequence for workers including starting times. Constraint (15) ensures that, for all previous operations $r \in J_q$ of every previous job $q \in I$ at every workstation $m \in K$ and for all operations $g \in G_h$ of every job $h \in I$ at every workstation $k \in K$, if an operation $r \in J_q$ of a job $q \in I$ at a workstation $m \in K$ precedes an operation $g \in G_h$ of a job $h \in I$ at the workstation $k \in K$ no matter the worker, the difference between the starting time of the operation $g \in G_h$ of a job $h \in I$ at the workstation $k \in K$ must be at least as big as the completion time of the operation $r \in J_q$ of a job $q \in I$ at a workstation $m \in K$ that precedes it plus the time to turn on relevant equipment at workstation $k \in K$ if necessary before operation $g \in G_h$ of a job $h \in I$ and the set-up time required before operation $g \in G_h$ of a job $h \in I$ at workstation $k \in K$.

Constraint (16) ensures, for all operations $j \in J_i$ of every job $i \in I$, for all workstations $k \in K$ and for all workers $l \in L$, that: 1) at most as many previous operations $r \in J_q$ of a previous job $q \in I$ processed at a previous workstation $m \in K$ by a worker $l \in L$ as there are operations $j \in J_i$ of a job $i \in I$ processed at the workstation $k \in K$ and by the same worker $l \in L$; and 2) an operation $j \in J_i$ of a job $i \in I$ processed at workstation $k \in K$ and by a worker $l \in L$ can only be after an operation $r \in J_q$ of a job $q \in I$ processed at workstation $m \in K$ by the same worker $l \in L$ if it is to be processed at that specific workstation $k \in K$ by that specific worker $l \in L$.

Constraint (17) ensures, for all previous operations $r \in J_q$ of every previous job $q \in I$, for all previous workstation $m \in K$ and for all workers $l \in L$, that: 1) at most as many operations $j \in J_i$ of a job $i \in I$ processed at a workstation $k \in K$ by a worker $l \in L$ as there are previous operations $r \in J_q$ of a previous job $q \in I$ processed at a previous workstation $m \in K$ by the same worker $l \in L$, and 2) a previous operation $r \in J_q$ of a job $q \in I$ processed at workstation $m \in K$ by worker $l \in L$ can only precede an operation $j \in J_i$ of a job $i \in I$ processed at workstation $k \in K$ and by the same worker $l \in L$ if it is to be processed at that specific workstation $k \in K$ by that specific worker $l \in L$.

Constraint (18) ensures that, for all next operations $j \in J_i$ of a real job $i \in I_{real}$ done by a worker $l \in L$, there exists the same operation $j \in J_i$ of a real job $i \in I_{real}$ done by the same worker $l \in L$ as a previous operation of another operation done by the same or another worker $l \in L$.

Constraint (19) ensures that, all operations $r \in J_q$ of a real job $q \in I_{real}$ processed at a workstation $m \in K$ and by a worker $l \in L$ are the previous operations of another one scheduled for the same worker $l \in L$.

Constraints (20) to (23) define the relationship between interruption times. Constraint (20) ensures that, for all operations $j \in J_i$ of every job $i \in I$, for all next operations $g \in G_h$ of every next job $h \in I$ and for all workstations $k \in K$, the idle time between the operation $j \in J_i$ of a job $i \in I$ and the operation $g \in G_h$ of a next job $h \in I$ at a workstation $k \in K$ cannot take a value higher than zero unless the operation $j \in J_i$ of that specific job $i \in I$ precedes the operation $g \in G_h$ of that specific next job $h \in I$ at the workstation $k \in K$.

Constraint (21) ensures that, for all operations $j \in J_i$ of every job $i \in I$, for all next operations $g \in G_h$ of every next job $h \in I$, for all workstations $k \in K$ and for all workers $l \in L$, needing to start relevant equipment between an operation $j \in J_i$ of a job $i \in I$ and an operation $g \in G_h$ of a next job $h \in I$ at a workstation $k \in K$ can only be required if the operation $j \in J_i$ of that specific job $i \in I$ precedes the operation $g \in G_h$ of that specific next job $h \in I$ at the workstation $k \in K$.

Constraint (22) ensures that, for all operations $j \in J_i$ of every job $i \in I$, for all next operations $g \in G_h$ of every next job $h \in I$ and for all workstations $k \in K$, the time spent off at a workstation $k \in K$ between an operation $j \in J_i$ of a job $i \in I$ and an operation $g \in G_h$ of a next job $h \in I$ can only take a value higher than zero if it is required to turn back on the workstation $k \in K$ between an operation $j \in J_i$ of a job $i \in I$ and an operation $g \in G_h$ of a next job $h \in I$.

Constraint (23) ensures that, for all operations $j \in J_i$ of every job $i \in I_{start}$, for all next operations $g \in G_h$ of every next job $h \in I$, for all workstations $k \in K$ and for all workers $l \in L$, if an operation $j \in J_i$ of a job $i \in I$ precedes an operation $g \in G_h$ of a next job $h \in I$ done by a worker $l \in L$ at the same workstation $k \in K$, it is mandatory to start the relevant equipment between those two operations at that same workstation and by the same worker that is to process the next operation $g \in G_h$ of the next job $h \in I$.

Constraints (24) to (27) define the minimum thresholds for objectives. Constraint (24) ensures that the makespan $cmax$ is at least as big as the completion time of each job c_i for all jobs $i \in I$.

Constraint (25) ensures that the highest intensity of work $intmax$ is at least as big as the intensity of work t_l for all workers $l \in L$.

Constraint (26) ensures that the completion time c_i of a job $i \in I$ is at least as big as the completion time of each operation c_{ijk} no matter which workstation $k \in K$ is selected for all jobs $i \in I$ and all operations $j \in J_i$.

Constraint (27) ensures that, for all workers $l \in L$, the intensity of work t_l is at least as big as the sum of the total time spent processing jobs by that specific worker adjusted with the pace of work at which the processing occurred, the total time spent starting equipment by that worker and the total time spent setting up workstations to process jobs.

Constraints (28) to (34) define the value intervals for all variables. Constraint (28) to (31) ensure that starting times (s_{ijk}), completion times (c_{ijk}), job completion times (c_i), worker total work intensity (t_l), time spent idle (n_{ijhgk}) and time spent off (b_{ijhgk}) all take non-negative values.

Constraint (33) to (34) ensure that resource allocation variables (x_{ijklv}), workstation sequencing variables (w_{ijhgkl}), worker sequencing variables ($u_{qrmijkl}$) and restarting variables (y_{ijhgkl}) are all binary.

3.2.2 3-index formulation with sequence linking constraints (S1)

To the best of our knowledge, S1 is the first proposition of sequence linking constraints in job-shop problems. Without the flow conservation constraints, dummy jobs at the end are no longer required, hence, constraints (9) and (10) which were used to make sure dummy jobs at the end were only started at the end of a schedule are not used. Furthermore, (14) and (19) are not used in this variant because those forced the precedence variables to take a value for all real operations which was necessary to initiate the flow conservation constraint but, in S1, the precedence variables are directly linked to the allocation variables which makes those previously used constraints unnecessary. Finally, constraints (13) and (18) are replaced with (35) and (36). This means that flow conservation constraints are replaced by sequence linking constraints :

$$\sum_{i\in I}\sum_{j\in J_i}\sum_{h\in I}\sum_{g\in J_h}\sum_{l\in L} w_{ijhgkl} = \sum_{i\in I}\sum_{j\in J_i}\sum_{l\in L}\sum_{v\in V_k} x_{ijklv} - 1 \qquad \forall\, k\in K \tag{35}$$

$$\sum_{q\in I}\sum_{r\in J_q}\sum_{m\in K}\sum_{i\in I}\sum_{j\in J_i}\sum_{k\in K} u_{qrmijkl} = \sum_{i\in I}\sum_{j\in J_i}\sum_{k\in K}\sum_{v\in V_k} x_{ijklv} - 1 \qquad \forall\, l\in L \tag{36}$$

The result is as follows :

Min Z1, Z2 and Z3

Subject to :

(1)-(6), (7)-(8), (11)-(12), (35), (15)-(17), (36), (19), (20)-(23), (24)-(27), (28)-(31), (32)-(34)

(35) and (36) are the new sequence linking constraints that work by calculating exactly how many links between operations there should be for each resource. Doing so will restrict the problem to having exactly as many links as there are operations that precede each other. With constraints (11), (12), (16) and (17), it then becomes impossible to select any operation that did not occur to compute the idle and off times at times that will have less of an impact on makespan.

3.2.3 2-index formulation with flow conservation constraints (F2)

In the 2-index formulations, a simplification is done to reduce the indexes of the time variables. From now on, all following formulation variants, including this one, will have starting times and completion times that do not take into consideration the workstation. This will divide the number of variables for starting times and completion times by K. Starting time will represent the time at which operation $j \in J_i$ of job $i \in I$ started being processed (s_{ij}). Completion time, on the other hand, will represent the time at which operation $j \in J_i$ of job $i \in I$ finished being processed (c_{ij}). This formulation is closer to what can be found in the recent literature. For instance, Li et al. (2022) also had a formulation with 2-index variables for starting and completion times whereas F1 was closer to the basic formulation in Manne (1960). Comparing the results of this formulation with F1 could help determine which one is more efficient when solving sustainable flexible job-shop problems.

This change has numerous implications on the constraints. First, compared to the first formulation variant shown (F1), constraints (2) and (5) are no longer applied because all operations have starting and completion times and, because all completion times are exactly after the sum of the starting time and processing time, the inequality of constraint (4) and (5) can be replaced with an equality. The result is constraint (38). Second, constraints (3), (4), (6)-(10), (15), (26) and (30) have to be replaced with constraints (37)-(46) to adjust the indexes to only i and j instead of i, j and k. Those changes result in the following formulation :

$$s_{ij} \geq c_{ij-1} \qquad \forall\, i \in I, j = 2, \dots, |J_i| \qquad (37)$$

$$c_{ij} = s_{ij} + \sum_{k \in K} \sum_{l \in L} \sum_{v \in V_k} p_{ijklv} x_{ijklv} \qquad \forall\, i \in I, j \in J_i \qquad (38)$$

$$c_{ij} \leq 0 \qquad \forall\, i \in I_{start}, j \in J_i \qquad (39)$$

$$s_{hg} \geq c_{ij} + \sum_{k \in K} b_{ijhgk} + \sum_{k \in K} n_{ijhgk} + \sum_{k \in K} (d_k \sum_{l \in L} y_{ijhgkl}) + \sum_{k \in K} \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{k \in K} \sum_{l \in L} w_{ijhgkl}\right) \quad \forall\, i \in I, j \in J_i, h \in I, g \in J_h \tag{40}$$

$$s_{hg} \leq c_{ij} + \sum_{k \in K} b_{ijhgk} + \sum_{k \in K} n_{ijhgk} + d_k \sum_{k \in K} \sum_{l \in L} y_{ijhgkl} + \sum_{k \in K} \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} + M\left(1 - \sum_{k \in K} \sum_{l \in L} w_{ijhgkl}\right) \quad \forall\, i \in I, j \in J_i, h \in I, g \in J_h \tag{41}$$

$$s_{hg} \geq c_{ij} - M\left(1 - \sum_{v \in V_k} \sum_{l \in L} x_{ijklv}\right) - M\left(1 - \sum_{v \in V_k} \sum_{l \in L} x_{hgklv}\right) \quad \forall\, h \in I_{end}, g \in J_h, i \in I, j \in J_i, k \in K \tag{42}$$

$$s_{hg} \geq c_{ij} - M\left(1 - \sum_{k \in K} \sum_{v \in V_k} x_{ijklv}\right) - M\left(1 - \sum_{k \in K} \sum_{v \in V_k} x_{hgklv}\right) \quad \forall\, h \in I_{end}, g \in J_h, i \in I, j \in J_i, l \in L \tag{43}$$

$$s_{hg} \geq c_{qr} + \sum_{k \in K} (d_k \sum_{i \in I} \sum_{j \in J_i} \sum_{l \in L} y_{ijhgkl}) + \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{m \in K} \sum_{k \in K} \sum_{l \in L} u_{qrmhgkl}\right) \quad \forall\, q \in I, r \in J_q, h \in I, g \in J_h \tag{44}$$

$$c_i \geq c_{ij} \quad \forall\, i \in I, j \in J_i \tag{45}$$

$$s_{ij}, c_{ij} \geq 0 \quad \forall\, i \in I, j \in J_i \tag{46}$$

Resulting in the following formulation :

Min Z1, Z2 and Z3

Subject to :

(1), (37)-(39), (40)-(43), (11)-(14), (44), (16)-(19), (20)-(23), (24)-(25), (45), (27), (28)-(29), (46), (31), (32)-(34)

Those changes mean dividing the number of starting and completion times variables by K, thus also reducing the variables to which the modified constraints have to be applied to. Although it is still to be proven, this change alone could improve the efficiency of the formulation. More specifically, for constraint (38), it means having the completion time of each operation be exactly equal to its starting time plus the processing time. This is now always true because there does not exist a starting and a completion time for all workstations for each operation. In F1 and S1, both constraints (4) and (5) were needed because, when an operation was scheduled at a workstation, the completion time had to be exactly equal to the starting time plus the processing time but, when the operation was not scheduled at a workstation, both constraints needed not to apply because both completion times and starting times needed to take the value of zero in compliance with constraint (2). Forcing that equality would then make the model unsolvable.

3.2.4 2-index formulation with sequence linking constraints (S2)

The changes required to get from F2 to S2 are similar to the ones required to get from F1 to S1. To do so, from formulation F2, constraints (42), (43), (14) and (19) have to be removed and constraints (13) and (18) have to be replaced with (35) and (36).

The resulting formulation becomes:

Min Z1, Z2 and Z3

Subject to :

(1), (37)-(39), (40)-(41), (11)-(12), (35), (44), (16)-(17), (36), (20)-(23), (24)-(25), (45), (27), (28)-(29), (46), (32)-(34)

Those changes serve the same function as the changes required to get from F1 to S1. Replacing the flow conservation constraints used for sequencing by sequence linking constraints.

3.2.5 2-index formulation with flow conservation constraints and interruption times before operations (F3)

In this case, interruption times refer to both off times and idle times. Compared to the previously mentioned 2-index formulation variant with flow conservation constraints (F2), time spent off or idle at a workstation is no longer accounted for as being between operations but before operations instead. It means that the time spent idle or off between operation $j \in j_i$ of job $i \in I$ and operation $g \in J_h$ of job $h \in I$ at a workstation $k \in K$ (n_{ijhgk}, b_{ijhgk}) is now represented by the time spent idle or off before the next operation $g \in J_h$ of job $h \in I$ at workstation $k \in K$ (n_{hgk}, b_{hgk}). The same reasoning applies to the decision of having to start a workstation $k \in K$ between an operation $j \in j_i$ of a job $i \in I$ and an operation $g \in J_h$ of a job $h \in I$ (y_{ijhgkl}). It now becomes the decision of starting a workstation $k \in K$ before an operation $g \in J_h$ of a job $h \in I$ (y_{hgkl}). In this particular context, S2 and all other previous formulations had variables that could account for a workstation being in different states at the same time. Such a quality could be useful if, for a particular shop, it is relevant to consider multiple tools or multiple parts of a complex machine simultaneously in different states for different periods of time for a single workstation. It also might be interesting to have an operation being forcefully interrupted for a while at a specific workstation nearby where another previous operation occurred that might have discharged toxic particles in its vicinity. Thus, to allow interruption times between two operations that are not processed at the same workstation or two operations that do not follow each other. By removing that ability, however, a degree of integration that could be relevant in certain business cases is lost but the number of variables of the problem is significantly decreased. Numerous changes to the constraints must be made to accommodate such updates. First of all, starting from F2, the third objective (Z3) has to be replaced by (Z4) and the constraints (40), (41), (44), (20), (21), (22), (23), (27), (46) and (33) have to be replaced by (47), (48), (49), (50), (51), (52), (53), (54), (55), (56) and (57). All of these serve the same purpose but must be adjusted for the new set of indexes which is smaller than it was in the previous formulation. The result is the following:

$$
\begin{aligned}
Min \sum_{i\in I}\sum_{j\in J_i}\sum_{k\in K}\sum_{l\in L}\sum_{v\in V_k} \pi_{ijkv}p_{ijklv}x_{ijklv} &+ \sum_{h\in I}\sum_{g\in J_h}\sum_{k\in K}\beta_k b_{hgk} \\
&+ \sum_{h\in I}\sum_{g\in J_h}\sum_{k\in K}\sum_{l\in L}\delta_k d_k y_{hgkl} \\
&+ \sum_{i\in I}\sum_{j\in J_i}\sum_{h\in I}\sum_{g\in J_h}\sum_{k\in K}\sum_{l\in L}\alpha_{ijhgk}a_{ijhgkl}w_{ijhgkl}
\end{aligned}
\tag{Z4}
$$

$$
\begin{aligned}
s_{hg} \geq c_{ij} &+ \sum_{k\in K} b_{hgk} + \sum_{k\in K} n_{hgk} \\
&+ \sum_{k\in K}(d_k \sum_{l\in L} y_{hgkl}) \\
&+ \sum_{k\in K}\sum_{l\in L} a_{ijhgkl}w_{ijhgkl} \\
&- M\left(1 - \sum_{k\in K}\sum_{l\in L} w_{ijhgkl}\right)
\end{aligned}
\qquad \forall\, i\in I, j\in J_i, h\in I, g\in J_h
\tag{47}
$$

$$
\begin{aligned}
s_{hg} \leq c_{ij} &+ \sum_{k\in K} b_{hgk} + \sum_{k\in K} n_{hgk} \\
&+ \sum_{k\in K}(d_k \sum_{l\in L} y_{hgkl}) \\
&+ \sum_{k\in K}\sum_{l\in L} a_{ijhgkl}w_{ijhgkl} \\
&+ M\left(1 - \sum_{k\in K}\sum_{l\in L} w_{ijhgkl}\right)
\end{aligned}
\qquad \forall\, i\in I, j\in J_i, h\in I, g\in J_h
\tag{48}
$$

$$
\begin{aligned}
s_{hg} \geq c_{qr} &+ \sum_{k\in K}(d_k \sum_{l\in L} y_{hgkl}) \\
&+ \sum_{i\in I}\sum_{j\in J_i}\sum_{k\in K}\sum_{l\in L} a_{ijhgkl}w_{ijhgkl} \\
&- M\left(1 - \sum_{m\in K}\sum_{k\in K}\sum_{l\in L} u_{qrmhgkl}\right)
\end{aligned}
\qquad \forall\, q\in I, r\in J_q, h\in I, g\in J_h
\tag{49}
$$

$$
b_{hgk} + n_{hgk} \leq M\left(\sum_{i\in I}\sum_{j\in J_i}\sum_{l\in L} w_{ijhgkl}\right) \qquad \forall\, h\in I, g\in J_h, k\in K
\tag{50}
$$

$$
y_{hgkl} \leq \sum_{i\in I}\sum_{j\in J_i} w_{ijhgkl} \qquad \forall\, h\in I, g\in J_h, k\in K, l\in L
\tag{51}
$$

$$n_{hgk} \leq M\left(\sum_{l \in L} y_{hgkl}\right) \qquad \forall\, h \in I, g \in J_h, k \in K \tag{52}$$

$$y_{hgkl} \geq w_{ijhgkl} \qquad \forall\, i \leq K \in I, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{53}$$

$$t_l \geq \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{v \in V_k} \varphi_{kv} p_{ijklv} x_{ijklv} + \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} d_k y_{hgkl} + \sum_{i \in I} \sum_{j \in J_i} \sum_{h \in I} \sum_{g \in J_h} \sum_{k \in K} a_{ijhgkl} w_{ijhgkl} \qquad \forall\, l \in L \tag{54}$$

$$n_{hgk}, b_{hgk} \geq 0 \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{55}$$

$$y_{hgkl} \in \{0,1\} \qquad \forall\, h \in I, g \in J_h, k \in K, l \in L \tag{56}$$

$$w_{ijhgkl} \in \{0,1\} \qquad \forall\, i \in I, j \in J_i, h \in I, g \in J_h, k \in K, l \in L \tag{57}$$

F3 would minimize the following objectives subject to the following constraints:

Min Z1, Z2 and Z4

Subject to :

(1), (37)-(39), (47)-(48), (42)-(43), (11)-(14), (49), (16)-(19), (50)-(53), (24)-(25), (45), (54), (28)-(29), (46), (55), (32), (56)-(57), (34)

All constraints serve the same purpose as in previous formulations. However, comparing the performance of F3 and S3 with F2 and S2 will give some idea about the difference in efficiency for business cases in which workstations might be in different states, in which interruption times are required between operations done at different workstations or in which interruption times are required between operations that do not follow each other. Therefore, the modifications on constraints imply adapting the indexes of the modified variables to the constraints (40), (41), (44), (20), (21), (22), (23), (27), (46) and (33).

3.2.6 2-index formulation without flow conservation constraints and interruption times before operations (S3)

This formulation applies the same changes enumerated in the section on the 3-index formulation with sequence linking constraints (S1) to the previously mentioned formulation variant (F3). The resulting formulation would then be S3. Starting from F3, once again it is required to remove constraints (42), (43), (14) and (19) and to replace (13) and (18) with (35) and (36) to get S3.

Formulation S3 is as follows :

Min Z1, Z2 and Z4

Subject to :

(1), (37)-(39), (47)-(48), (11)-(12), (35), (49), (16)-(17), (36), (50)-(53), (24)-(25), (45), (54), (28)-(29), (46), (55), (32), (56)-(57), (34)

Comparing the performances of F3 with S3 will give insights into the difference in resolution performances between the use of flow conservation constraints compared to the use of the new sequence linking constraints.

3.2.7 2-index formulation with flow conservation constraints, interruption times before operations and simplified worker sequence variables (F4)

Compared to the last formulation variant with flow conservation constraints mentioned (F3), this one seeks to simplify the worker sequencing variables. Instead of considering that a worker $l \in L$ does an operation $j \in J_i$ of a job $i \in I$ at a workstation $k \in K$ after processing an operation $r \in J_q$ of a job $q \in I$ at a workstation $m \in K$ ($u_{qrmijkl}$), it considers that a worker $l \in L$ does an operation $j \in J_i$ of a job $i \in I$ after processing an operation $r \in J_q$ of a job $q \in I$ (u_{qrijl}). Again, at the expense of integration, the number of variables is decreased. The variable $u_{qrmijkl}$ computed from which workstation a worker came and to which one that worker is headed. Such information allows for computing travel times without losing linearity if needed. To lose such ability allows for having a formulation with fewer variables which may make the formulation more efficient during resolution. Numerous changes to the constraints must be made to accommodate such updates. Starting with the previously presented formulation variant with flow conservation constraints (F3), constraints (49), (16), (17), (18), (19) and (34) are replaced with (58), (59), (60), (61), (62) and (63) :

$$s_{hg} \geq c_{qr} + \sum_{k \in K} (d_k \sum_{l \in L} y_{hgkl}) + \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{l \in L} a_{ijhgkl} w_{ijhgkl} - M\left(1 - \sum_{l \in L} u_{qrhgl}\right) \quad \forall\, q \in I, r \in J_q, h \in I, g \in J_h \tag{58}$$

$$\sum_{q \in I} \sum_{r \in J_q} u_{qrijl} \leq \sum_{k \in K} \sum_{v \in V_k} x_{ijklv} \quad \forall\, i \in I, j \in J_i, l \in L \tag{59}$$

$$\sum_{i \in I} \sum_{j \in J_i} u_{qrijl} \leq \sum_{k \in K} \sum_{v \in V_k} x_{qrklv} \quad \forall\, q \in I, r \in J_q, l \in L \tag{60}$$

$$\sum_{q \in I} \sum_{r \in J_q} u_{qrijl} = \sum_{q \in I} \sum_{r \in J_q} u_{ijqrl} \quad \forall\, i \in I_{real}, j \in J_i, l \in L \tag{61}$$

$$\sum_{i \in I} \sum_{j \in J_h} u_{qrijl} \geq \sum_{k \in K} \sum_{v \in V_m} x_{qrklv} \quad \forall\, q \in I_{real}, r \in J_q, l \in L \tag{62}$$

$$u_{qrijl} \in \{0,1\} \quad \forall\, q \in I, r \in J_q, i \in I, j \in J_i, l \in L \tag{63}$$

F4 is then as follows:

Min Z1, Z2 and Z4

Subject to :

(1), (37)-(39), (47)-(48), (42)-(43), (11)-(14), (58)-(62), (50)-(53), (24)-(25), (45), (54), (28)-(29), (46), (55), (32), (56)-(57), (63)

All constraints still serve the same purpose but are adapted to do so using a worker sequencing variable with fewer indexes. However, losing the ability to have variables ready to integrate travel times for resources without losing linearity allows for a formulation with fewer variables which may influence the solver's capability.

3.2.8 2-index formulation without flow conservation constraints, interruption times before operations and simplified worker sequence variables (S4)

Compared to its variant with flow conservation constraints (F4), this variant can be formulated by applying all the same changes mentioned earlier to formulation F4 except for constraint (61). Instead, constraint (61) must be replaced by constraint (64). Both constraints serve the same purpose, but the indexes have to be adapted with the change of variable :

$$\sum_{q \in I} \sum_{r \in J_q} \sum_{i \in I} \sum_{j \in J_i} u_{qrijl} = \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{v \in V_k} x_{ijklv} - 1 \quad \forall\, l \in L \tag{64}$$

Therefore, starting with F4, S4 would be obtained by removing constraints (42), (43), (14) and (62) and replacing (13) and (61) with (35) and (64).

Formulation S4 would then include the following objectives and constraints:

Min Z1, Z2 and Z4

Subject to :

(1), (37)-(39), (47)-(48), (11)-(12), (35), (58)-(60), (64), (50)-(53), (24)-(25), (45), (54), (28)-(29), (46), (55), (32), (56)-(57), (63) The resulting formulation is S4. Constraint (61) had to be modified considering the fact that the same amount of information, meaning the allocation and sequencing of jobs to workers, had to be computed through fewer variables which meant adapting the summations to fewer indexes.

CHAPTER 4
NUMERICAL EXPERIMENTS

This chapter is dedicated to testing the performance and quality of the eight different formulations made in the previous chapter. This chapter will now describe the process used to generate random instances of the problem. Those instances will then be used to compare the efficiency of the different formulations of the problem, first, in a preliminary study and, afterward, in an exhaustive study in hopes of differentiating the performances of the best formulations from each other. Finally, using the formulation of the problem that performed best in the previous tests, the last part of the chapter is dedicated to showing how pareto optimal solutions may be approximated by solving formulations previously proposed. The analysis of the set of approximated pareto optimal solutions for all instances will reveal the relationship between the three objectives.

4.1 Resolution method

The SFJSSP* is a multi-objective optimization problem and many resolution methods could be used to solve it. For instance, the epsilon-constrained (ε-constrained) method minimizes one objective while the others are included in constraints bound by ε. Such method can find all pareto optimal solutions including solutions part of a non-convex solution space. Because the multi-objective problem is turned into a single-objective one, it is also used with widely known effective single objective optimization methods such as the simplex algorithm. However, its effectiveness depends on associating the right values to ε. In the case of a problem never studied before with new instances never solved, being able to associate effective values to ε to find pareto optimal solutions effectively is a complex task. On the other hand, for a first study on a relatively unknown problem, a simpler resolution method is more appropriate. Moreover, in the case of this thesis, because the contribution is mainly about the formulation aspect of the problem, it was not a priority to develop efficient heuristics and, instead, the weighted sum using Gurobi as the solver was applied. The weighted sum is one of the simplest multi-objective resolution methods. It works by concatenating all objectives within a single objective while assigning weights to each objective. This allows a problem to be solved with efficient single-objective resolution methods such as the simplex algorithm. In Marler and Arora (2010), it is explained that if all weights are positive and none are equal to zero, this resolution method finds pareto optimal solutions when solved to optimality. However, the weighted sum also has its drawbacks. For instance, it cannot find pareto optimal solutions that are not part of the convex domain of the pareto front. In short, there are some pareto optimal solutions that might never be found using that method no matter which weights are applied. Even with such drawbacks, considering the studied problem is unknown, the simplicity of the weighted sum and the opportunity to use it with efficient single objective resolution methods, it was still preferred over other resolution methods.

The main objective of the preliminary and extensive study was to gather data on the resolution performance of the eight different formulations. The goal was to identify the formulation with the best performances for solving the randomly generated instances and to approximate pareto optimal solutions by solving each instance multiple times with the best performing formulation once it is identified. Apart from exploring the relative performances of all eight formulations, the preliminary and extensive study served another purpose. It was used to get some data on the relative size of each objective compared to one another. This is important because, different objectives expressed in different units may show a big difference between one another that can be hard to offset with weights. To make sure that weights stay effective, objectives must be converted on an equivalent basis. To do so, the weights were given a value of one and the conversion factor was also given a value of one for the preliminary and extensive study to gather data that could be used to set weights and conversion factors for the next experiments. Therefore, the weighted-sum method with an equal weight of one and a conversion factor of one for each objective was used in the preliminary and extensive study. Using this method, our three objective functions Z1, Z2 and Z3 for F1, S1, F2 and S2 become one single objective as follows :

$$\tau_1\rho_{1\omega}Z1 + \tau_2\rho_{2\omega}Z2 + \tau_3\rho_{3\omega}Z3$$

For F3, S3, F4 and S4, objective functions Z1, Z2 and Z4 become one single objective as follows :

$$\tau_1\rho_{1\omega}Z1 + \tau_2\rho_{2\omega}Z2 + \tau_3\rho_{3\omega}Z4$$

With only one experiment (ω) per instance, a value of one for each weight ($\rho_{1\omega}$= $\rho_{2\omega}$=$\rho_{3\omega}$=1) and a value of one for each conversion factor (τ_1=τ_2=.τ_3=1).

After the two previous studies namely, the preliminary and extensive studies on resolution time, some data could now be used to estimate the relative magnitude of each objective compared to one another. Indeed, each objective is expressed in different units so, to ensure the weights perform their function accordingly, it was necessary to assign a conversion factor to each objective to equal the playing field between all objectives. If not, objectives expressed in units of greater magnitude would be overrepresented and weights would not serve their purpose of prioritizing certain objectives as effectively as possible. Using the data from the two previous studies, it was found that the objective expressed through the smallest number of units was the minimization of work intensity. Taking that into account, it was decided to bring down all other objectives to its level. In the two previous studies, energy was about 20 times bigger than work intensity and work intensity was about 30% smaller than makespan.

Table 4.1 : Conversion factor for each objective

Energy (τ_1)	Labor intensity (τ_2)	Makespan (τ_3)
0.05	1	0.7

To bring all objectives on a similar basis, work intensity was assigned a conversion factor of one while makespan had a conversion factor of 0.7 and energy had a conversion factor of 0.05.

Weights were established analytically based on what could be a desirable prioritization between the three objectives. Ultimately, only managers can decide what should be prioritized in real production systems, but the weights here were chosen to represent some of the choices they might make. First, no objective can have a weight of zero or parts of the model won’t work properly. Furthermore, to represent the relative importance between objectives, it was chosen that the sum of all weights should always be equal to 1 or 100%. For the model to function properly, it was also necessary that no weights were set to a negative value. Again, according to Marler and Aurora (2010), to obtain a pareto optimal solution through the weighted-sum method, all weights must be positive and none can be equal to zero. Table 4.2 presents all sets of weights used for each experiment.

Table 4.2 : Table of weights for each experiment and each objective

Experiment (ω)	Energy ($\rho_{1\omega}$)	Labor intensity ($\rho_{2\omega}$)	Makespan ($\rho_{3\omega}$)
Experiment 1	98%	1%	1%
Experiment 2	1%	98%	1%
Experiment 3	1%	1%	98%
Experiment 4	33%	33%	33%
Experiment 5	50%	25%	25%
Experiment 6	25%	50%	25%
Experiment 7	25%	25%	50%
Experiment 8	2%	49%	49%
Experiment 9	49%	2%	49%
Experiment 10	49%	49%	2%
Experiment 11	24%	74%	2%
Experiment 12	74%	24%	2%
Experiment 13	2%	74%	24%
Experiment 14	2%	24%	74%
Experiment 15	24%	2%	74%
Experiment 16	74%	2%	24%

Table 4.2 shows the weights for each objective associated with each of the 16 experiments from 1 to 16 for all randomly generated instances. For the sake of reproducibility, any study interested in replicating the results should use the same weights during resolution.

The first three weights were established to see the best objective according to each of the objectives while giving minimal consideration to the other objectives. This allows for trying to find the best solution regarding each objective individually. Then, splitting the weight equally in experiment 4 allows for seeking the best solution when no objective can be prioritized over the other. The next set of weights (experiments 5 to 7) allows for prioritizing one objective while giving the same weight to the other two. Then, the next set (experiments 8 to 10) was used to find a solution that prioritizes two objectives with minimal regard to the other. The final set (experiment 11 to 16) was made to seek the optimal solution for a case in which one objective is the most important one, and in which there is some interest in one other objective while the last objective is of minimal interest.

Thereby, for each experiment (ω), the following weighted-sum equation was minimized :

$\tau_1\rho_{1\omega}Z1 + \tau_2\rho_{2\omega}Z2 + \tau_3\rho_{3\omega}Z4$

4.2 Data description

In the literature review, it was an important point to discuss how the formulation variants were unique compared to what was formulated before in other papers. This feature ensures that this paper has an original contribution to the literature. However, one of the drawbacks of having an original formulation is that there are no benchmark instances with all the specific features required in the problem studied.

To compare the different formulations and to study the results without any access to data from real production systems, it was necessary to develop randomly generated instances. Because most FJSSPs are hard to solve and require heuristics to provide solutions for large problems, all profiles had to be designed on a smaller scale than what such businesses would look like in real life. However, there are indeed real FJSPs in which the total number of jobs processed during a day is low. For instance, the production of luxurious goods or custom goods might be done for lower quantities like the randomly generated instances made for this thesis. Furthermore, even with a lower number of jobs processed during a day, a good schedule of operations might still be important considering that operations may be longer and scheduling errors may be costly.

To test the different formulations, three instance profiles based on flexible job shops inspired by real businesses were designed. To make those profiles, some assumptions about these three real production systems had to be made. The validity of the following analysis mainly comes from solving the same instances, with the same machine and the same resolution algorithm. In short, each of the eight different problem formulations was solved under the same circumstances to isolate all variables except for the change of formulation variants to compare their specific performances solving a set of the same 30 randomly generated instances. Moreover, an attempt was made to make the randomly generated instances realistic, even if access to exact real systems data was scarce.

The first profile is inspired by a custom paint shop. The second one is inspired by a custom guitar shop. Finally, the last one is inspired by a sewing manufacturer for custom-made clothing or garments. Those three shops were chosen to represent all workstation cases: automatic, semi-automatic and manual. The first one is dominated by manual workstations, the second one is dominated by automatic workstations and the last one is dominated by semi-automatic workstations. Although workstation speeds are randomly generated, if a workstation is declared manual, it will automatically only have one available speed. This does not mean that the processing time does not vary with the workers because they have different skills, but it states that, at a manual workstation, a given worker will only have one available and constant speed, representing the best work rhythm they can do. However, the best performance of a worker is not the same as their colleagues.

For each profile, all parameters are randomly generated between a minimum and a maximum value except some parameters that require specific rules, which will be explained.

For all resource and skills, odds are applied for each element in the required set, to model a stochastic process. Said odds are fixed for all instances inside a given profile to properly represent different behaviours. For instance, in a manual profile, the odds of having a worker with no skill for a given station is higher than it would be in an automatic station.

Namely, in a given instance profile, the odds of being manual for a workstation, the odds of being semi-automatic, the odds for a workstation to not be able to process an operation, the odds for a workstation speed to not be able to process an operation, the odds for a worker to not be able to process an operation, the odds for a worker to not be able to use a workstation or the odds for a worker to not be qualified to process operations at specific workstation speeds, are defined as follows. If an element is deemed unable to use a resource or process an operation, its value is set to a big number (999999) to make sure that we do not reduce any possibility through that parameter. For instance, if the odds of being unable to process an operation at a workstation is 7%, it means that for all operations and workstations, a value was rolled randomly with a 7% chance of being inside a certain threshold. If the value is indeed inside that threshold, the operation cannot be processed at that workstation and the processing time for that specific resource will be equal to a big number. If the value is not inside the threshold, then the processing time will be determined randomly within the specified minimum and maximum value of that specific profile.

For speeds, if a worker cannot perform at a certain workstation speed, they will not be able to perform at all other faster speeds available at that specific workstation. The reader must take into consideration that, without many resources, the odds of making an instance infeasible by increasing the odds of having a resource being unable to process one or many operations or not being able to use another resource is quite high. Therefore, such odds must be kept low and must only be increased when it makes sense in the context of the real shops that profiles are inspired by.

For processing times, at an automatic workstation, only the maximum processing time (the processing time at the slowest speed) is randomly generated. For the remaining processing times, for each speed increment, the processing time is twice as fast. This principle means that an operation done at speed 2 will take 50% of the time it took at speed 1. An operation done at speed 3 will take 50% of the time required at speed 2, and so on.

For a semi-automatic workstation, the same rule as the automatic workstation is applied except that the value determined by the automatic workstation rule can vary randomly between an interval of $\pm$ 25% of the automatic processing time. It accounts for the different levels of skill between workers at a workstation where the bottleneck is partly because of the equipment, and partly caused by the worker's skills.

Processing powers at automatic and semi-automatic workstations evolve according to processing speed following a linear function. It means that only two points, in this case, the minimum and the maximum power must be randomly generated. All remaining processing powers for all remaining speeds can be determined linearly between the minimum and maximum processing powers. The starting power is a multiplier of the maximum processing power for each workstation. This multiplier is randomly generated.

For power calculations, what is important is that power is computed using the same unit in an instance and that some rules are followed. Furthermore, although data from real machine tools were not available and used to generate the values for parameters related to power, many considerations inspired by the literature were included. First, the study from Sealy *et al.* (2015) interested in the energy consumption of milling tools used for cutting hard materials shows that processing power at a faster speed must be higher than processing power at a slower speed for all workstations.

However, the material removal rate increased faster with higher speeds than power consumption which resulted in less energy spent per amount of work done when increasing the processing speed. This principle was followed for data generation meaning that, for all speeds, productivity increases were greater than processing power increases for all speed increments. This resulted in less energy consumed by the amount of work done for higher processing speeds. For most remaining parameters, the considerations were inspired by Wu *et al.* (2019). According to the authors, a machine tool consumes less energy in an idle state than in any processing state and a peak power consumption is recorded when starting the machine. The starting power consumption could have been modeled through a constant value only fluctuating by workstation in the case of this thesis but it was instead chosen to model it through the same equation presented before : $Energy = power * time$. A fixed value can also be the result of a product. The equation presented before was only used for consistency with the method of calculation for power consumption of other parameters. Although many means could have worked, it was important, to stay consistent with the literature. Doing so, the starting power consumption was greater than all processing powers of all speeds. Thus, Power expanded during any idle state must be less than power expanded at any processing speed for all workstations and power expanded during the starting time is always bigger than the maximum power expanded during the processing of an operation at all workstations. Finally, although there is energy spent turning off a machine in Wu *et al.* (2019), in this thesis, for all shops modeled, no energy was required to turn off tools at a workstation or while being in that state. This is closer to what can be found in Wei *et al.* (2021) in which no power is required to turn a machine off, and no power is expanded while being in that state.

For each instance generated, a specific French name was assigned. All instance names follow the same pattern. These start with “atelier” which is the French word for shop. Then, it is followed by the denunciation of the profile using the French word associated with each profile. Guitar, sewing and painting become “*guitare*”, “*couture*” and “*peinture*”. Finally, a specific ID is added at the end of all instance names to identify each instance and differentiate it from other instances of the same category.

4.2.1 Custom Paint Shop (Manual Workshop)

Depending on the level of automation and the level of standardization of the paint jobs, one can consider a paint shop as a simple job shop or a flexible job shop. Paint shops for uniform colors on standardized cars would lean more towards a regular job shop or a flow shop. On the other hand, a paint shop that would focus on custom paint jobs with lots of specific characteristics would lean more towards a flexible job shop. In this specific case, the type of paint shop described will be a paint shop in which the focus is on custom paints with operations such as painting, washing, drying or covering parts of the cars that need to be painted or not to be painted on depending on the state of the vehicle upon arrival. Depending on the design and the demand of the clients, some parts of the paint could be done at some point and some other parts might need the car to be dried to finish the design which would mean a drying operation or doing other work while the paint of that specific job dries. In any case, for this specific profile, not many operations were needed because this type of paint shop was seen from a higher level and some integration could be made to simplify the operations and, therefore, the schedule.

Table 4.3 : Custom paint shop parameters intervals

Parameters	Minimum value	Maximum value
Number of jobs	4	5
Number of operations per job	2	3
Number of workstations	3	4
Number of workers	2	3
Number of speeds per workstation	N/A	3
Processing time for a manual workstation	360	600
Maximum processing time	540	600
Power expanded during processing time at the slowest speed	7	10
Power expanded during processing time at the fastest speed	30	40
Power expended during processing time at a manual workstation	7	40
Power expanded in idle state	3	5
Multiplier of the power expanded during the starting time	5	8
Set-up time	30	240
Starting time	45	120

In this specific case, it was thought that a custom paint shop might paint four to five cars a day with two to three operations per car. Three to four workstations are considered enough to paint the cars and with only two to three employees. In such a paint shop, workstations would represent areas in which to do the work. Most areas would be set up for a specific purpose but, for instance, if more cars needed to be painted than washed for that specific day, equipment might always be moved to paint cars in the area that is usually used for another purpose (*i.e.* to wash cars). In such a case, in the data, it would mean a workstation that needs a bigger set-up time or a bigger processing time to process the same job depending on the decision of the worker to get all relevant equipment before the job starts or to only get equipment as required if there are only a few. All of those different cases are taken into account randomly during the creation of the instance through the generation of a random number between a minimum and a maximum for all randomly generated parameters.

Up to 3 speeds that represent the surface area painted or surface area washed are available for each workstation. Most work is done manually although some of it might be done semi-automatically. For instance, a paint gun might be configured to paint on a broader surface area, but it would not mean the worker is faster or slower proportionally with the augmentation or diminution of the surface area. Depending on the level of skill of the worker, the diminution or augmentation of the processing time.

There is always a small chance that, for washing cars or for a simple paint job, a process could be automated with an employee that is present mostly to start and supervise the process. So, the possibility of having an automatic workstation still exists. Working with bigger objects such as cars meant having bigger set-up times to set up or move those between workstations for different operations. Whether it is for washing or painting, start-up times had to be faster than set-up times considering the type of equipment used. However, set-up times could never quite be equal to zero considering that a paint gun or a water hose might have to wait for pressure to be used properly.

For resource skills, in the paint shop, most workstation areas should be able, considering some amount of set-up time, to fulfill most purposes. This means the odds for a workstation to be unable to process an operation are low. If an operation is done at a lower speed, most of the time, because the shop is dominated by manual or semi-automatic workstations, an operation could be done at a higher speed as well. In a mainly manual shop, worker skills are key. That explains why the chance of a worker not being able to process an operation is quite high. The same goes for the odds of having a worker not being able to use a workstation area (although a little lower because most workstations can be repurposed). Then, if a worker can perform at a workstation, most of the time, because most workstations are semi-automatic or manual, they should be able to perform at all its speeds.

4.2.2 Custom guitar shop (Automatic Workshop)

A custom guitar shop is a prime example of flexible job shop where all types of workstations may coexist. There might be some manual labor for some woodwork or for putting strings on guitars. There might be some semi-automatic workstations. For instance, there could be drills that have numerous speeds but, in that specific case, ultimately, the skill of the worker using the tool would be the biggest factor for processing time considering that the worker is the bottleneck. There might also be some parts of the process that are automated as well. For instance, if a first raw cut is done on bigger pieces of wood for shaping the body of the guitar, that is an operation that might be automated with minor supervision from employees. Or, if different serialized or custom parts would still have standard characteristics such as holes placed at the same spot, assembly could still be completely or partially automated. Even if a workstation did not need any supervision from employees, the formulation would not need any changes to solve such an instance and could represent it with minor adjustments. For instance, a dummy employee that processes operations with a processing time equal to a big number at all workstations except the fully automated one would be enough to represent a fully automated workstation.

Although all types of workstations might exist in a custom guitar shop, in the case of this paper, it was thought that such a shop may be dominated by automatic workstations. Depending on the level of customization, clients may order guitars with a unique set of characteristics chosen from predetermined sets of possibilities. It would mean that the process could be partly automated while still requiring to be modeled like a flexible job-shop considering all guitars would be unique. For instance, if clients have the choice between three types of woods for the fingerboard and 12 fingerboard designs, there would already be multiple possibilities of fingerboards without even getting into the other parts of the guitar. Restraining the clients' choice between a couple of options for each piece would allow for a job that can be partly automated. However, it would still give the clients the possibility of coming up with something unique that represents them. In that case, custom guitars would be made with a different choice of standard parts. Producing the different standard parts would require automatic processes while there could be some manual processes for things like putting strings and semi-automatic processes for specific custom demands made by clients.

Table 4.4 : Custom guitar shop parameters intervals

Parameters	Minimum value	Maximum value
Number of jobs	3	3
Number of operations per job	4	6
Number of workstations	3	4
Number of workers	2	3
Number of speeds per workstation	N/A	3
Processing time for a manual workstation	45	480
Maximum processing time	360	480
Power expanded during processing time at the slowest speed	7	10
Power expanded during processing time at the fastest speed	35	45
Power expended during processing time at a manual workstation	7	45
Power expanded in idle state	3	5
Multiplier of the power expanded during the starting time	5	8
Set-up time	0	180
Starting time	30	90

It was thought that custom guitars, requiring more work and being more expensive than fully standardized guitars, would not sell as many copies as cheaper serialized guitars. Such different parts would require more specialized tools. Therefore, there would be fewer jobs per shift. In that case, a total of three custom guitars was selected. Those guitars, having multiple different parts needing assembly, would require more operations. It was thought that four to six operations per job would be enough to take that into consideration. The range from four to six operations per job would allow for some guitar parts available to customers to be already partly assembled when entering the shop. Having more workstations than workers made sense if many different standard parts needed different equipment to be crafted. Up to three available speeds per workstation allowed for a smaller problem to solve while still taking into consideration the relationship between speeds and workers' skills. Because these custom guitars are designed from a unique choice of standard parts made available to the clients. It is being dominated by automatic workstations. However, the custom guitar shop still has a chance of having manual and semi-automatic workstations. It was thought that operations done on guitars would take less time than it would painting or washing a car in a paint shop. The power chosen in that profile still follows the rules previously explained in the description of the last profile. The power expenditures in that profile are somewhat close to the previous ones but do not have to be expressed through the same unit. It would be acceptable to have 2 different shop profiles using two different units of power (as long as two solutions are compared through the same units to make for fair comparisons of data). In a custom guitar shop, there could be some operations that do not require set-up considering starting tools would be part of the starting time instead (if necessary). If tools were turned off at a workstation, at least, some amount of time would have to be expanded to start up equipment. In such a shop, workstations would not be able to process all operations. A mainly automatic shop might have more specialized equipment. However, if a workstation is able to process an operation, it was thought that it would be able to do so at most of its speeds. Requiring some training to operate or supervise workstations completing automated processes, the odds of seeing an employee not be able to do something on a guitar would be quite important because workers could specialize in only part of the production. For instance, setting up an automated CNC machine requires different programming for all specific operation types which a model like the one in this thesis can compute because set-up times vary with the worker. The odds of the employee not being able to use a workstation (considering most are automatic) are a bit lower but still considerable. In that case, the staff is specialized in operating or supervising certain types of machinery (itself being specialized in certain operations) instead of others. However, being able to work with a specific tool does not mean that the worker is trained to use all its functions. This, in turn, explains why a worker might be able to use a workstation but not be able to process a certain operation at that workstation because it is not qualified to calibrate the tools for that specific operation. Finally, considering most workstations are automatic, the odds of seeing an employee not being able to process operations at a certain workstation speed is quite low.

4.2.3 Custom sewing workshop

The custom sewing workshop was selected because a sewing machine is a great example of semi-automatic workstation. Using the same machine and set-up at the same processing speed, two employees with different skills would sew at a different pace. To study FJSPs with such workstations, the custom sewing shop profile was made to be dominated by semi-automatic workstations.

Table 4.5 : Custom sewing workshop parameters intervals

Parameters	Minimum value	Maximum value
Number of jobs	5	6
Number of operations per job	2	3
Number of workstations	3	4
Number of workers	2	3
Number of speeds per workstation	N/A	4
Processing time for a manual workstation	60	360
Maximum processing time	240	360
Power expanded during processing time at the slowest speed	7	10
Power expanded during processing time at the fastest speed	40	50
Power expended during processing time at a manual workstation	7	50
Power expanded in idle state	3	5
Multiplier of the power expanded during the starting time	5	8
Set-up time	0	180
Starting time	1	30

It was thought that a sewing shop would have more jobs but fewer operations per job if operations were seen from a higher-level point of view or if jobs were mainly about custom adjustments or custom modifications on pieces of clothing. The number of workstations had to be at least as big as the number of workers without complicating the resolution of the model too much. The number of speeds available at workstations was increased compared to the two other profiles. Most workstations are semi-automatic, and the rest are primarily manual. There is still a chance for workstations to be declared automatic because the odds of being manual are applied to all workstations and the odds of being semi-automatic are applied to the remaining workstations that are not manual afterward. The rest of the workstations that are neither semi-automatic nor manual are automatic. The power consumption follows the same rules as the last two profiles. Specifically, the main differences are the maximal processing power for semi-automatic and automatic workstations which varies from 40 to 50 power units. For the manual workstations, it varies from 7 to 50 power units. The set-up time can be minimal or require more work if a piece of clothing needs measures before starting the operation. The starting of equipment is small considering starting most sewing machines is a quick process. Because equipment is mainly multipurpose in such a workshop, workstations should be able to process most operations. However, some operations require more care. That explains why operations cannot be performed at all speeds. Worker skills are key for sewing. Sensitive operations should be done by workers with more experience. Because most tools in such a sewing workshop are sewing machines, workers should be able to use most equipment which means mostly just being able to work with a sewing machine. Workers who are not as experienced might not be able to perform some tasks at high speeds and might need to process operations at a slower pace.

4.3 Preliminary study

To approximate the pareto front, multiple pareto optimal solutions must be generated. However, with eight formulation variants, generating enough results to make a thorough analysis requires a sizeable amount of time. This is why this preliminary analysis will be performed using the same methodology but for a shorter amount of time. First, each instance is solved to identify which formulations perform the best in solving the 30 solvable randomly generated instances inside a predetermined time limit. As the problem at hand is an operational one, a short time limit is defined. Hence, to first identify the most efficient formulations and study those more thoroughly, all eight formulation variants were solved once on all 30 instances with a time limit of 20 minutes. The results of this preliminary study are reported in Appendix A. For each instance resolution, we gather information on the termination condition reported by Gurobi (i.e., the instance is proved unsolvable, the resolution reached the time limit, the optimal solution was found and no feasible solutions were found at the end of the time limit), the value of the lower bound, value of the best upper bound or the best objective found, resolution time and optimization gap as reported by the solver.

The reader will find the table compiling all the results of the preliminary study in Appendix A.

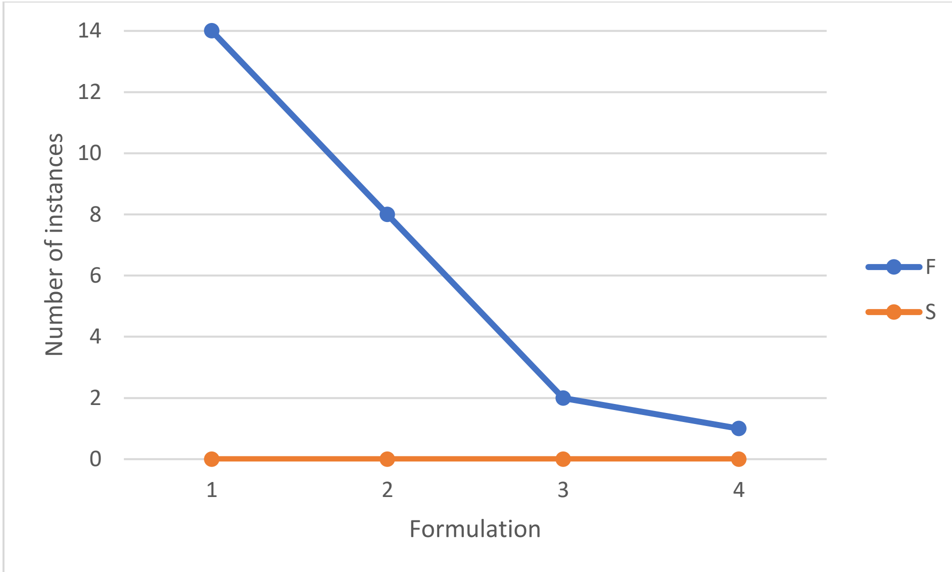


Figure 4.1 : Formulation variants according to the number of instances without a feasible solution with a runtime of 20 minutes

In Figure 4.1, each formulation variant with flow conservation constraints (identified by the blue line) and with sequence linking constraints (identified by the orange line) are distributed according to the number of instances for which no feasible solution was found after 20 minutes. For all formulations using sequence linking constraints, at least one feasible solution was found for each of the 30 random instances. For formulations with flow conservation constraints, the performance is in accord with the number of variables. The F1, which has the most decision variables out of all the formulations, has the worst results. In terms of percentages, it means that out of the 30 instances, the formulation F1 did not find a solution for about 46.67% of those (in absolute numbers, it equates to 14 instances without a feasible solution). On the other hand, F4, which has the best results out of all flow conservation constraint variants, has the least amount of decision variables. In terms of percentages, between F2, F3 and F4, the percentage of instances without a feasible solution after 20 minutes starts at 26.67% for F2, goes down to 6.67% for F3 and ends up at 3.33% for F4. All variants with sequence linking constraints performed better than all variants with flow conservation constraints and formulations got marginally better results from F1 to F4.

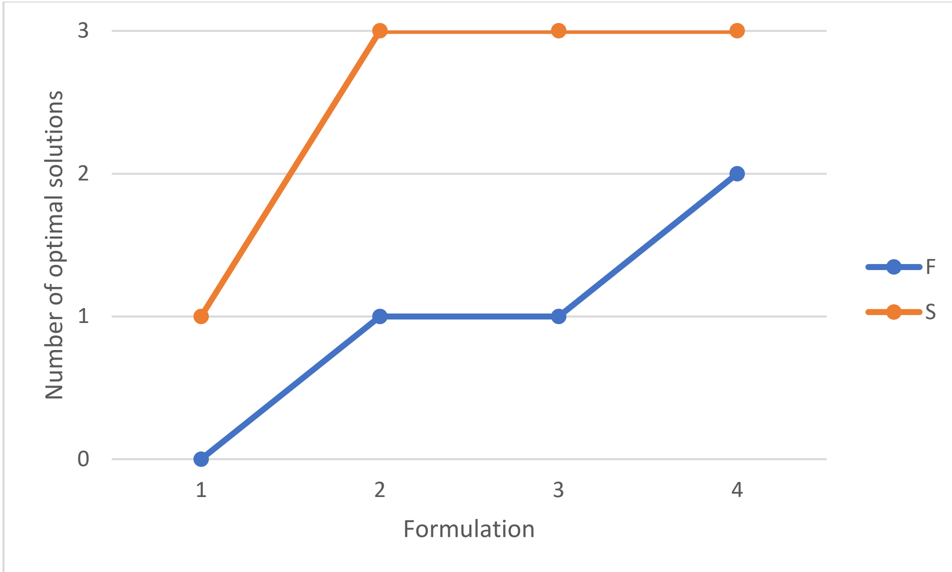


Figure 4.2 : Formulation variants according to the number of optimal solutions found with a runtime of 20 minutes

In Figure 4.2, each formulation variant with flow conservation constraints (identified by the blue line) with the sequence linking constraints (identified by the orange line) is distributed according to the number of optimal solutions found in 20 minutes solving the 30 randomly generated instances. Over those 30 instances, it appears that, for all formulations, the ones without the flow conservation constraints performed better than their counterparts that use it. F1 and S1 performed the worst out of all formulations in their categories. For the formulations with flow conservation constraints, the F4 performed the best overall. For formulations without flow conservation constraints, the number of optimal solutions found over the 30 randomly generated instances does not show enough difference to identify a better-performing formulation. The S2, S3 and S4 variants all found three optimal solutions for solving the 30 random instances. Therefore, finding the optimal solution for 10% of instances in the sample. The closest formulation to such performance was F4 with an optimal solution for 6.67% of the sampled instances. All other formulations found an optimal solution for 1 of the instances or 3.33% of the sample except F1 which did not find any optimal solution for any of the sampled instances.

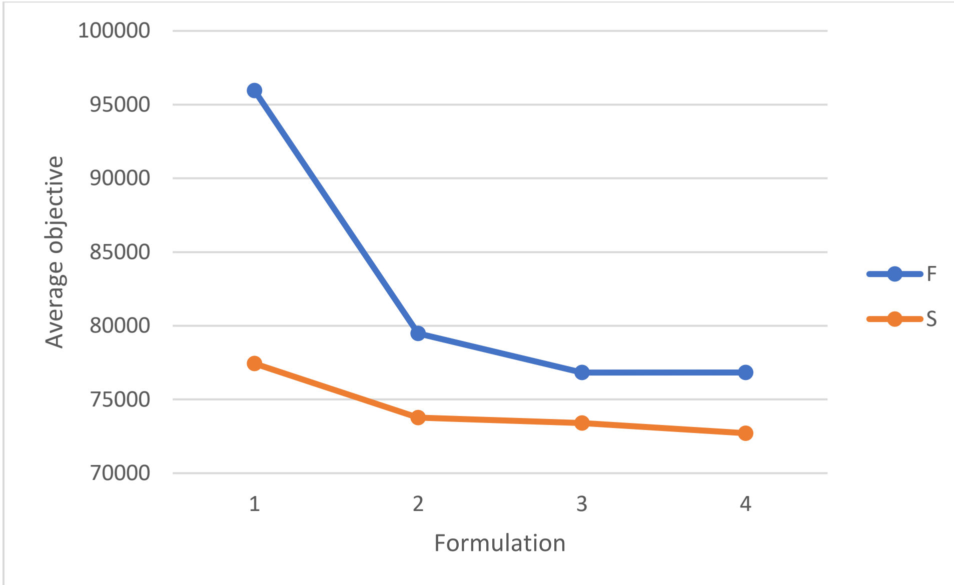


Figure 4.3 : Formulation variants according to average objective value with a runtime of 20 minutes

In Figure 4.3, all formulation variants are classified by average objective value based on their results on the 30 randomly generated instances during 20 minutes of resolution time. Seeing the results, it is possible to conclude that, inside the time limit of the study, the formulations without flow conservation constraints performed better than their counterparts with flow conservation constraints for all formulation variants. For both categories (with flow conservation constraints and with sequence linking constraints), the worst average objective was obtained with F1 and S1 and the best one with F4 and S4. Differences in average objective could be considered slim between variants S2, S3 and S4. Further analysis of those three could help more clearly identify the best-performing among them. Overall, for formulations with flow conservation, there's a 20.73% improvement between F1 and F2, a 3,45% improvement between F2 and F3 and a 0.02% deterioration between F3 and F4. For formulations without flow conservation constraints, there's a 4.96% improvement between S1 and S2, a 0.5% improvement between S2 and S3 and a 0.95% improvement between S3 and S4.

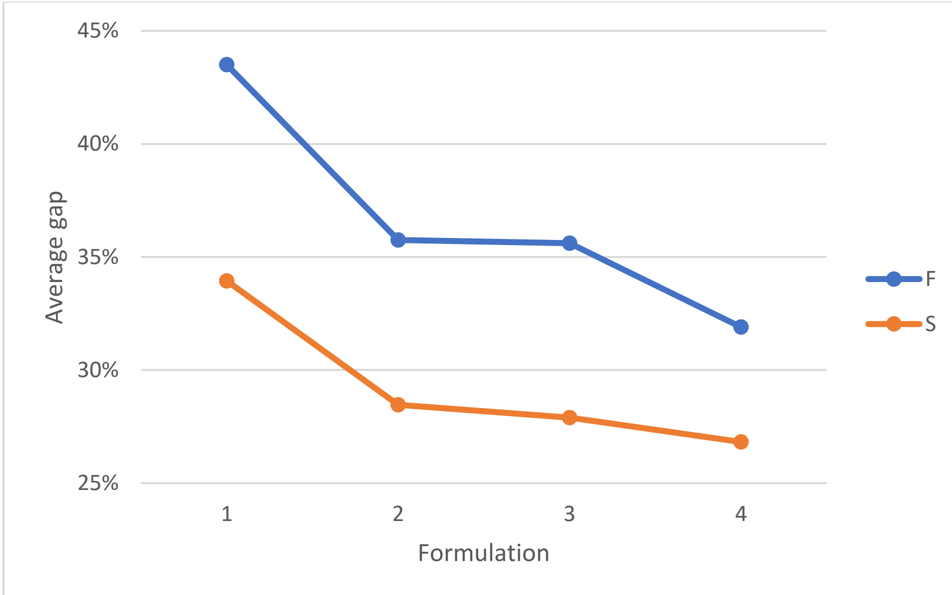


Figure 4.4 : Formulation variants according to average gap with a runtime of 20 minutes

In Figure 4.4, all formulation variants are distributed according to the average gap. For all formulations inside the time limit of the study, the variants without flow conservation constraints performed better than their counterparts with flow conservation constraints. The best performance for that indicator was given by the S4 and the worst one was given by F1. There does not seem to be such a sizeable difference between the performances of S2, S3 and S4 in their variants with sequence linking constraints. Further analysis of those three could prove useful to further differentiate them. For formulations without flow conservation constraints, the difference was of 5.48% between S1 and S2, 0.57% between S2 and S3 and 1.08% between S3 and S4.

In conclusion, all indicators demonstrated that, over the sample of 30 random instances, the F4 and S4 formulations performed the best overall in their category. Although the relationship between resolution performance and decision variables can be complex, this experiment suggests that, in the case of the studied formulations, fewer decision variables lead to better resolution performances. For all indicators and all formulations, the variants without flow conservation constraints performed better than their counterparts with flow conservation constraints. This could be because the use of a flow conservation constraint requires dummy jobs at the end of the schedule. This results in more jobs to schedule and, thus, a problem harder to solve. F1 and S1 performed the worst in their category overall. Those formulation variants were the ones with the decision variables for starting times and completion times that were the closest to Manne (1960). F2 and S2 which are almost identical to F1 and S1 except for having 2-index variables for starting and completion time instead had better or equal results for all indicators compared to the F1 and S1. Thus, demonstrating that modifying the formulation from 3-index to 2-index proved to have better results for all instances of the sample and for all indicators inside the time limit of the study. This leads us to a couple of conclusions from the preliminary study within a 20-minute time limit:

(1) For all indicators and all formulations, the formulation without flow conservation constraints performed better than the formulations with flow conservation constraints for solving the 30 randomly generated instances in the sample.
(2) For all indicators and all formulations, S2 and F2 which have 2-index variables for starting and completion times performed better than F1 and S1 which have 3-index variables for starting and completion times for solving the 30 random instances in the sample.
(3) Although the data shows that the S4 and F4 performed the best overall in their category for all indicators generated through the resolution of the sampled instances, further studies would help differentiate the performance of F2, F3 and F4 and S2, S3 and S4 further.
(4) Although there seem to be costs to having decision variables that allow for accounting transportation times and off or idle time between operations that do not precede each other, the data suggests that the difference in performance could be negligible compared to the benefits of incorporating such refinements in certain business cases (meaning the difference in resolution performance between two, three and four in both categories might be negligible in certain business cases).

4.4 Extensive study

Since we were not able to conclude which is the best formulation among S2, S3, and S4 in section 4.2 in the preliminary studies, we conducted a second experiment with another analysis with a longer time limit. This will help determine if there are observable differences in performance between formulations that had similar performances and how much progress can be made over a resolution time three times as big as the previous one. The same experiment was conducted as in the last section except that it was only conducted for the three closest formulations in terms of performance (S2, S3, S4) for each indicator and that the resolution time was of one hour instead of 20 minutes. The Appendix B compiles all the data generated during this experiment.

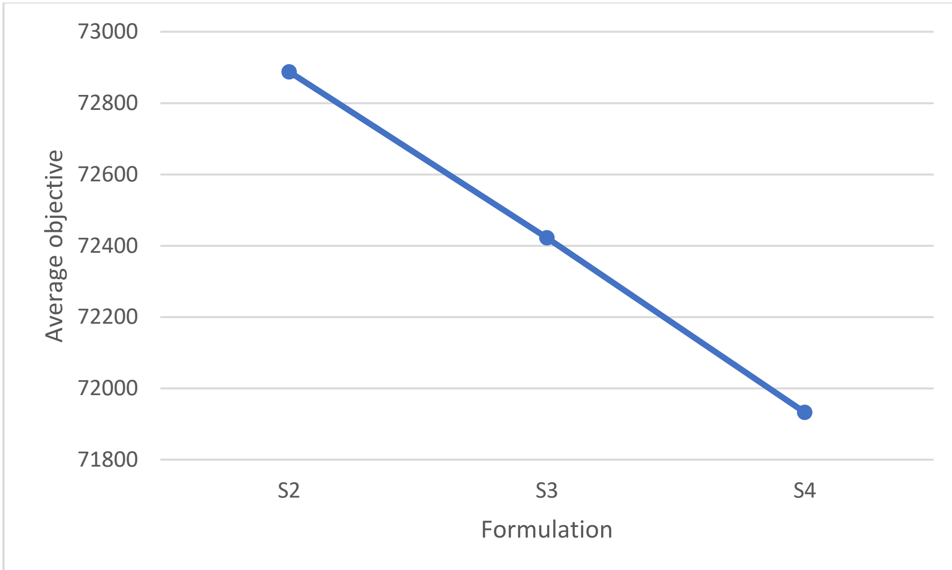


Figure 4.5 : Formulation S2, S3 and S4 according to the average best objective with a runtime of one hour

Figure 4.5 shows the distribution of S2, S3 and S4 according to their average best objective after one hour of resolution time. The S4 performs the best for the average best objective with an average objective of 71932.51. That is an improvement of 1,83% for 40 more minutes of resolution time. For S3, it is an improvement of 1.35% or 980.45. For S2, it was an improvement of 1.21% or 885.15. S4 shows an improvement of 0.68% over S3 and 1.33% over S2. Although present, the difference between these three formulations is still marginal. However, the difference is a bit bigger than the previous marginal improvements obtained between formulations for the 20-minute experiment which were 0.5% and 0.95% between S2 and S3 and S3 and S4 respectively.

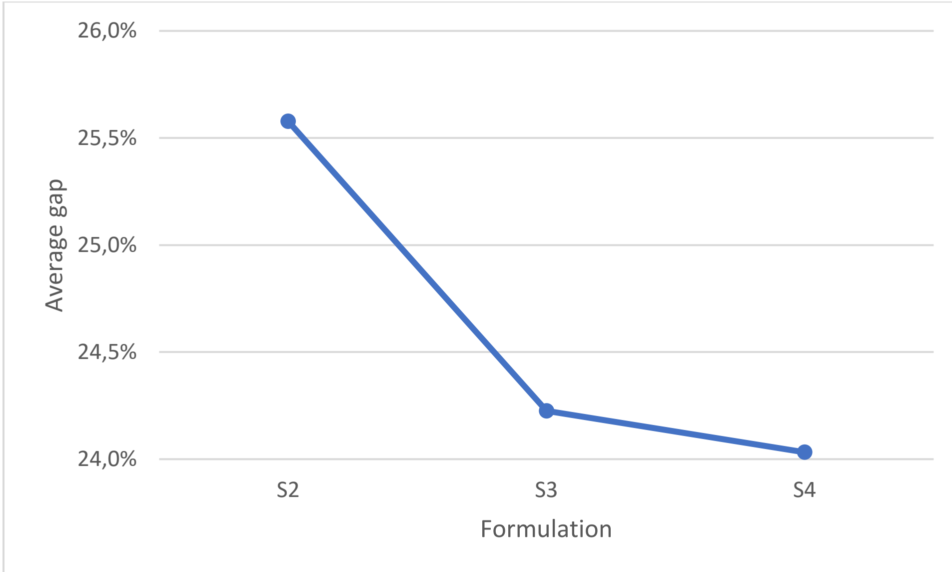


Figure 4.6 : Formulation S2, S3 and S4 according to average gap with a runtime of one hour

Figure 4.6 shows the average gap for formulations S2, S3 and S4 after one hour of resolution time on sampled instances. On this indicator again, S4 performed the best out of the three with an average gap of 24.03%. A difference of 0.19% with S3 and 1.55% with S2. Increasing the resolution time did improve the gap overall. The difference between the gap after 1 hour compared to the previous one obtained after 20 minutes of resolution time is 2.89% for S2, 3.67% for S3 and 2.79% for S4. For an augmentation of three times the resolution times, the improvement is marginal. The difference between the gap obtained through these three formulations remains slim.

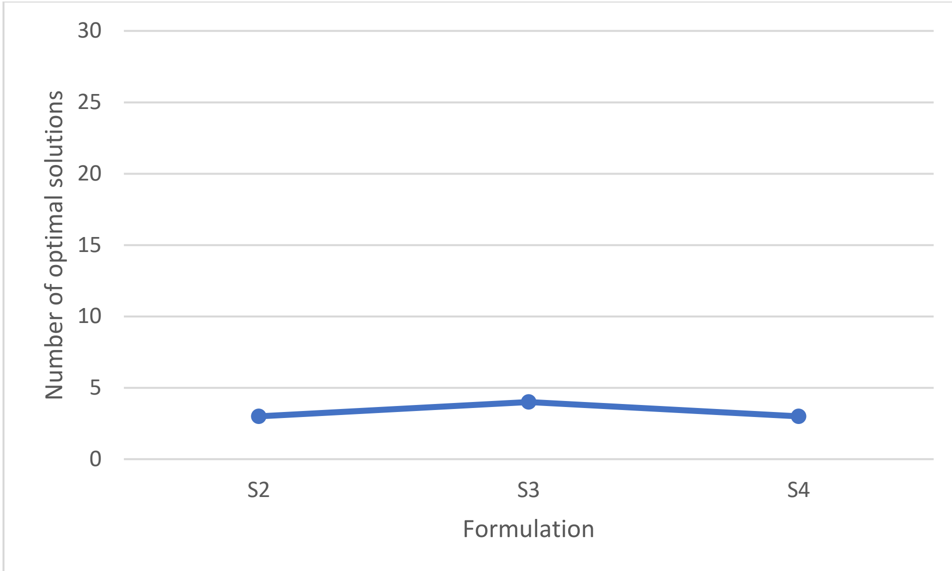


Figure 4.7 : Formulation S2, S3 and S4 according to the number of optimal solutions found with a runtime of one hour

Figure 4.7 shows the number of optimal solutions found after one hour of resolution over 30 randomly generated instances. None of the three formulations showed any changes over the 40 additional minutes except S3. S3 found 3 optimal solutions out of 30 sampled instances in the last experiment. However, in one hour, S3 was able to find a total of four optimal instances. Therefore, compared to the others for which an optimal solution was only found for 10% of the sampled instances, S3 found an optimal solution for 13% of the 30 randomly generated instances. The instance S3 was able to solve that the two other formulations failed to resolve was atelierpeinture4. However, both found the same optimal solution S3 discovered but were not able to prove its optimality in the imparted time.

Although S4 performed the best according to most indicators, the number of optimal instances found after one hour of resolution serves as a reminder that resolution performance cannot be reduced to the number of variables and constraints of a problem formulation. Because of its better performance according to all indicators except the last one presented, S4 will be the formulation used for the analysis of pareto front approximation and interpretation of the next section. Unless solved to optimality, it cannot be certain that a formulation has a better performance solving an instance compared to another. However, it can be said that over the seven indicators shown on the

30 randomly generated instances for 20 minutes and one hour of resolution time, S4 performed the best in four out of seven of the indicators with it being tied for first place for two other indicators. Therefore, such data would suggest that it is the superior formulation for solving the 30 sampled instances with a time limit of 20 minutes or one hour.

4.5 Pareto front approximation and interpretation

Pareto fronts are used in multi-objective optimization to represent the set of non-dominated solutions for a problem. Analyzing that set gives insights into the relationship or trade-off between objectives. To learn more about the relationship between objectives for the problem presented in this thesis, the pareto front will be approximated for all randomly generated instances. For the following analysis, the weighted-sum method was used to generate the data solving each of the 30 instances with formulation S4 a total of 16 times with different weights for a maximum of one hour (meaning the solver would stop searching after one hour, keep the best solution found and move on to the next instance to be solved). The weights used for each of the 16 resolutions can be found in Table 4.2. The same solver used in previous sections was also employed for that experiment. Because the instances were not necessarily solved to optimality in an hour, there still exists a distance between the true pareto front and the one that can only be approximated by using the gathered data. However, compared to certain heuristics with which it is not possible to know how far the solution is from pareto optimality, at least, this method gives an idea of that distance with the gap. Not solving the instances to optimality also meant that the best solution found after an hour could be dominated by another solution found using another weight. Therefore, the data was filtered to only keep the solutions that were not dominated among the 16 solutions found. This is the reason why there are less than 16 solutions in most cases. Filtering was done in four different ways. First, it was done considering all three objectives. Second, it was done considering only makespan and energy. Third, it was done only considering makespan and labor intensity. Finally, it was also done considering only Labor intensity and energy. The filtering was made with a degree of precision of 0.1% which means a solution being dominated by another on a certain objective for less than 0.1% would be considered non-dominated. For this section, non-dominated will not mean pareto optimal. A solution that is non-dominated will mean that it is not dominated by any of the other 15 found using different combinations of weights. Moreover, although an attempt will be made at approximating the pareto front for all instances, such a result can only be guaranteed by solving instances to optimality. Because, in most cases, that is not achieved, the front obtained will only represent the best attempt at approximation made with a maximum of one hour per experiment. Afterwards, the pattern followed by most experiments will be presented. Sizeable differences with the dominant pattern for most experiments and the possible causes of the results will also be explored for exceptions to the dominant pattern. The data without filter for dominated solutions compiled during this experiment can be found in Appendix C. The data filtered for dominated solutions compiled during this experiment can be found in Appendix D.

4.5.1 Relationship between makespan, labor intensity and energy

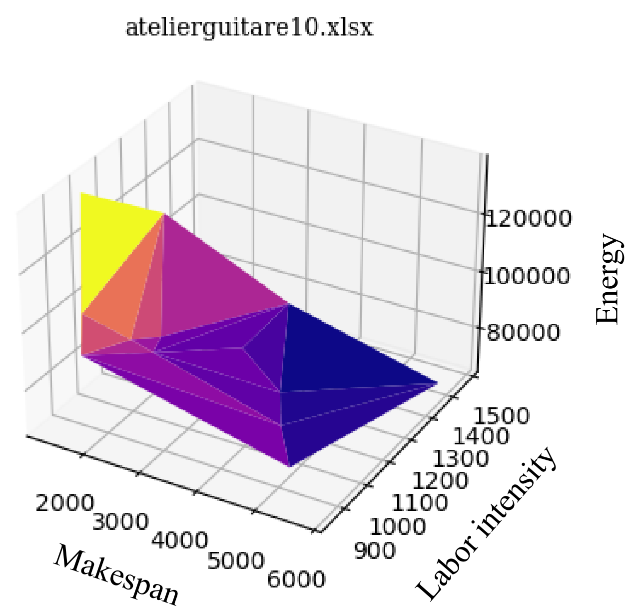


Figure 4.8 : Approximation of the pareto front for ateliergutare10 using weighted-sum for a maximum of one hour

Figure 4.8 is the result obtained trying to solve instance ateliergutare10 with the previously presented weights for a maximum of one hour for each experiment. This shape is obtained once the dominated solutions among the set of best solutions found are filtered. All figures representing the best approximation found after one hour are listed in Appendix E. Figure 4.8 represents the pattern of most figures in Appendix E. This pattern is obtained when there are negative relationships among all objectives. Minimizing makespan leads to an increase in energy consumption and/or labor intensity and minimizing labor intensity or Energy has the same consequences on the two other objectives. Almost all instances follow this pattern except ateliercouture5 and atelierpeinture5. Although it seems that atelierpeinture7 presents an atypic shape, in fact, the summit of its pyramid-like shape is not towards the front of the figure like it seems. It is towards the back which indicates that minimizing makespan comes at a great cost for energy consumption and maximum labor intensity which relates to the pattern present in atelierguitare1 and present in most of the other instances. It seems that the other atypic shapes are obtained because there are not many solutions left after filtering through dominated solutions. Ateliercouture5 only has two non-dominated solutions among the set of best solutions found after one hour based on labor intensity and energy and atelierpeinture5 only has one between makespan and labor intensity and 2 between labor intensity and energy. There could be many reasons that could explain this. First, the weighted-sum method does not allow for finding all pareto optimal solutions of a non-convex feasible solution space. Therefore, other pareto optimal solutions might exist but were not found. Second, there might not be much conflict between the two objectives for that specific instance. Because ateliercouture5 was solved to optimality for all experiments except one, the answer would most likely be the first or the second reason (although conflict still exists as long as there is more than one pareto optimal solution between two objectives). So, for ateliercouture5, it is likely that either there is less conflict between objectives or that there are other solutions but not part of a convex feasible solution space. For almost all instances tested, inside the time limit fixed, there is conflict and a negative relationship between all pairs of the 3 objectives.

4.5.2 Relationship between makespan and energy consumption

In this section, all data used for generating the following figures are available in Appendix D. All figures for each of the 30 randomly generated instances solved are in Appendix F.

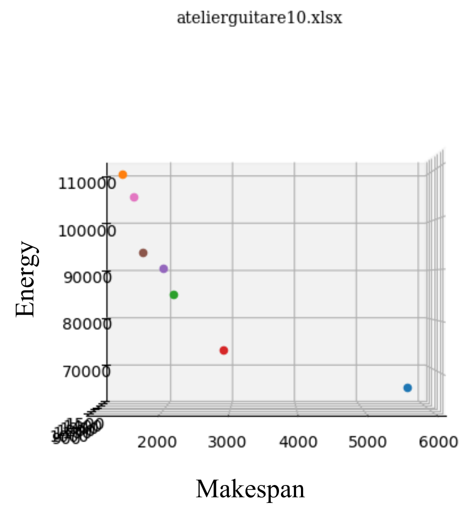


Figure 4.9 : Approximation of the pareto front between makespan and energy for ateliergitare10 using weighted-sum for a maximum of one hour per experiment

Figure 4.9 represents the negative relationship between makespan and energy obtained when trying to approximate the pareto front for ateliercouture10. This pattern is similar for all instances although instances atelierpeinture9 and atelierpeinture10 only had two dominating solutions. Figure 4.9 shows that minimizing makespan increases energy consumption and that minimizing energy consumption increases makespan as well. Specifically for ateliercouture4, from left to right, it seems that, at the left of the figure, sizeable progress can be made on energy consumption for little loss of efficiency in makespan. Closer to the middle, little gains for one of the objectives can be made at the price of little losses on the other objective. Closer to the right of the figure, little gains in energy consumption come at a great price in terms of makespan. Chapter 5 will go into further detail about how decision-makers can pick a solution from a non-dominated set. Examples presented in 3.4 will also apply to figures such as Figure 4.9. Notably, figure 4.9 seems to follow a non-convex pattern. The next section will explore an explanation of how such an outcome may be possible.

4.5.3 Relationship between makespan and labor intensity

In this section, all data used for generating the following figures are available in Appendix D. All figures for each of the 30 randomly generated instances solved are in Appendix G.

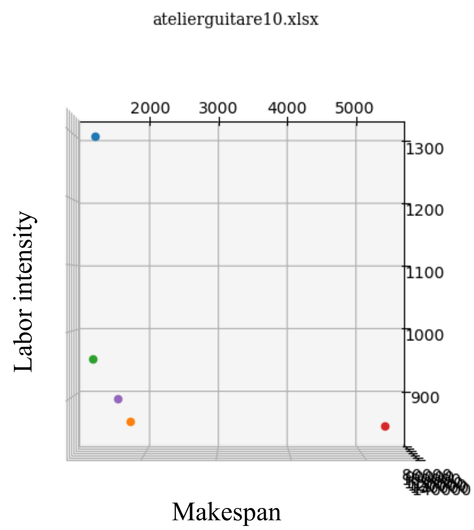


Figure 4.10 : Approximation of the pareto front between makespan and labor intensity for ateliergguitare10 using weighted-sum for a maximum of one hour per experiment

Figure 4.10 represents the set of filtered solutions for ateliergguitare10 with a maximum resolution time of one hour per experiment. It depicts the most common relationship between the variables. Like the relationship between makespan and energy, the relationship between makespan and labor intensity is negative. However, ateliergguitare6 more specifically follows a non-convex pattern. There are other examples in Appendix G of such behavior. Most notably, ateliercouture3 also depicts the same pattern. An explanation could be that non-convex solutions considering only two objectives were found because weights were considering three objectives. Therefore, solutions that might seem non-convex from a 2-objective point of view might have been found that way. A second explanation could be that the optimal solution was not found, and the solutions presented found for ateliergguitare6 are not pareto optimal. Moreover, some sets only contain 1 non-dominated solution. That means that either there is no conflict between the objectives for that particular instance or other non-dominated solutions were not found. This is the case for atelierpeinture5 and atelierpeinture9. However, other than that, the relationship between makespan and labor intensity remains somewhat similar to the previous one. In order to make some progress in regard to one of the objectives, there is some loss to be expected in regard to the other. Once again, chapter 5 will present how a decision maker might select a solution from a set of pareto optimal solutions in more detail.

4.5.4 Relationship between labor intensity and energy consumption

In this section, all data used for generating the following figures are available in Appendix D. All figures for each of the 30 randomly generated instances solved are in Appendix H.

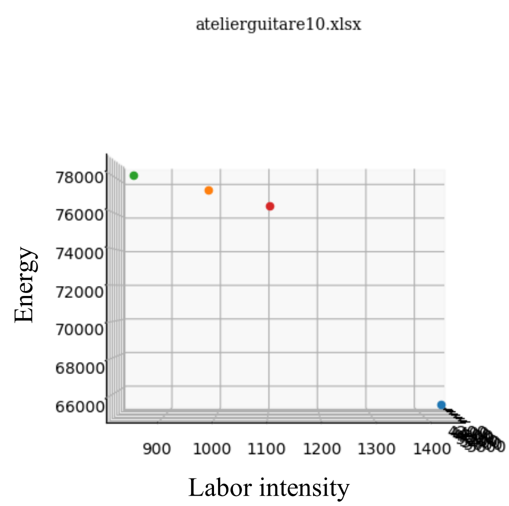


Figure 4.11 : Approximation of the pareto front between labor intensity and energy for atelierguitare10 using weighted-sum for a maximum of one hour per experiment

Figure 4.11 shows the set of filtered solutions for atelierguitare10 and represent the most common pattern. The relationship between energy and makespan is also negative and similar to the one between energy and makespan. This means that improving energy consumption would require some kind of loss in terms of minimizing the maximum labor intensity. However, for this relationship altogether, fewer non-dominated solutions were found compared to previous relationships. In fact, more than a third of all instances had three or fewer non-dominated solutions after filtering. That being noted, as long as there are two solutions or more, conflict exists between two objectives and only one instance had just one non-dominated solution. The next chapter will take a closer look at how decision-makers can make a choice of solution between a set of non-dominated solutions using data gathered during this experiment.

CHAPTER 5
USING THE MODEL AS A DECISION TOOL

Filtering all the dominated solutions out of a set will still leave decision-makers with many different solutions to choose from. Making such a decision can often come with some difficulty. In this section, some a-priori tools will be shown to present how decision-makers might select a particular solution over other ones in a set. Thus, this section is dedicated to showing tools managers might use to select solutions from a set and to share and communicate the resulting schedules to their team while the previous section was dedicated to understanding the resolution performance of the different formulations and the relationship between the objectives.

5.1 Comparing two solutions

Although comparing many solutions together can be challenging in some cases, comparing only two solutions together is simpler. For instance, Table 5.1 presents the two first solutions of ateliergutiare1 after filtering dominated solutions.

Table 5.1 : The two first filtered solutions of ateliergutiare1 according to objective value

ateliergutiare1.xlsx		
Makespan/Labor intensity/Energy		
5787,00	1420,00	65619,00
2478,00	955,00	93309,00

In Table 5.1, the two first solutions obtained after filtering for dominated solutions are distributed according to objective value. First of all, the difference for each objective can be noted. From solution 1 to solution 2, makespan has improved by 3309 units of time, maximum labor intensity has improved by 465 units and energy consumption has increased by 27 690 units. However, because each objective is expressed in different units, decision-makers have to be cautious of the over-representation of objectives consisting of big numbers of small units like energy consumption in this specific case. Second, in relative terms, units of energy are not the same as units of time, therefore, noting the difference in relative terms may prove more helpful than the exact number of units. For makespan, it consists in a difference of 57.18%. For labor intensity, a difference of 32.75%. Finally, for energy, it consists in a difference of 42.20%. Considering the variation in percentages weighs differently. Although the high number of energy units seemed to highly favor the first solution in the first case, with relative percentages, a decrease of 3309 units, which is a difference of 57.18% for makespan, and a decrease of 465 units, which may not seem like much but is, in fact, a difference of 32.75% for labor intensity, may now weigh more in the direction of the second solution compared to what seems like a high number of units with 27690 units of energy but consisting in a difference of 42.20%. However, only the decision maker knows the relative importance of each objective and certain business cases may consider different values for different objectives.

5.2 Comparing many solutions using weights

If decision-makers know the relative importance of each objective a-priori, that information can be factored in using weights. Using weights for prioritizing different objectives can be a useful a-priori tool to choose the solution that reflects the most interests of the decision makers among a set of multiple non-dominated solutions.

Table 5.2 : Filtered solutions of ateliergiutare1 according to objective value

Cmax	Intmax	Total energy	Total objective
Makespan/Labor intensity/Energy			
5787,00	1420,00	65619,00	72826,00
2478,00	955,00	93309,00	96742,00
2146,00	1086,00	85192,00	88424,00
2855,00	1476,50	73395,00	77726,50
1823,00	1024,50	97340,00	100187,50
1315,00	1050,00	102145,00	104510,00
1848,00	1387,50	91400,00	94635,50
5651,00	1198,00	67809,00	74658,00
5588,00	1038,75	73252,00	79878,75
5585,00	1325,50	65895,00	72805,50
1401,00	1012,00	103352,00	105765,00
1283,00	1159,00	104578,00	107020,00
1359,00	1353,25	99221,00	101933,25
3238,00	1643,00	70281,00	75162,00

Table 5.2 presents the filtered solutions of ateliergutare1 according to objective value with the 4th column representing the total objective value. If all objectives were equal, the solution with the lowest total objective value would be selected. This would favor the 10th solution from the top with a total objective value of 72805.50 units. However, decision-makers might consider that some objectives are of more importance than others. This could have an effect on the selected solutions. For instance, if the makespan was three times as important as the two other objectives, such consideration could result in the following weights : 60% for makespan, 20% for labor intensity and 20% for energy. Using such weight would now favor the last solution that presents a compromise that might represent the interests of decision-makers more accurately. However, it could still be argued that energy consumption, with such a high number of units, is still overrepresented among the different objectives. To address such inconvenience, an equivalence factor can be applied to all objectives to make sure that those are all expressed in equivalent terms. Among the data presented in Table 6.2, on average, labor intensity is about equal to 1.5% of energy consumption and 53.78% of makespan. Those percentages could be used as equivalence factors. Using those would result in Table 5.3.

Table 5.3 : Filtered solutions of ateliergutare1 according to objective value with equivalence factor

Cmax	Intmax	Total energy	Total objective
Makespan/Labor intensity/Energy			
3112,31	1420,00	987,00	5519,31
1332,70	955,00	1403,49	3691,19
1154,14	1086,00	1281,40	3521,54
1535,45	1476,50	1103,96	4115,91
980,43	1024,50	1464,12	3469,05
707,22	1050,00	1536,40	3293,62
993,88	1387,50	1374,78	3756,15
3039,17	1198,00	1019,94	5257,11
3005,29	1038,75	1101,81	5145,85
3003,68	1325,50	991,15	5320,32
753,47	1012,00	1554,55	3320,02
690,01	1159,00	1572,99	3422,00
730,89	1353,25	1492,42	3576,55
1741,43	1643,00	1057,12	4441,55

Without using any weights, considering all objectives as relatively equal, the selected solution would now be the 6th from the top with a total equivalent objective value of 3293.62 units. Once expressed on equivalent terms, using weights on objective values can now better fulfill its purpose not being as influenced by the difference in units and now focused on the relative importance of each objective. Although using the same weights as the previous example would still favor the 6th solution from the top, different sets of weights would show different outcomes. For instance, giving a weight of 20% for makespan, 20% for labor intensity and 60% for energy consumption would now favor the 3rd solution from the top.

If decision-makers know the relative importance of each objective beforehand, finding the pareto set is still a worthwhile venture. In combination with a factor of equivalence to some extent negate the difference in units and with weights to represent the relative importance of each objective, the pareto set can be used by decision-makers to more accurately select the solution that best fit their interests.

5.3 Implementing and communicating the selected solution

Although a solution supplied by Gurobi in its unaltered form might seem like an infinite number of binary values for many decision variables, there are multiple ways to represent selected solutions in simpler terms. The one that will be presented in this thesis is the use of Gantt charts. A Gantt chart per resource seems appropriate. For all following Gantt charts, the index of colors will be according to Table 5.4.

Table 5.4 : Index of colors for all Gantt charts

	Starting time
	Set-up time
	Processing time
	Idle time
	Off time

Any amount of time specified in a Gantt chart will follow the index of colors presented in Table 5.4. In Figure 5.1, a Gantt chart representing the work schedule of ateliergitare1 for experiment 1 is presented. It gives the manager the processing order of all operations for all resources and speeds. For each activity, a color specifying the type of activity is presented. For processing activities, a variable O_{ijv} is also included. The index j of job i in O_{ijv} indicates which operation of which job is supposed to take place at the specified workstation or which operation of which job is to be processed by the specified worker in the specified order and index v indicates at which speed the operation is expected to be processed. This Gantt chart presents an easy way of presenting the daily schedule to a team, so everyone is on the same page when it comes to the order and allocation of operations. Using such a tool, any employee would know exactly where to be at which time and what to do. Therefore, it allows for an efficient and fast way to communicate specific work assignments.

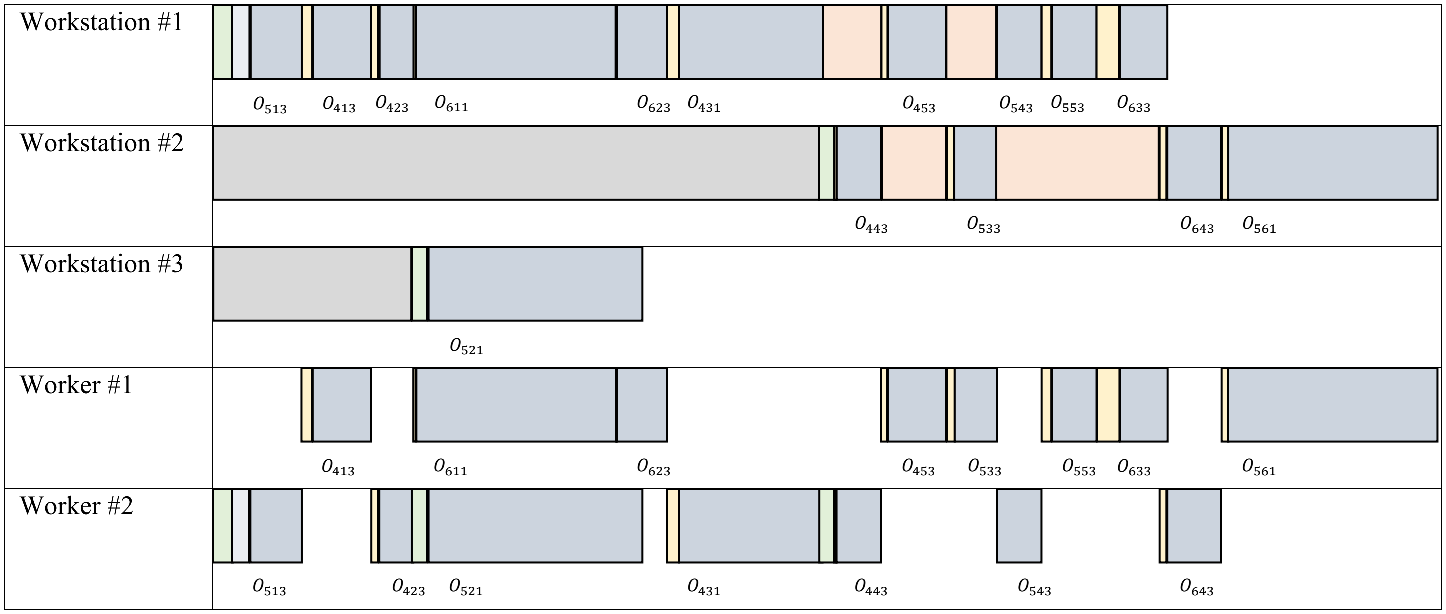


Figure 5.1 : Gantt chart for ateliergiutare1 experiment 1

CONCLUSION

The goal of this thesis was to provide decision-makers with a detailed tool to manage sustainable flexible job-shops with many features. Specifically, those features include sequence-dependent set-up times, choosing between off or idle state, machine speeds and worker scheduling. To do so, 8 different innovative formulations of the same problem were formulated. Those formulations were inspired by the literature and incorporated new sets of constraints specifically developed for this thesis. Manne (1960) used a 3-index formulation for starting and completion times while 2-index formulations could be found in the literature. Although flow conservation constraints are well known and well documented, other authors in the field did not use such constraints for sequencing in flexible job-shop problems. Moreover, a new innovative sequence linking system of constraints was invented and tested against well-known flow conservation constraints to study the difference in performance. All these elements inspired the 8 formulation variants presented. Last parts of Chapter 5 present how to use the formulation that was the most efficient during the first two experiments to show how to approximate pareto fronts and select solutions among a pareto set. The very last part gives decision-makers a tool to present selected solutions and communicate the work schedule to their team. To solve all instances in this thesis, the weighted sum method was employed. Gurobi was the solver employed to generate all the results. To compare the performance of the 8 different formulations, 30 random instances inspired by real production systems were generated. Although including some assumptions, the performances of each formulation were generated by solving the exact same instances with the exact same machine with the exact same solver and the exact same resolution method. That is to say that a considerable effort was made to isolate all variables that could have influenced the results and left only the change of formulation as the only reasonable explanation left for any difference in performances. Doing so showed that for all experiments conducted, the formulation variants with sequence linking constraints performed better than formulation variants with flow conservation constraints. It also showed that the formulation closest to Manne (1960) showed the poorest results. The best out of all the formulations was S4. Formulation S3 with a worker sequencing variable ready to incorporate transportation times without losing linearity showed interesting results. Its performance stayed close to S4 while finding one more optimal solution in the one-hour experiment. To approximate pareto fronts, different weights with an equivalence factor for each objective were used with the weighted-sum method. Doing so revealed the relationship between objectives. All objectives had a negative relationship with each other and showed signs of conflict.

There were many interesting results acquired in the process and the main contribution of the thesis is in the proposition and analysis of the different formulations. However, many critiques could be addressed in future work. First, choosing the weighted-sum method came with weaknesses. The weighted-sum method does not allow for finding all solutions in a non-convex feasible solution space. Therefore, there might exist pareto optimal solutions that the employed resolution method does not allow to find. Then, even after 1 hour of resolution time, many instances were not solved to optimality. When that is the case, it is impossible to state that a formulation performs better than another solving an instance. It is only possible to conclude that according to the specified indicator, a formulation showed better results than another in the imparted time. There is no guarantee of what will happen with more or less time. Because it is the case with most data generated in this thesis, The results must be treated with, at least, that amount of caution. For the pareto front approximation part, not solving to optimality meant not guaranteeing the pareto optimality of the solution. Therefore, the true pareto front might be quite different from the ones shown in this thesis when non-optimal solutions were used to approximate. However, the selected method through Gurobi did have an advantage over other heuristics used in the literature. Unless the optimal solution is known for a problem, most heuristics used in the literature do not provide knowledge of how far the resulting solutions are from optimality. In this thesis, the data compiled at least gave some idea of that distance through the gap. For future study, starting from S3 which is the formulation closest to a formulation that includes transportation times would be interesting to study the difference in performance for instances of similar sizes when incorporating another feature: transportation times. Although it may be costly in terms of resolution performance, S3 keeping it close to S4 showed promises and transportation times are an important part of multiple business cases. Whatever loss in performance suffered from that addition may well be worth it in some cases.

APPENDIX A

DISTRIBUTION OF FORMULATION VARIANTS ACCORDING TO TERMINATION CONDITION, BEST SOLUTION, LOWER BOUND, UPPER BOUND AND GAP

Variant	Data	Termination condition	Best solution	Resolution Time	Lower bound	Gap
S4	ateliergguitare5	Time	73585,25	1201,10	55211,53	24,97%
S3	atelierguitare1	Time	72039,50	1201,74	53007,48	26,42%
S4	atelierguitare1	Time	72039,50	1201,79	52950,17	26,50%
S4	atelierguitare11	Time	69143,00	1200,81	49448,56	28,48%
S2	atelierguitare1	Time	73390,50	1202,95	52470,59	28,50%
S2	atelierguitare11	Time	69310,00	1201,20	49485,21	28,60%
F1	ateliercouture1FCC	No feasible solution found	24147,00	1200,00		
F1	ateliercouture2FCC	No feasible solution found	22818,00	1200,00		
F1	ateliercouture3FCC	No feasible solution found	27662,00	1200,00		
F1	ateliercouture4FCC	No feasible solution found	19468,00	1200,00		
F1	ateliercouture5FCC	No feasible solution found	24767,00	1200,00		
F1	ateliercouture6FCC	No feasible solution found	20218,00	1200,00		
F1	ateliercouture8FCC	No feasible solution found	32527,00	1200,00		
F1	ateliercouture9FCC	No feasible solution found	19822,00	1200,00		
S3	atelierguitare11	Time	69981,00	1201,57	49832,67	28,79%
S1	atelierguitare1	Time	72769,00	1201,49	51369,60	29,41%
F4	atelierguitare1FCC	Time	73516,00	1201,33	51588,75	29,83%
S3	atelierguitare4	Time	81081,00	1201,03	55958,57	30,98%
S4	atelierguitare4	Time	82335,00	1201,08	56656,93	31,19%
F3	atelierguitare1FCC	Time	72570,50	1203,32	49846,74	31,31%
F2	ateliercouture1FCC	No feasible solution found	24346,00	1200,00		
F2	ateliercouture2FCC	No feasible solution found	23127,00	1200,00		

F2	ateliercouture4FCC	No feasible solution found	19777,00	1200,00		
F4	atelierguitare4FCC	Time	82154,25	1200,96	55181,43	32,83%
S4	atelierguitare3	Time	72412,00	1201,31	46716,90	35,48%
F3	ateliercouture2FCC	No feasible solution found	23329,00	1200,00		
S4	atelierguitare2	Time	72768,25	1200,99	45804,83	37,05%
F4	ateliercouture2FCC	No feasible solution found	23016,00	1200,00		
S2	atelierguitare3	Time	74344,85	1201,26	46285,47	37,74%
F4	atelierguitare3FCC	Time	74230,50	1200,89	45646,78	38,51%
S4	atelierguitare10	Time	89959,01	1200,95	54970,69	38,89%
S3	atelierguitare5	Time	88382,00	1201,04	53975,99	38,93%
F3	atelierguitare10FCC	Time	87255,50	1203,01	52759,63	39,53%
F3	ateliercouture1FCC	Time	36281,24	1204,67	24736,99	31,82%
F4	ateliercouture1FCC	Time	35563,00	1201,25	25384,04	28,62%
S1	ateliercouture1	Time	35543,00	1202,29	25519,19	28,20%
S2	ateliercouture1	Time	36089,00	1201,64	25897,62	28,24%
S3	ateliercouture1	Time	36030,00	1201,42	26018,49	27,79%
S4	ateliercouture1	Time	35447,65	1201,52	26080,77	26,42%
S1	ateliercouture2	Time	30413,30	1202,08	24218,19	20,37%
S2	ateliercouture2	Time	28798,00	1201,25	24553,29	14,74%
S3	ateliercouture2	Time	28765,49	1201,27	25357,36	11,85%
S4	ateliercouture2	Time	28858,49	1200,94	25401,20	11,98%
F3	ateliercouture3FCC	Time	40760,00	1202,01	28067,25	31,14%
F4	ateliercouture3FCC	Time	40678,23	1201,06	29938,83	26,40%
F2	ateliercouture3FCC	Time	40784,00	1201,51	28435,12	30,28%
S1	ateliercouture3	Time	37193,61	1201,40	29930,93	19,53%
S2	ateliercouture3	Time	36887,23	1201,16	30705,63	16,76%
S3	ateliercouture3	Time	39989,00	1201,24	31076,06	22,29%
S4	ateliercouture3	Time	36897,52	1201,25	31389,10	14,93%
F3	ateliercouture4FCC	Time	31778,22	1202,70	20120,23	36,69%
F4	ateliercouture4FCC	Time	30394,00	1201,14	21425,32	29,51%

S1	ateliercouture4	Time	30452,22	1202,22	21675,85	28,82%
S2	ateliercouture4	Time	30452,22	1201,75	22106,60	27,41%
S3	ateliercouture4	Time	30192,00	1201,51	22307,04	26,12%
S4	ateliercouture4	Time	30452,22	1201,51	22374,22	26,53%
F3	ateliercouture5FCC	Found optimal	30875,00	598,20	30875,00	0,00%
F4	ateliercouture5FCC	Found optimal	30875,00	132,73	30875,00	0,00%
F2	ateliercouture5FCC	Found optimal	30875,00	804,11	30875,00	0,00%
S1	ateliercouture5	Found optimal	30875,00	18,56	30875,00	0,00%
S2	ateliercouture5	Found optimal	30875,00	9,60	30875,00	0,00%
S3	ateliercouture5	Found optimal	30875,00	26,33	30875,00	0,00%
S4	ateliercouture5	Found optimal	30872,01	10,05	30872,01	0,00%
F3	ateliercouture6FCC	Time	40179,69	1202,22	20829,04	48,16%
F4	ateliercouture6FCC	Time	35647,00	1201,02	22051,16	38,14%
F2	ateliercouture6FCC	Time	35357,00	1201,48	21162,81	40,15%
S1	ateliercouture6	Time	35355,00	1201,50	22156,21	37,33%
S2	ateliercouture6	Time	35351,00	1201,66	22876,29	35,29%
S3	ateliercouture6	Time	35355,00	1201,46	22990,04	34,97%
S4	ateliercouture6	Time	35429,00	1201,48	23001,04	35,08%
F1	ateliercouture7FCC	Time	41794,50	1201,39	26208,86	37,29%
F3	ateliercouture7FCC	Time	40935,50	1201,65	29998,51	26,72%
F4	ateliercouture7FCC	Time	40451,50	1200,86	31986,80	20,93%
F2	ateliercouture7FCC	Time	40761,50	1201,27	30410,23	25,39%
S1	ateliercouture7	Time	40451,50	1201,32	31731,83	21,56%
S2	ateliercouture7	Time	40451,50	1201,53	31878,21	21,19%
S3	ateliercouture7	Time	40451,50	1202,12	32674,26	19,23%
S4	ateliercouture7	Time	40451,50	1201,45	32458,31	19,76%
F3	ateliercouture8FCC	Time	43403,60	1201,59	33616,98	22,55%
F4	ateliercouture8FCC	Time	43510,60	1201,24	34711,87	20,22%
F2	ateliercouture8FCC	Time	43733,20	1201,24	33052,23	24,42%
S1	ateliercouture8	Time	43901,20	1201,37	34452,89	21,52%

S2	ateliercouture8	Time	44053,20	1201,69	35090,03	20,35%
S3	ateliercouture8	Time	44054,20	1201,17	35079,29	20,37%
S4	ateliercouture8	Time	43926,20	1202,24	35057,48	20,19%
F3	ateliercouture9FCC	Time	36513,51	1201,25	21710,81	40,54%
F4	ateliercouture9FCC	Time	31479,99	1201,16	22745,68	27,75%
F2	ateliercouture9FCC	Time	36939,07	1201,53	20899,28	43,42%
S1	ateliercouture9	Time	31004,22	1201,36	22611,86	27,07%
S2	ateliercouture9	Time	29784,27	1201,35	22901,65	23,11%
S3	ateliercouture9	Time	31418,99	1201,30	23475,28	25,28%
S4	ateliercouture9	Time	29784,27	1201,48	23876,90	19,83%
F1	ateliercouture10FCC	Time	42646,11	1201,43	25087,31	41,17%
F3	ateliercouture10FCC	Time	36102,45	1201,36	25628,25	29,01%
F4	ateliercouture10FCC	Time	35406,45	1200,86	27066,17	23,56%
F2	ateliercouture10FCC	Time	41970,42	1201,16	24813,59	40,88%
S1	ateliercouture10	Time	35991,08	1201,56	26541,06	26,26%
S2	ateliercouture10	Time	35991,08	1201,02	27094,36	24,72%
S3	ateliercouture10	Time	36166,45	1201,22	27843,10	23,01%
S4	ateliercouture10	Time	35904,08	1200,82	27611,42	23,10%
S2	atelierguitare5	Time	89259,76	1201,35	53943,70	39,57%
S3	atelierguitare2	Time	75455,00	1201,15	45127,43	40,19%
S1	atelierguitare3	Time	74755,80	1201,73	44678,93	40,23%
F2	atelierguitare11FCC	Time	74312,50	1201,77	44341,95	40,33%
S1	atelierguitare2	Time	74452,75	1201,85	44186,46	40,65%
S3	atelierguitare3	Time	78379,50	1201,03	46481,85	40,70%
S4	atelierguitare6	Time	81685,50	1201,21	48212,25	40,98%
S3	atelierguitare7	Time	92082,00	1200,95	53904,11	41,46%
S1	atelierguitare10	Time	90753,00	1201,56	53060,87	41,53%
F4	atelierguitare7FCC	Time	91980,25	1200,85	53395,39	41,95%
S2	atelierguitare6	Time	81613,00	1201,55	47348,47	41,98%
S3	atelierguitare6	Time	82252,25	1201,07	47672,36	42,04%

F3	atelierguitare3FCC	Time	74620,00	1202,22	43093,15	42,25%
S3	atelierguitare9	Time	81393,50	1201,20	46967,65	42,30%
S2	atelierguitare2	Time	78175,25	1201,34	44912,00	42,55%
S4	atelierguitare7	Time	93636,00	1201,20	53217,91	43,17%
S1	atelierguitare4	Time	98096,50	1201,42	55723,94	43,19%
F3	atelierguitare11FCC	Time	77515,50	1201,06	43854,99	43,42%
S2	atelierguitare7	Time	92429,00	1201,18	52220,22	43,50%
S2	atelierguitare9	Time	81892,82	1201,41	46203,07	43,58%
F4	atelierguitare6FCC	Time	82037,75	1200,94	46167,20	43,72%
S2	atelierguitare10	Time	97911,75	1201,34	54501,49	44,34%
F4	atelierguitare11FCC	Time	82532,00	1200,98	45582,65	44,77%
S3	atelierguitare10	Time	99076,00	1201,09	54570,67	44,92%
F2	atelierguitare3FCC	Time	79936,75	1202,95	43084,41	46,10%
F1	atelierguitare1FCC	Time	90993,25	1202,96	48558,88	46,63%
F4	atelierguitare10FCC	Time	100850,50	1201,02	53320,09	47,13%
F3	atelierguitare7FCC	Time	91427,25	1202,55	47377,83	48,18%
F3	atelierguitare6FCC	Time	85286,50	1202,85	44073,90	48,32%
S1	atelierguitare11	Time	90345,50	1201,54	46454,36	48,58%
S1	atelierguitare5	Time	103082,50	1201,84	52957,34	48,63%
F1	atelierguitare5FCC	Time	99250,00	1202,69	50943,03	48,67%
S4	atelierguitare9	Time	94260,05	1201,38	47260,42	49,86%
F2	atelierguitare7FCC	Time	92126,00	1201,59	45553,80	50,55%
F4	atelierguitare2FCC	Time	89359,25	1201,16	43741,27	51,05%
F3	atelierguitare4FCC	Time	109194,96	1202,34	53332,90	51,16%
F4	atelierguitare5FCC	Time	107095,00	1201,08	51489,58	51,92%
S1	atelierguitare9	Time	94752,85	1201,40	45331,06	52,16%
F4	atelierguitare9FCC	Time	94705,85	1200,74	44864,52	52,63%
F3	atelierguitare2FCC	Time	91933,50	1203,01	42906,57	53,33%
S1	atelierguitare6	Time	97825,25	1201,39	45171,81	53,82%
F3	atelierguitare9FCC	Time	94812,17	1201,85	43339,36	54,29%

F2	atelierguitare9FCC	Time	95598,55	1201,06	42884,78	55,14%
S1	atelierguitare7	Time	109142,99	1201,55	48577,37	55,49%
F2	atelierguitare6FCC	Time	99739,75	1201,36	43998,87	55,89%
F1	atelierguitare9FCC	Time	101203,02	1201,24	41064,64	59,42%
S1	atelierguitare4	Time	134356,50	1202,30	54377,26	59,53%
F1	atelierguitare7FCC	Time	114618,00	1202,49	41940,27	63,41%
F1	atelierguitare2FCC	No feasible solution found	41931,00	1200,00		
F1	atelierguitare3FCC	No feasible solution found	42485,00	1200,00		
F1	atelierguitare4FCC	No feasible solution found	52175,00	1200,00		
F1	atelierguitare6FCC	No feasible solution found	43815,00	1200,00		
F1	atelierguitare10FCC	No feasible solution found	51849,00	1200,00		
F2	atelierguitare1FCC	No feasible solution found	48495,00	1200,00		
F2	atelierguitare2FCC	No feasible solution found	42021,00	1200,00		
F2	atelierguitare4FCC	No feasible solution found	52878,00	1200,00		
F2	atelierguitare5FCC	No feasible solution found	50952,00	1200,00		
F2	atelierguitare10FCC	No feasible solution found	52112,00	1200,00		
F3	atelierguitare5FCC	No feasible solution found	50825,00	1200,00		
F1	atelierpeinture1FCC	Time	86037,50	1201,82	53426,17	37,90%
F3	atelierpeinture1FCC	Time	85955,50	1202,67	57801,71	32,75%
F4	atelierpeinture1FCC	Time	85868,50	1200,94	59281,82	30,96%
F2	atelierpeinture1FCC	Time	85744,50	1201,17	57036,66	33,48%
S1	atelierpeinture1	Time	85782,50	1201,39	58383,40	31,94%
S2	atelierpeinture1	Time	85744,50	1200,98	58903,30	31,30%
S3	atelierpeinture1	Time	85955,50	1201,09	61309,44	28,67%
S4	atelierpeinture1	Time	85955,50	1201,84	62682,64	27,08%
F1	atelierpeinture2FCC	Time	99121,50	1201,27	77949,74	21,36%
F3	atelierpeinture2FCC	Time	99355,00	1202,74	80476,30	19,00%
F4	atelierpeinture2FCC	Time	98715,50	1200,82	92171,86	6,63%
F2	atelierpeinture2FCC	Time	98715,50	1201,00	82502,89	16,42%
S1	atelierpeinture2	Time	98418,00	1201,06	82507,87	16,17%

S2	atelierpeinture2	Found optimal	98418,00	726,77	98418,00	0,00%
S3	atelierpeinture2	Found optimal	98418,00	621,24	98418,00	0,00%
S4	atelierpeinture2	Found optimal	98418,00	549,69	98418,00	0,00%
F1	atelierpeinture4FCC	Time	107572,00	1201,68	67708,75	37,06%
F3	atelierpeinture4FCC	Time	106936,00	1202,08	82972,80	22,41%
F4	atelierpeinture4FCC	Time	106329,00	1200,87	89308,95	16,01%
F2	atelierpeinture4FCC	Time	106936,00	1201,25	80062,06	25,13%
S1	atelierpeinture4	Time	106599,00	1201,09	81119,31	23,90%
S2	atelierpeinture4	Time	106599,00	1201,02	93159,88	12,61%
S3	atelierpeinture4	Time	106599,00	1201,12	94549,68	11,30%
S4	atelierpeinture4	Time	106599,00	1201,01	88932,68	16,57%
F1	atelierpeinture5FCC	Time	152358,00	1201,65	83188,25	45,40%
F3	atelierpeinture5FCC	Time	152231,66	1202,22	93758,21	38,41%
F4	atelierpeinture5FCC	Time	150539,00	1201,14	104216,85	30,77%
F2	atelierpeinture5FCC	Time	155454,00	1201,14	87789,91	43,53%
S1	atelierpeinture5	Time	154157,00	1201,09	95726,60	37,90%
S2	atelierpeinture5	Time	153012,00	1356,72	104631,99	31,62%
S3	atelierpeinture5	Time	153405,00	1201,27	106879,30	30,33%
S4	atelierpeinture5	Time	155746,00	1201,52	106404,15	31,68%
F1	atelierpeinture6FCC	Time	92957,75	1202,46	42308,81	54,49%
F3	atelierpeinture6FCC	Time	92546,00	1202,88	45925,89	50,38%
F4	atelierpeinture6FCC	Time	92546,00	1201,04	47135,21	49,07%
F2	atelierpeinture6FCC	Time	92684,00	1201,83	44240,08	52,27%
S1	atelierpeinture6	Time	92984,00	1201,21	46168,64	50,35%
S2	atelierpeinture6	Time	92662,00	1201,13	48638,78	47,51%
S3	atelierpeinture6	Time	92684,00	1201,00	48272,85	47,92%
S4	atelierpeinture6	Time	92672,00	1200,98	48016,18	48,19%
F1	atelierpeinture7FCC	Time	74070,25	1201,40	46610,05	37,07%
F3	atelierpeinture7FCC	Time	73995,50	1202,69	48389,11	34,61%
F4	atelierpeinture7FCC	Time	73995,50	1200,96	49067,07	33,69%

F2	atelierpeinture7FCC	Time	74091,25	1201,28	47815,27	35,46%
S1	atelierpeinture7	Time	73995,50	1201,03	48975,18	33,81%
S2	atelierpeinture7	Time	73993,00	1202,46	49340,09	33,32%
S3	atelierpeinture7	Time	73995,50	1201,49	49408,72	33,23%
S4	atelierpeinture7	Time	74104,75	1200,84	49148,83	33,68%
F1	atelierpeinture8FCC	Time	107926,25	1201,43	55449,76	48,62%
F3	atelierpeinture8FCC	Time	107012,75	1201,88	69692,00	34,88%
F4	atelierpeinture8FCC	Time	106798,25	1200,89	63143,98	40,88%
F2	atelierpeinture8FCC	Time	107047,00	1201,49	62144,72	41,95%
S1	atelierpeinture8	Time	106332,75	1201,07	65836,80	38,08%
S2	atelierpeinture8	Time	106332,75	1201,55	76181,99	28,36%
S3	atelierpeinture8	Time	106332,75	1201,39	70713,12	33,50%
S4	atelierpeinture8	Time	106279,00	1201,37	75629,45	28,84%
F1	atelierpeinture9FCC	Time	96034,00	1201,14	75690,24	21,18%
F3	atelierpeinture9FCC	Time	96034,00	1202,68	85643,31	10,82%
F4	atelierpeinture9FCC	Found optimal	96034,00	940,39	96034,00	0,00%
F2	atelierpeinture9FCC	Time	96034,00	1201,06	91049,00	5,19%
S1	atelierpeinture9	Time	96034,00	1200,87	86264,93	10,17%
S2	atelierpeinture9	Found optimal	96034,00	496,72	96029,29	0,00%
S3	atelierpeinture9	Found optimal	96034,00	183,11	96034,00	0,00%
S4	atelierpeinture9	Found optimal	96034,00	204,63	96034,00	0,00%
F1	atelierpeinture10FCC	Time	116904,00	1201,80	56827,67	51,39%
F3	atelierpeinture10FCC	Time	103897,00	1203,15	69450,71	33,15%
F4	atelierpeinture10FCC	Time	103897,00	1200,82	72572,81	30,15%
F2	atelierpeinture10FCC	Time	104315,00	1201,34	65841,32	36,88%
S1	atelierpeinture10	Time	103897,00	1201,29	68393,35	34,17%
S2	atelierpeinture10	Time	103897,00	1201,15	75497,13	27,33%
S3	atelierpeinture10	Time	103897,00	1200,96	76875,26	26,01%
S4	atelierpeinture10	Time	104315,00	1201,24	75279,14	27,83%
F1	atelierpeinture12FCC	Time	111673,00	1202,12	61448,25	44,97%

F2	atelierpeinture12FCC	Time	115221,00	1201,55	64961,81	43,62%
S4	atelierpeinture12	Time	111339,00	1200,99	70879,46	36,34%
F3	atelierpeinture12FCC	Time	111604,00	1201,34	64299,18	42,39%
S3	atelierpeinture12	Time	111339,00	1201,34	68646,99	38,34%
S2	atelierpeinture12	Time	111339,00	1201,22	70540,42	36,64%
S1	atelierpeinture12	Time	111339,00	1201,33	65502,54	41,17%
F4	atelierpeinture12FCC	Time	111016,00	1201,36	69357,64	37,52%
F1	atelierguitare11FCC	No feasible solution found	42658,00	1200,00		

APPENDIX B

DISTRIBUTION OF S2, S3 AND S4 ACCORDING TO TERMINATION CONDITION, BEST SOLUTION, LOWER BOUND, UPPER BOUND AND GAP

Variant	Data	Termination condition	Best solution	Resolution Time	Lower bound	Gap
S4	ateliergguitare1	Time	72039,50	3602,59	54498,45	24,35%
S4	atelierguitare2	Time	72768,25	3602,71	46366,08	36,28%
S4	atelierguitare3	Time	66173,50	3602,91	47555,18	28,14%
S4	atelierguitare4	Time	82335,00	3602,60	57436,71	30,24%
S4	atelierguitare5	Time	73539,50	3601,36	55648,65	24,33%
S4	atelierguitare6	Time	81685,50	3603,17	48996,08	40,02%
S4	atelierguitare7	Time	93636,00	3601,17	56575,11	39,58%
S4	atelierguitare9	Time	80798,88	3603,23	49010,08	39,34%
S4	atelierguitare10	Time	89959,01	3601,98	55597,00	38,20%
S4	atelierguitare11	Time	69143,00	3601,62	49870,31	27,87%
S4	ateliercouture1	Time	35423,65	3603,81	26290,55	25,78%
S4	ateliercouture2	Time	28765,49	3601,60	25607,93	10,98%
S4	ateliercouture3	Time	36897,52	3603,63	31831,04	13,73%
S4	ateliercouture4	Time	30192,00	3604,05	22699,16	24,82%
S4	ateliercouture5	Found optimal	30872,01	8,86	30872,01	0,00%
S4	ateliercouture6	Time	35385,00	3604,63	23446,74	33,74%
S4	ateliercouture7	Time	40451,50	3602,87	33390,59	17,46%
S4	ateliercouture8	Time	43926,20	3604,09	35418,73	19,37%
S4	ateliercouture9	Time	29784,27	3603,90	24465,44	17,86%
S4	ateliercouture10	Time	35904,08	3601,52	28328,12	21,10%
S4	atelierpeinture1	Time	85955,50	3601,33	81039,96	5,72%
S4	atelierpeinture2	Found optimal	98418,00	534,45	98418,00	0,00%

S4	atelierpeinture4	Time	106599,00	3601,30	93441,77	12,34%
S4	atelierpeinture5	Time	153012,00	3603,63	112386,64	26,55%
S4	atelierpeinture6	Time	92672,00	3601,55	48985,71	47,14%
S4	atelierpeinture7	Time	74090,00	3601,54	49451,07	33,26%
S4	atelierpeinture8	Time	106279,00	3603,27	79610,83	25,09%
S4	atelierpeinture9	Found optimal	96034,00	203,00	96034,00	0,00%
S4	atelierpeinture10	Time	103897,00	3601,53	79009,44	23,95%
S4	atelierpeinture12	Time	111339,00	3601,61	73776,52	33,74%
S3	ateliergu itare1	Time	72039,50	8170,37	54309,11	24,61%
S3	ateliergu itare2	Time	75372,00	3602,78	45958,18	39,02%
S3	ateliergu itare3	Time	73692,50	3602,28	47662,22	35,32%
S3	ateliergu itare4	Time	81081,00	3601,31	56588,25	30,21%
S3	ateliergu itare5	Time	88378,00	3601,42	55178,28	37,57%
S3	ateliergu itare6	Time	80576,50	3602,51	48312,77	40,04%
S3	ateliergu itare7	Time	92082,00	3601,24	56182,15	38,99%
S3	ateliergu itare9	Time	81347,08	3602,44	48703,83	40,13%
S3	ateliergu itare10	Time	82909,75	3602,07	55179,20	33,45%
S3	ateliergu itare11	Time	68837,50	3602,91	50713,03	26,33%
S3	ateliercouture1	Time	36030,00	3603,48	26250,17	27,14%
S3	ateliercouture2	Time	28765,49	3603,94	25625,19	10,92%
S3	ateliercouture3	Time	37047,23	3602,73	31575,13	14,77%
S3	ateliercouture4	Time	30192,00	3604,40	22675,65	24,90%
S3	ateliercouture5	Found optimal	30875,00	23,86	30875,00	0,00%
S3	ateliercouture6	Time	35355,00	3604,24	23460,64	33,64%
S3	ateliercouture7	Time	40451,50	3602,76	33972,46	16,02%
S3	ateliercouture8	Time	43718,20	3603,39	35404,71	19,02%
S3	ateliercouture9	Time	29558,27	3602,80	24260,48	17,92%
S3	ateliercouture10	Time	36166,45	3602,45	28692,23	20,67%
S3	atelierpeinture1	Time	85744,50	3601,47	74213,24	13,45%
S3	atelierpeinture2	Found optimal	98418,00	506,10	98418,00	0,00%

S3	atelierpeinture4	Found optimal	106599,00	2644,35	106599,00	0,00%
S3	atelierpeinture5	Time	153153,00	3602,26	112538,58	26,52%
S3	atelierpeinture6	Time	92678,00	3601,61	55355,26	40,27%
S3	atelierpeinture7	Time	73995,50	3604,68	49767,35	32,74%
S3	atelierpeinture8	Time	106332,75	3601,54	74489,02	29,95%
S3	atelierpeinture9	Found optimal	96034,00	186,26	96034,00	0,00%
S3	atelierpeinture10	Time	103897,00	3601,14	83652,70	19,48%
S3	atelierpeinture12	Time	111339,00	3601,46	73838,32	33,68%
S2	atelierguitare1	Time	73390,50	3603,67	53852,54	26,62%
S2	atelierguitare2	Time	77275,25	3602,56	45828,95	40,69%
S2	atelierguitare3	Time	74340,85	3602,81	47235,45	36,46%
S2	atelierguitare4	Time	82335,00	3601,51	56345,84	31,57%
S2	atelierguitare5	Time	83343,75	3601,63	55144,46	33,83%
S2	atelierguitare6	Time	81359,75	3602,96	48028,98	40,97%
S2	atelierguitare7	Time	92429,00	3601,66	54518,17	41,02%
S2	atelierguitare9	Time	80309,35	3602,92	47654,55	40,66%
S2	atelierguitare10	Time	97905,75	3603,92	55129,65	43,69%
S2	atelierguitare11	Time	68798,50	3602,95	50589,31	26,47%
S2	ateliercouture1	Time	35405,24	3603,80	26169,64	26,09%
S2	ateliercouture2	Time	28765,49	3603,35	24974,51	13,18%
S2	ateliercouture3	Time	36561,53	3601,80	31212,06	14,63%
S2	ateliercouture4	Time	30192,00	3605,76	22437,29	25,68%
S2	ateliercouture5	Found optimal	30875,00	8,74	30875,00	0,00%
S2	ateliercouture6	Time	35351,00	3604,89	23243,86	34,25%
S2	ateliercouture7	Time	40448,00	3602,51	32874,10	18,73%
S2	ateliercouture8	Time	44053,20	3604,21	35378,15	19,69%
S2	ateliercouture9	Time	29558,27	3603,11	23514,02	20,45%
S2	ateliercouture10	Time	35904,08	3601,50	27970,42	22,10%
S2	atelierpeinture1	Time	85744,50	3601,54	60391,76	29,57%
S2	atelierpeinture2	Found optimal	98418,00	666,62	98418,00	0,00%

S2	atelierpeinture4	Time	106599,00	3601,14	102421,38	3,92%
S2	atelierpeinture5	Time	153012,00	3602,75	109902,29	28,17%
S2	atelierpeinture6	Time	92662,00	3601,83	59519,34	35,77%
S2	atelierpeinture7	Time	73993,00	3605,54	49771,38	32,74%
S2	atelierpeinture8	Time	106332,75	3603,10	80772,86	24,04%
S2	atelierpeinture9	Found optimal	96034,00	485,95	96029,29	0,00%
S2	atelierpeinture10	Time	103897,00	3601,39	80986,39	22,05%
S2	atelierpeinture12	Time	111339,00	3601,77	73154,25	34,30%

APPENDIX C

DISTRIBUTION OF SOLUTIONS ACCORDING TO BEST OBJECTIVE VALUE, GAP AND TIME

ateilerguitare1.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	5787,00	1420,00	65619,00	72826,00	22,49%	3602,49
Experiment 2	2478,00	955,00	93309,00	96742,00	0,00%	249,81
Experiment 3	1297,00	1297,00	109686,00	112280,00	39,22%	3601,35
Experiment 4	2146,00	1086,00	85192,00	88424,00	24,73%	3602,60
Experiment 5	2855,00	1476,50	73395,00	77726,50	23,92%	3602,85
Experiment 6	1823,00	1024,50	97340,00	100187,50	24,29%	3603,17
Experiment 7	1323,00	1113,00	103804,81	106240,81	28,24%	3602,28
Experiment 8	1315,00	1050,00	102145,00	104510,00	15,87%	3602,04
Experiment 9	1848,00	1387,50	91400,00	94635,50	34,30%	3602,77
Experiment 10	5651,00	1198,00	67809,00	74658,00	16,99%	3603,13
Experiment 11	5588,00	1038,75	73252,00	79878,75	12,15%	3603,04
Experiment 12	5585,00	1325,50	65895,00	72805,50	16,86%	3602,22
Experiment 13	1401,00	1012,00	103352,00	105765,00	4,11%	3601,69
Experiment 14	1283,00	1159,00	104578,00	107020,00	25,29%	3602,43
Experiment 15	1359,00	1353,25	99221,00	101933,25	31,77%	3601,60
Experiment 16	3238,00	1643,00	70281,00	75162,00	26,76%	3602,62
atelierguitare2.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4979,00	677,50	56411,00	62067,50	24,61%	3601,64
Experiment 2	1641,00	562,00	72256,00	74459,00	7,30%	3601,53
Experiment 3	696,00	695,00	116139,00	117530,00	17,93%	3601,34
Experiment 4	991,00	592,00	81054,01	82637,01	32,59%	3601,26
Experiment 5	1309,00	683,00	75302,03	77294,03	33,83%	3601,16
Experiment 6	1179,00	631,00	79027,00	80837,00	30,30%	3602,37
Experiment 7	1088,00	599,00	78026,00	79713,00	32,86%	3601,62
Experiment 8	749,00	670,00	116620,00	118039,00	22,23%	3601,63
Experiment 9	1088,00	599,00	78026,00	79713,00	34,72%	3601,20
Experiment 10	4657,00	639,75	56788,00	62084,75	21,68%	3602,05
Experiment 11	4106,00	664,25	59995,00	64765,25	24,82%	3601,22
Experiment 12	4584,00	635,25	56785,00	62004,25	23,88%	3601,09
Experiment 13	979,00	612,00	82772,00	84363,00	18,66%	3601,71
Experiment 14	668,00	668,00	116639,00	117975,00	22,31%	3601,00

Experiment 15	976,00	652,00	79886,00	81514,00	35,51%	3601,40
Experiment 16	2015,00	799,25	63227,00	66041,25	28,99%	3601,07
ateliergguitare3.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	6208,00	1344,00	59099,00	66651,00	26,62%	3602,25
Experiment 2	4731,00	1017,00	71306,00	77054,00	0,00%	2721,75
Experiment 3	1288,00	1288,00	149823,00	152399,00	0,00%	1271,74
Experiment 4	3289,00	1386,45	72609,00	77284,45	29,70%	3601,97
Experiment 5	3139,00	1160,00	68731,00	73030,00	28,14%	3602,08
Experiment 6	3135,00	1118,50	68149,00	72402,50	20,38%	3601,90
Experiment 7	1929,00	1389,70	90739,04	94057,74	22,62%	3601,70
Experiment 8	1316,00	1195,00	149530,00	152041,00	11,80%	3601,67
Experiment 9	3275,00	1534,55	71679,00	76488,55	31,09%	3602,01
Experiment 10	5847,00	1101,50	58975,00	65923,50	19,00%	3602,47
Experiment 11	5949,00	1125,50	59266,00	66340,50	17,67%	3602,31
Experiment 12	4911,00	1104,50	67678,00	73693,50	33,23%	3602,53
Experiment 13	2122,00	1071,50	113787,00	116980,50	12,23%	3602,13
Experiment 14	1544,00	1242,00	138949,00	141735,00	19,59%	3601,75
Experiment 15	2091,00	1336,20	95698,00	99125,20	27,68%	3602,13
Experiment 16	3112,00	1142,00	68265,00	72519,00	31,46%	3602,66
ateliergguitare4.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	7975,00	2380,00	70073,00	80428,00	25,69%	3601,29
Experiment 2	4002,00	1323,00	118009,00	123334,00	0,00%	173,42
Experiment 3	1792,00	1649,48	134821,02	138262,50	42,48%	3600,97
Experiment 4	3134,00	1687,00	80998,00	85819,00	24,35%	3601,47
Experiment 5	2928,00	1651,50	80740,00	85319,50	25,74%	3602,17
Experiment 6	2928,00	1651,50	80740,00	85319,50	17,75%	3601,56
Experiment 7	2593,00	1728,83	87432,00	91753,83	23,76%	3601,23
Experiment 8	1816,00	1622,00	142356,00	145794,00	16,03%	3601,39
Experiment 9	3028,00	1905,75	80448,00	85381,75	30,49%	3601,39
Experiment 10	5205,00	1546,00	79036,00	85787,00	21,36%	3601,36
Experiment 11	5439,00	1478,25	79313,00	86230,25	9,85%	3601,52
Experiment 12	5155,00	1768,50	75829,00	82752,50	26,38%	3602,00
Experiment 13	2321,00	1436,84	130112,00	133869,84	8,99%	3601,64
Experiment 14	1819,00	1614,00	143079,00	146512,00	24,00%	3601,45
Experiment 15	2623,00	2020,31	90817,00	95460,31	32,35%	3601,11
Experiment 16	3507,00	1851,01	77655,00	83013,01	30,66%	3601,65
ateliergguitare5.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time

Experiment 1	7238,00	1284,50	65311,00	73833,50	20,82%	3601,43
Experiment 2	2268,00	1016,75	117657,00	120941,75	7,26%	3601,76
Experiment 3	1182,00	1178,00	130842,99	133202,99	36,16%	3600,99
Experiment 4	1385,00	1201,25	110865,00	113451,25	36,78%	3601,61
Experiment 5	2390,00	1423,25	89595,00	93408,25	35,70%	3601,16
Experiment 6	2565,00	1126,75	80629,00	84320,75	26,57%	3601,40
Experiment 7	1601,00	1214,00	98194,00	101009,00	34,32%	3601,21
Experiment 8	1428,00	1173,00	129819,00	132420,00	28,01%	3601,23
Experiment 9	1298,00	1276,00	112784,00	115358,00	42,39%	3601,70
Experiment 10	6585,00	1084,25	65980,00	73649,25	15,76%	3601,74
Experiment 11	6696,00	1153,75	66247,00	74096,75	16,78%	3601,35
Experiment 12	6616,00	1106,00	66001,00	73723,00	19,12%	3602,14
Experiment 13	1333,00	1101,50	132218,00	134652,50	17,04%	3601,24
Experiment 14	1314,00	1179,00	127636,00	130129,00	32,46%	3601,02
Experiment 15	1281,00	1245,00	113558,02	116084,02	41,71%	3601,18
Experiment 16	3390,00	1266,50	74665,00	79321,50	30,00%	3601,59
ateliergutare6.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	3882,00	762,50	76698,00	81342,50	41,05%	3602,78
Experiment 2	1571,00	593,25	90848,00	93012,25	6,28%	3601,81
Experiment 3	947,00	797,00	121146,00	122890,00	23,46%	3601,33
Experiment 4	1270,00	693,25	87699,00	89662,25	33,09%	3602,15
Experiment 5	1897,00	713,50	81127,00	83737,50	35,44%	3602,37
Experiment 6	1293,00	639,00	89950,00	91882,00	30,48%	3602,09
Experiment 7	1129,00	700,00	89734,00	91563,00	32,73%	3602,14
Experiment 8	1177,00	687,50	94234,00	96098,50	25,93%	3602,30
Experiment 9	1150,00	795,00	88433,00	90378,00	35,34%	3602,80
Experiment 10	5691,00	626,00	67432,00	73749,00	28,27%	3603,02
Experiment 11	4370,00	652,25	65838,00	70860,25	21,32%	3602,68
Experiment 12	5795,00	688,00	65493,00	71976,00	28,80%	3602,48
Experiment 13	1186,00	641,00	90918,00	92745,00	16,83%	3602,00
Experiment 14	1078,00	718,00	93043,00	94839,00	29,29%	3602,01
Experiment 15	1087,00	902,00	91317,00	93306,00	35,94%	3601,53
Experiment 16	2672,00	794,50	69571,00	73037,50	32,23%	3602,42
ateliergutare7.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	3650,00	1819,25	88983,00	94452,25	40,74%	3601,05
Experiment 2	1998,00	1138,00	110994,00	114130,00	0,00%	264,49
Experiment 3	1374,00	1374,00	140461,00	143209,00	35,10%	3601,01
Experiment 4	2076,00	1279,00	91476,00	94831,00	22,11%	3601,38

Experiment 5	2076,00	1279,00	91476,00	94831,00	30,00%	3601,22
Experiment 6	1680,00	1307,00	92160,00	95147,00	16,96%	3601,37
Experiment 7	1802,00	1426,00	97028,00	100256,00	25,52%	3601,29
Experiment 8	1380,00	1300,00	115944,02	118624,02	12,41%	3601,43
Experiment 9	1696,00	1582,00	91226,00	94504,00	25,41%	3601,23
Experiment 10	2523,00	1227,25	90589,00	94339,25	24,89%	3601,10
Experiment 11	2523,00	1227,25	90589,00	94339,25	11,80%	3601,03
Experiment 12	2639,00	1485,25	88659,00	92783,25	32,38%	3601,00
Experiment 13	1696,00	1172,00	110342,00	113210,00	0,00%	3587,16
Experiment 14	1432,00	1287,00	115924,00	118643,00	24,03%	3601,38
Experiment 15	1617,00	1453,00	90727,00	93797,00	28,46%	3601,37
Experiment 16	1786,00	1573,00	89028,00	92387,00	31,86%	3601,34
ateliergguitare9.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	3954,00	1651,44	74537,00	80142,44	40,68%	3603,65
Experiment 2	4681,00	775,65	109360,00	114816,65	0,00%	867,13
Experiment 3	1094,00	1078,00	107331,00	109503,00	37,48%	3601,28
Experiment 4	1335,00	980,00	99835,00	102150,00	39,78%	3602,83
Experiment 5	1732,00	1279,00	83976,00	86987,00	37,57%	3602,60
Experiment 6	1225,00	994,00	100974,01	103193,01	33,72%	3602,76
Experiment 7	1149,00	954,00	100165,00	102268,00	36,51%	3602,38
Experiment 8	1207,00	967,00	106419,01	108593,01	18,94%	3602,16
Experiment 9	1660,00	1465,00	83571,00	86696,00	39,75%	3602,34
Experiment 10	4765,00	993,56	76878,00	82636,56	32,73%	3601,98
Experiment 11	4619,00	917,14	91555,00	97091,14	32,41%	3602,41
Experiment 12	4727,00	1056,05	76050,00	81833,05	39,12%	3602,59
Experiment 13	1314,00	918,44	103684,00	105916,44	11,12%	3602,41
Experiment 14	1108,00	1006,00	101908,00	104022,00	22,50%	3602,24
Experiment 15	1207,00	1057,00	100845,00	103109,00	40,88%	3601,84
Experiment 16	2301,00	1729,00	77566,00	81596,00	38,22%	3603,57
ateliergguitare10.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	5787,00	1420,00	65619,00	72826,00	22,49%	3602,49
Experiment 2	2478,00	955,00	93309,00	96742,00	0,00%	249,81
Experiment 3	1297,00	1297,00	109686,00	112280,00	39,22%	3601,35
Experiment 4	2146,00	1086,00	85192,00	88424,00	24,73%	3602,60
Experiment 5	2855,00	1476,50	73395,00	77726,50	23,92%	3602,85
Experiment 6	2024,00	992,50	90253,00	93269,50	25,35%	3602,23
Experiment 7	1754,00	856,50	93171,00	95781,50	24,14%	3601,74
Experiment 8	1339,00	962,00	138651,00	140952,00	22,10%	3601,85

Experiment 9	2292,00	1020,50	85307,00	88619,50	30,24%	3601,98
Experiment 10	4703,00	981,25	77438,00	83122,25	26,24%	3602,32
Experiment 11	5400,00	846,75	78022,00	84268,75	18,01%	3602,00
Experiment 12	4205,00	1101,50	76732,00	82038,50	29,95%	3602,70
Experiment 13	1607,00	895,00	103799,00	106301,00	14,06%	3602,10
Experiment 14	1356,00	1034,00	141216,00	143606,00	29,34%	3601,32
Experiment 15	1792,00	1053,00	97782,00	100627,00	30,44%	3601,46
Experiment 16	3250,00	1172,25	81412,00	85834,25	34,01%	3602,25
ateliergguitare11.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	6336,00	1258,50	61223,00	68817,50	23,55%	3602,60
Experiment 2	3268,00	958,50	103823,00	108049,50	2,64%	3601,52
Experiment 3	1290,00	1261,00	131111,00	133662,00	6,23%	3601,06
Experiment 4	2653,00	1033,00	88531,00	92217,00	26,29%	3602,07
Experiment 5	3371,00	1190,00	73331,00	77892,00	27,36%	3602,24
Experiment 6	2724,00	1071,00	88616,00	92411,00	22,51%	3602,31
Experiment 7	1744,00	1190,00	103014,00	105948,00	20,43%	3601,94
Experiment 8	1477,00	1041,00	131201,00	133719,00	8,29%	3602,02
Experiment 9	2503,00	1431,00	87526,00	91460,00	29,27%	3602,08
Experiment 10	6347,00	1146,50	61738,00	69231,50	19,15%	3602,47
Experiment 11	5637,00	1111,00	69200,00	75948,00	19,62%	3603,20
Experiment 12	6419,00	1169,00	61226,00	68814,00	24,28%	3602,65
Experiment 13	1381,00	1028,00	126349,00	128758,00	3,28%	3601,68
Experiment 14	1322,00	1089,00	131910,00	134321,00	7,51%	3601,56
Experiment 15	1836,00	1171,00	103307,00	106314,00	20,82%	3601,73
Experiment 16	4452,00	1144,50	67962,00	73558,50	32,50%	3602,18
ateliercouture1.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1285,00	762,01	34050,00	36097,01	27,08%	3602,59
Experiment 2	1058,00	254,52	41391,00	42703,52	9,13%	3601,38
Experiment 3	546,00	444,01	38526,00	39516,01	66,57%	3601,09
Experiment 4	588,00	326,00	36857,00	37771,00	26,26%	3601,62
Experiment 5	651,00	352,12	35028,00	36031,12	24,95%	3601,58
Experiment 6	608,00	314,00	37657,00	38579,00	25,90%	3601,46
Experiment 7	576,00	316,00	36693,00	37585,00	30,91%	3601,29
Experiment 8	503,00	376,00	40971,00	41850,00	36,55%	3601,40
Experiment 9	647,00	484,00	36617,00	37748,00	32,90%	3601,41
Experiment 10	1036,00	338,00	34710,00	36084,00	23,34%	3601,39
Experiment 11	1202,00	286,00	36500,00	37988,00	20,45%	3601,55
Experiment 12	1168,00	331,38	34847,00	36346,38	25,55%	3601,42

Experiment 13	608,00	282,92	38064,00	38954,92	17,19%	3601,89
Experiment 14	499,00	375,00	38134,00	39008,00	46,87%	3601,81
Experiment 15	530,00	388,00	36397,00	37315,00	37,48%	3601,20
Experiment 16	934,00	452,00	34330,00	35716,00	28,27%	3603,25
ateliercouture2.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1388,00	669,30	26902,00	28959,30	12,11%	3604,09
Experiment 2	1020,00	275,00	36361,00	37656,00	0,00%	2774,36
Experiment 3	513,00	477,00	49319,00	50309,00	56,08%	3601,25
Experiment 4	666,00	347,96	32954,00	33967,96	20,63%	3602,26
Experiment 5	775,00	341,00	29542,00	30658,00	13,67%	3602,38
Experiment 6	754,00	346,00	31199,00	32299,00	17,79%	3602,18
Experiment 7	715,00	360,00	31001,00	32076,00	23,77%	3602,08
Experiment 8	593,00	347,00	36553,00	37493,00	30,45%	3602,49
Experiment 9	753,00	360,00	29776,00	30889,00	21,82%	3602,27
Experiment 10	1247,00	391,49	27233,00	28871,49	11,10%	3602,22
Experiment 11	1082,00	348,49	28483,00	29913,49	7,34%	3602,10
Experiment 12	1169,00	391,49	27500,00	29060,49	8,00%	3602,63
Experiment 13	676,00	298,50	34964,00	35938,50	16,45%	3602,37
Experiment 14	569,00	376,00	39205,00	40150,00	40,58%	3602,15
Experiment 15	588,00	420,00	35208,00	36216,00	33,30%	3601,85
Experiment 16	871,00	535,55	27554,00	28960,55	13,58%	3602,76
ateliercouture3.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	3012,00	949,73	33100,00	37061,73	13,79%	3601,47
Experiment 2	3240,00	429,37	50498,00	54167,37	0,00%	832,76
Experiment 3	937,00	815,00	73366,00	75118,00	51,27%	3601,38
Experiment 4	1348,00	688,00	41262,00	43298,00	22,59%	3601,29
Experiment 5	2063,00	686,25	35120,00	37869,25	19,11%	3602,56
Experiment 6	1471,00	637,37	44246,00	46354,37	24,77%	3601,33
Experiment 7	1382,00	652,00	44272,00	46306,00	29,81%	3601,30
Experiment 8	1110,00	678,00	63144,00	64932,00	32,51%	3601,22
Experiment 9	1535,00	796,80	39107,00	41438,80	27,95%	3601,38
Experiment 10	4303,00	483,25	33813,00	38599,25	4,31%	3601,71
Experiment 11	4318,00	460,61	34043,00	38821,61	2,91%	3601,49
Experiment 12	2566,00	601,41	36092,00	39259,41	15,16%	3601,61
Experiment 13	1629,00	622,00	51688,00	53939,00	31,64%	3601,34
Experiment 14	972,00	739,00	75863,00	77574,00	40,05%	3601,14
Experiment 15	1223,00	788,00	47965,00	49976,00	36,83%	3601,20
Experiment 16	1680,00	816,00	37493,00	39989,00	22,99%	3601,61

ateliercouture4.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1042,00	384,00	28766,00	30192,00	26,03%	3601,46
Experiment 2	1248,00	192,78	35943,00	37383,78	0,00%	567,01
Experiment 3	421,00	405,01	46212,00	47038,01	45,18%	3601,08
Experiment 4	520,00	337,00	32506,00	33363,00	25,74%	3601,59
Experiment 5	659,00	296,00	31125,00	32080,00	26,74%	3602,99
Experiment 6	532,00	289,00	33897,00	34718,00	22,96%	3602,61
Experiment 7	538,00	294,00	33753,00	34585,00	27,35%	3602,61
Experiment 8	512,00	289,00	35099,00	35900,00	30,70%	3601,46
Experiment 9	607,00	607,00	29975,00	31189,00	28,45%	3601,54
Experiment 10	1696,00	246,88	28587,00	30529,88	20,27%	3601,21
Experiment 11	1628,00	221,84	29331,00	31180,84	12,37%	3602,58
Experiment 12	1919,00	358,22	28651,00	30928,22	24,00%	3601,55
Experiment 13	622,00	244,30	38159,00	39025,30	21,81%	3601,82
Experiment 14	431,00	345,80	37856,00	38632,80	36,09%	3601,26
Experiment 15	473,00	430,00	33345,00	34248,00	34,16%	3601,23
Experiment 16	646,00	604,00	29748,00	30998,00	27,32%	3601,44
ateliercouture5.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1320,00	582,00	28989,00	30891,00	0,00%	10,12
Experiment 2	1091,00	433,44	39526,00	41050,44	0,00%	14,59
Experiment 3	662,00	661,00	36374,00	37697,00	0,00%	699,85
Experiment 4	767,00	582,00	30976,00	32325,00	0,00%	57,06
Experiment 5	803,00	652,00	29699,00	31154,00	0,00%	26,71
Experiment 6	807,00	514,00	32400,01	33721,01	0,00%	23,40
Experiment 7	737,00	558,01	32011,00	33306,01	0,00%	274,93
Experiment 8	712,00	558,01	35849,96	37119,98	0,00%	1603,24
Experiment 9	803,00	652,00	29699,00	31154,00	0,00%	91,70
Experiment 10	1152,00	538,00	29813,00	31503,00	0,00%	9,60
Experiment 11	1152,00	538,00	29813,00	31503,00	0,00%	14,15
Experiment 12	1320,00	582,00	28989,00	30891,00	0,00%	5,88
Experiment 13	1078,00	433,44	39858,00	41369,44	0,00%	192,77
Experiment 14	671,00	602,00	35753,99	37026,99	4,26%	3601,05
Experiment 15	739,00	626,00	30863,00	32228,00	0,00%	1487,45
Experiment 16	803,00	652,00	29699,00	31154,00	0,00%	26,62
ateliercouture6.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1408,00	729,00	33311,00	35448,00	34,55%	3603,98

Experiment 2	1866,00	228,36	42944,00	45038,36	0,00%	184,97
Experiment 3	491,00	450,00	58248,99	59189,99	40,38%	3601,16
Experiment 4	961,00	442,00	34568,00	35971,00	27,66%	3602,62
Experiment 5	961,00	442,00	34568,00	35971,00	28,59%	3603,19
Experiment 6	948,00	305,45	39778,00	41031,45	25,03%	3603,08
Experiment 7	759,00	384,00	40526,00	41669,00	29,57%	3602,77
Experiment 8	530,00	354,12	56496,00	57380,12	17,06%	3601,96
Experiment 9	1066,00	554,00	33735,00	35355,00	34,17%	3603,16
Experiment 10	1972,00	317,00	35025,00	37314,00	29,12%	3604,05
Experiment 11	1881,00	251,00	38055,00	40187,00	20,33%	3603,17
Experiment 12	1976,00	380,61	34191,00	36547,61	31,13%	3603,64
Experiment 13	669,00	323,99	47894,00	48886,99	13,59%	3602,80
Experiment 14	506,00	405,00	53531,00	54442,00	23,90%	3601,92
Experiment 15	669,00	489,00	46125,00	47283,00	38,09%	3602,99
Experiment 16	1066,00	554,00	33735,00	35355,00	32,53%	3603,69
ateliercouture7.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	1810,00	583,50	38058,00	40451,50	17,49%	3601,36
Experiment 2	1003,00	515,00	47653,00	49171,00	0,00%	170,07
Experiment 3	704,00	669,00	66750,00	68123,00	34,67%	3600,79
Experiment 4	1003,00	515,00	47653,00	49171,00	13,71%	3602,60
Experiment 5	1614,00	600,50	39013,00	41227,50	15,68%	3601,64
Experiment 6	1120,00	540,00	44467,00	46127,00	11,23%	3601,94
Experiment 7	989,00	668,00	44104,00	45761,00	19,36%	3601,86
Experiment 8	908,00	535,00	52966,00	54409,00	15,80%	3601,80
Experiment 9	1032,00	668,00	43172,00	44872,00	17,14%	3601,84
Experiment 10	1810,00	583,50	38058,00	40451,50	9,13%	3601,98
Experiment 11	1704,00	539,50	39866,00	42109,50	4,85%	3601,30
Experiment 12	1810,00	583,50	38058,00	40451,50	13,49%	3602,35
Experiment 13	1003,00	515,00	47653,00	49171,00	0,00%	1377,06
Experiment 14	783,00	618,00	56753,00	58154,00	26,84%	3601,24
Experiment 15	820,00	812,00	53780,00	55412,00	24,07%	3601,73
Experiment 16	1404,00	740,00	39683,00	41827,00	17,81%	3602,65
ateliercouture8.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4549,00	1565,20	38514,00	44628,20	17,13%	3604,13
Experiment 2	2766,00	991,20	52632,00	56389,20	0,00%	112,88
Experiment 3	1495,00	1392,00	100019,00	102906,00	64,14%	3601,17
Experiment 4	2322,00	1156,46	43209,00	46687,46	24,08%	3602,85
Experiment 5	2885,00	1239,67	40804,00	44928,67	25,53%	3603,34

Experiment 6	2498,00	1195,07	44074,00	47767,07	22,03%	3603,44
Experiment 7	2337,00	1247,41	42692,00	46276,41	33,00%	3602,62
Experiment 8	1547,00	1172,90	84693,00	87412,90	30,90%	3603,36
Experiment 9	2423,00	1413,32	40814,00	44650,32	32,08%	3602,97
Experiment 10	3572,00	1158,52	40146,00	44876,52	10,50%	3603,12
Experiment 11	2968,00	1089,45	44504,00	48561,45	7,46%	3602,24
Experiment 12	2350,00	1195,92	40177,00	43722,92	13,82%	3603,87
Experiment 13	1886,00	1098,45	81490,00	84474,45	19,56%	3603,75
Experiment 14	1464,00	1128,00	88303,00	90895,00	43,83%	3602,37
Experiment 15	2170,00	1333,60	52744,00	56247,60	47,69%	3601,78
Experiment 16	2478,00	1367,64	40120,00	43965,64	23,26%	3603,70
ateliercouture9.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	2537,00	785,15	27192,00	30514,15	19,86%	3602,25
Experiment 2	1635,00	278,65	48528,00	50441,65	0,00%	192,17
Experiment 3	623,00	570,96	51970,00	53163,96	40,18%	3600,92
Experiment 4	901,00	393,00	37154,00	38448,00	21,65%	3602,65
Experiment 5	1072,00	394,27	35672,00	37138,27	26,37%	3602,93
Experiment 6	1040,00	407,00	36714,00	38161,00	20,52%	3602,94
Experiment 7	750,00	532,27	37375,00	38657,27	22,24%	3603,21
Experiment 8	683,00	383,64	51576,00	52642,64	16,21%	3602,72
Experiment 9	1194,00	602,63	28614,00	30410,63	26,29%	3603,03
Experiment 10	1383,00	373,77	35377,00	37133,77	24,82%	3603,85
Experiment 11	1462,00	341,30	36162,00	37965,30	14,73%	3602,41
Experiment 12	1649,00	550,99	27945,00	30144,99	18,28%	3603,79
Experiment 13	891,00	308,00	48400,00	49599,00	0,00%	2929,69
Experiment 14	639,00	453,77	43054,00	44146,77	26,45%	3602,04
Experiment 15	699,00	484,00	40334,00	41517,00	28,05%	3602,48
Experiment 16	1189,00	602,63	28614,00	30405,63	20,92%	3603,32
ateliercouture10.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	3224,00	1587,45	31357,00	36168,45	17,40%	3601,97
Experiment 2	2351,00	856,92	51424,00	54631,92	0,00%	113,58
Experiment 3	1097,00	1097,00	77812,00	80006,00	54,04%	3601,48
Experiment 4	1921,00	976,53	34388,00	37285,53	17,72%	3602,90
Experiment 5	1866,00	1015,24	34472,00	37353,24	18,46%	3603,27
Experiment 6	1859,00	927,29	35067,00	37853,29	11,66%	3602,89
Experiment 7	1635,00	1102,74	41083,00	43820,74	28,06%	3603,30
Experiment 8	1177,00	970,00	69141,00	71288,00	20,38%	3603,62
Experiment 9	1992,00	1111,57	32843,00	35946,57	30,99%	3603,91

Experiment 10	2564,00	1006,20	32580,00	36150,20	9,48%	3602,48
Experiment 11	1921,00	911,21	35333,00	38165,21	0,00%	3401,79
Experiment 12	2934,00	1032,24	32245,00	36211,24	14,42%	3602,14
Experiment 13	1137,00	930,84	72785,00	74852,84	6,72%	3602,66
Experiment 14	1065,00	1051,00	75114,00	77230,00	33,70%	3602,89
Experiment 15	1448,00	1137,92	45858,00	48443,92	39,62%	3603,40
Experiment 16	1953,00	1103,08	32895,00	35951,08	22,08%	3602,94
atelierpeinture1.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	7365,00	2584,00	76094,00	86043,00	0,00%	3511,06
Experiment 2	6518,00	1970,50	85422,00	93910,50	0,00%	270,04
Experiment 3	2552,00	2477,50	169931,00	174960,50	41,61%	3601,00
Experiment 4	6549,00	1981,00	84525,00	93055,00	29,26%	3601,57
Experiment 5	7115,00	1981,50	77767,00	86863,50	26,42%	3601,54
Experiment 6	6549,00	1981,00	84525,00	93055,00	19,17%	3603,13
Experiment 7	3809,00	2363,50	120488,00	126660,50	31,59%	3601,53
Experiment 8	2430,00	2430,00	159268,00	164128,00	17,41%	3602,43
Experiment 9	4568,00	3013,50	98983,00	106564,50	34,04%	3601,44
Experiment 10	7138,00	1992,00	76869,00	85999,00	1,10%	3600,72
Experiment 11	7138,00	1992,00	76869,00	85999,00	0,01%	1951,78
Experiment 12	7138,00	1992,00	76869,00	85999,00	0,00%	1803,88
Experiment 13	3834,00	1994,00	136317,00	142145,00	12,38%	3601,95
Experiment 14	2547,00	2418,00	149852,00	154817,00	29,31%	3601,30
Experiment 15	2598,00	2455,00	142673,00	147726,00	28,82%	3601,21
Experiment 16	7052,00	2007,00	76986,00	86045,00	32,96%	3601,52
atelierpeinture2.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	6489,00	2493,50	89556,00	98538,50	0,00%	1006,32
Experiment 2	5037,00	2107,50	97902,00	105046,50	0,00%	43,30
Experiment 3	2341,00	2341,00	169750,00	174432,00	29,67%	3600,84
Experiment 4	3540,00	2449,50	101805,00	107794,50	7,10%	3601,34
Experiment 5	4691,00	2401,50	91697,00	98789,50	0,00%	1164,09
Experiment 6	4218,00	2265,50	98332,00	104815,50	3,06%	3600,92
Experiment 7	2960,00	2517,50	111658,00	117135,50	11,00%	3601,61
Experiment 8	2500,00	2209,00	161146,00	165855,00	4,14%	3601,13
Experiment 9	3490,93	3190,50	97571,99	104253,41	0,00%	2355,99
Experiment 10	5313,00	2115,00	92065,00	99493,00	0,00%	283,31
Experiment 11	5313,00	2115,00	92065,00	99493,00	0,00%	55,68
Experiment 12	5281,00	2184,00	90953,00	98418,00	0,00%	1036,21
Experiment 13	2698,00	2158,00	161364,00	166220,00	0,01%	1738,46

Experiment 14	2411,00	2411,00	170709,00	175531,00	19,04%	3601,30
Experiment 15	2752,00	2517,50	117527,00	122796,50	13,91%	3601,74
Experiment 16	4011,00	2900,00	94120,00	101031,00	0,00%	1397,86
atelierpeinture4.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4507,00	3514,00	98824,00	106845,00	3,47%	3600,71
Experiment 2	3542,00	2495,00	119142,00	125179,00	0,00%	67,16
Experiment 3	2637,00	2633,00	161906,72	167176,72	39,91%	3600,91
Experiment 4	2825,00	2825,00	106186,00	111836,00	0,00%	2608,85
Experiment 5	2825,00	2825,00	106186,00	111836,00	0,00%	3503,24
Experiment 6	2825,00	2825,00	106186,00	111836,00	3,69%	3601,20
Experiment 7	2825,00	2825,00	106186,00	111836,00	5,13%	3601,28
Experiment 8	2607,00	2607,00	169134,00	174348,00	11,34%	3601,36
Experiment 9	2825,00	2825,00	106186,00	111836,00	0,00%	3516,29
Experiment 10	4266,00	2722,00	100724,00	107712,00	1,31%	3600,72
Experiment 11	4266,00	2722,00	100724,00	107712,00	4,27%	3601,13
Experiment 12	4396,00	2788,00	99942,00	107126,00	0,00%	3308,18
Experiment 13	2675,00	2598,00	158050,00	163323,00	3,39%	3601,49
Experiment 14	2607,00	2607,00	169134,00	174348,00	19,63%	3601,24
Experiment 15	2797,00	2797,00	122284,00	127878,00	25,63%	11986,96
Experiment 16	3479,00	3195,00	101607,97	108281,98	8,80%	3601,49
atelierpeinture5.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	6128,00	3874,00	143512,00	153514,00	25,42%	3603,49
Experiment 2	4945,00	3323,00	194331,00	202599,00	0,00%	218,42
Experiment 3	3528,00	3528,00	195994,00	203050,00	47,48%	3601,65
Experiment 4	3811,00	3654,00	148880,00	156345,00	14,98%	3602,68
Experiment 5	3795,00	3785,00	146983,00	154563,00	17,35%	3602,77
Experiment 6	3798,00	3664,00	147446,00	154908,00	12,51%	3603,34
Experiment 7	3680,00	3680,00	151312,00	158672,00	16,82%	3603,36
Experiment 8	3417,00	3417,00	186053,00	192887,00	14,42%	3603,38
Experiment 9	3927,00	3759,00	146380,00	154066,00	22,20%	3602,90
Experiment 10	5482,00	3652,00	146094,00	155228,00	19,95%	3603,20
Experiment 11	4425,00	3564,00	145602,00	153591,00	10,94%	3602,79
Experiment 12	6128,00	3874,00	143512,00	153514,00	22,17%	3602,94
Experiment 13	3417,00	3417,00	186053,00	192887,00	5,27%	3602,70
Experiment 14	3541,00	3541,00	188424,00	195506,00	31,14%	3603,01
Experiment 15	3773,00	3773,00	148731,00	156277,00	26,76%	3603,57
Experiment 16	4059,00	4015,00	145331,00	153405,00	21,54%	3603,23
atelierpeinture6.xlsx						

Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	2779,00	1247,00	88924,00	92950,00	44,30%	3602,86
Experiment 2	1823,00	674,00	96478,00	98975,00	0,00%	67,94
Experiment 3	989,00	955,00	127191,00	129135,00	0,00%	975,63
Experiment 4	1199,00	827,50	94126,00	96152,50	26,88%	3602,36
Experiment 5	1737,00	796,00	91576,00	94109,00	33,31%	3602,62
Experiment 6	1350,00	765,50	95092,00	97207,50	23,75%	3602,56
Experiment 7	1168,00	833,50	94132,00	96133,50	18,32%	3602,14
Experiment 8	1139,00	833,50	94993,00	96965,50	10,12%	3601,42
Experiment 9	1116,00	933,00	95062,00	97111,00	33,05%	3602,12
Experiment 10	2717,00	717,00	91003,00	94437,00	38,44%	3603,24
Experiment 11	2679,00	674,00	92468,00	95821,00	24,45%	3602,46
Experiment 12	2883,00	780,75	89541,00	93204,75	43,13%	3602,90
Experiment 13	1370,00	746,50	94911,00	97027,50	0,00%	1895,72
Experiment 14	1150,00	805,00	97622,00	99577,00	17,05%	3601,88
Experiment 15	1116,00	933,00	95062,00	97111,00	24,64%	3601,47
Experiment 16	1387,00	1142,00	92301,00	94830,00	40,28%	3602,20
atelierpeinture7.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4041,00	860,25	69725,00	74626,25	32,72%	3601,28
Experiment 2	2326,00	675,00	73242,00	76243,00	0,00%	1438,16
Experiment 3	1390,00	1390,00	142730,00	145510,00	51,71%	3601,72
Experiment 4	1920,00	712,00	72506,00	75138,00	33,91%	3601,79
Experiment 5	1920,00	712,00	72506,00	75138,00	32,16%	3605,18
Experiment 6	1924,00	713,00	72912,00	75549,00	30,58%	3602,06
Experiment 7	1920,00	712,00	72506,00	75138,00	37,11%	3604,16
Experiment 8	1920,00	712,00	72506,00	75138,00	40,24%	3601,62
Experiment 9	1924,00	713,00	72912,00	75549,00	37,50%	3604,49
Experiment 10	3519,00	683,75	70688,00	74890,75	28,00%	3601,52
Experiment 11	3160,00	674,75	71405,00	75239,75	21,75%	3601,60
Experiment 12	3344,00	721,00	70257,00	74322,00	31,07%	3600,96
Experiment 13	1920,00	712,00	72506,00	75138,00	23,56%	3602,00
Experiment 14	1619,00	996,00	92608,00	95223,00	50,45%	3601,38
Experiment 15	1989,00	794,00	72757,00	75540,00	47,66%	3601,44
Experiment 16	1915,00	722,00	72502,00	75139,00	34,80%	3601,61
atelierpeinture8.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4437,00	1276,75	100618,99	106332,74	27,37%	3603,45
Experiment 2	2271,00	1026,00	144296,00	147593,00	0,00%	167,81
Experiment 3	1568,00	1338,00	133660,01	136566,01	31,30%	3600,97

Experiment 4	1787,00	1104,00	107710,00	110601,00	15,18%	3602,14
Experiment 5	1787,00	1104,00	107710,00	110601,00	21,05%	3601,96
Experiment 6	1887,00	1102,00	108153,01	111142,01	16,30%	3601,56
Experiment 7	1787,00	1104,00	107710,00	110601,00	11,09%	3601,71
Experiment 8	1787,00	1104,00	107710,00	110601,00	9,76%	3601,77
Experiment 9	1752,00	1408,00	107419,00	110579,00	18,53%	3601,78
Experiment 10	4382,00	1116,00	102115,00	107613,00	21,14%	3601,55
Experiment 11	3890,00	1074,00	103104,00	108068,00	9,83%	3601,70
Experiment 12	4094,00	1146,75	101324,00	106564,75	25,28%	3601,38
Experiment 13	1860,00	1075,00	109356,00	112291,00	0,00%	2532,87
Experiment 14	1578,00	1434,00	129728,00	132740,00	23,34%	3601,94
Experiment 15	1751,00	1408,25	107422,00	110581,25	13,54%	3601,61
Experiment 16	1752,00	1408,00	107422,00	110582,00	25,38%	3602,78
atelierpeinture9.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4681,00	3176,00	88430,00	96287,00	0,00%	141,31
Experiment 2	4678,00	2424,00	92507,00	99609,00	0,00%	7,28
Experiment 3	2642,00	2642,00	109987,00	115271,00	0,00%	749,22
Experiment 4	2702,00	2587,00	96902,00	102191,00	0,00%	175,77
Experiment 5	2702,00	2587,00	96902,00	102191,00	0,00%	247,60
Experiment 6	2702,00	2587,00	96902,00	102191,00	0,00%	173,45
Experiment 7	2702,00	2587,00	96902,00	102191,00	0,00%	136,78
Experiment 8	2709,00	2481,00	103416,02	108606,02	0,00%	129,14
Experiment 9	2702,00	2587,00	96902,00	102191,00	0,01%	420,79
Experiment 10	4708,00	2476,00	90208,00	97392,00	0,00%	86,00
Experiment 11	4678,00	2424,00	92507,00	99609,00	0,00%	48,43
Experiment 12	4788,00	2524,00	89767,00	97079,00	0,00%	192,91
Experiment 13	2707,00	2481,00	103424,00	108612,00	0,00%	93,52
Experiment 14	2707,00	2481,00	103410,00	108598,00	0,00%	693,79
Experiment 15	2702,00	2587,00	96902,00	102191,00	0,00%	626,64
Experiment 16	2702,00	2587,00	96902,00	102191,00	0,00%	418,11
atelierpeinture10.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4125,00	2106,00	97666,00	103897,00	25,22%	3601,65
Experiment 2	4186,00	1414,00	107328,00	112928,00	0,00%	327,31
Experiment 3	1582,00	1582,00	177714,00	180878,00	0,00%	666,20
Experiment 4	2208,00	1600,00	114176,00	117984,00	20,17%	3601,82
Experiment 5	2263,00	1664,00	112555,00	116482,00	25,41%	3601,62
Experiment 6	2208,00	1600,00	114176,00	117984,00	17,75%	3601,64
Experiment 7	2208,00	1600,00	114176,00	117984,00	15,09%	3601,57

Experiment 8	1582,00	1582,00	177714,00	180878,00	7,84%	3601,29
Experiment 9	2263,00	1664,00	112555,00	116482,00	19,91%	3602,20
Experiment 10	4234,00	1506,00	99533,00	105273,00	19,19%	3601,47
Experiment 11	4341,00	1466,00	101664,00	107471,00	11,21%	3601,37
Experiment 12	4144,00	1597,00	98185,00	103926,00	23,59%	3601,51
Experiment 13	1647,00	1552,00	148718,00	151917,00	4,26%	3601,37
Experiment 14	1629,00	1583,00	145378,00	148590,00	4,78%	3600,98
Experiment 15	2196,00	1776,00	114293,00	118265,00	15,36%	3601,44
Experiment 16	4125,00	2106,00	97666,00	103897,00	25,57%	3601,64
atelierpeinture12.xlsx						
Experiment	Cmax	Intmax	Total energy	Total OBJ	MIPgap	Time
Experiment 1	4026,00	2288,00	105025,00	111339,00	32,53%	3603,28
Experiment 2	3622,00	1712,00	146606,00	151940,00	0,00%	1921,68
Experiment 3	1919,00	1919,00	200250,00	204088,00	21,39%	3600,93
Experiment 4	3743,00	2107,00	106251,00	112101,00	26,62%	3601,54
Experiment 5	3743,00	2107,00	106251,00	112101,00	26,83%	3601,56
Experiment 6	3799,00	2038,00	107343,00	113180,00	23,88%	3601,53
Experiment 7	2904,00	2101,00	118168,00	123173,00	24,45%	3601,67
Experiment 8	1957,00	1957,00	164467,00	168381,00	14,91%	3601,39
Experiment 9	3342,00	2390,00	110659,00	116391,00	30,46%	3601,50
Experiment 10	3799,00	2038,00	107343,00	113180,00	26,39%	3601,63
Experiment 11	5386,00	1816,00	115153,00	122355,00	18,68%	3601,66
Experiment 12	4026,00	2185,00	105212,00	111423,00	34,40%	3601,58
Experiment 13	2089,00	1859,00	161156,00	165104,00	10,07%	3601,67
Experiment 14	1957,00	1957,00	166067,00	169981,00	16,94%	3601,15
Experiment 15	2136,00	2136,00	143543,00	147815,00	27,32%	3601,38
Experiment 16	4026,00	2288,00	105024,99	111338,99	33,12%	3601,85

APPENDIX D

DISTRIBUTION OF NON-DOMINATED SOLUTIONS ACCORDING TO BEST OBJECTIVE, GAP AND TIME

ateliergitare1.xlsx			ateliergitare2.xlsx			ateliergitare3.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
5787,00	1420,00	65619,00	4979,00	677,50	56411,00	4731,00	1017,00	71306,00
2478,00	955,00	93309,00	1641,00	562,00	72256,00	1288,00	1288,00	149823,00
2146,00	1086,00	85192,00	696,00	695,00	116139,00	3135,00	1118,50	68149,00
2855,00	1476,50	73395,00	991,00	592,00	81054,01	1929,00	1389,70	90739,04
1823,00	1024,50	97340,00	1309,00	683,00	75302,03	1316,00	1195,00	149530,00
1315,00	1050,00	102145,00	749,00	670,00	116620,00	5847,00	1101,50	58975,00
1848,00	1387,50	91400,00	4106,00	664,25	59995,00	4911,00	1104,50	67678,00
5651,00	1198,00	67809,00	4584,00	635,25	56785,00	2122,00	1071,50	113787,00
5588,00	1038,75	73252,00	979,00	612,00	82772,00	1544,00	1242,00	138949,00
5585,00	1325,50	65895,00	668,00	668,00	116639,00	2091,00	1336,20	95698,00
1401,00	1012,00	103352,00	976,00	652,00	79886,00	3112,00	1142,00	68265,00
1283,00	1159,00	104578,00	2015,00	799,25	63227,00	Makespan, Energy		
1359,00	1353,25	99221,00	Makespan, Energy			1288,00	1288,00	149823,00
3238,00	1643,00	70281,00	4979,00	677,50	56411,00	3135,00	1118,50	68149,00
Makespan, Energy			1641,00	562,00	72256,00	1929,00	1389,70	90739,04
5787,00	1420,00	65619,00	696,00	695,00	116139,00	1316,00	1195,00	149530,00
2146,00	1086,00	85192,00	1309,00	683,00	75302,03	5847,00	1101,50	58975,00
2855,00	1476,50	73395,00	4106,00	664,25	59995,00	4911,00	1104,50	67678,00
1823,00	1024,50	97340,00	4584,00	635,25	56785,00	1544,00	1242,00	138949,00
1315,00	1050,00	102145,00	668,00	668,00	116639,00	3112,00	1142,00	68265,00
1848,00	1387,50	91400,00	976,00	652,00	79886,00	Makespan, Labor intensity		
5585,00	1325,50	65895,00	2015,00	799,25	63227,00	4731,00	1017,00	71306,00
1283,00	1159,00	104578,00	Makespan, Labor intensity			1288,00	1288,00	149823,00
1359,00	1353,25	99221,00	1641,00	562,00	72256,00	1316,00	1195,00	149530,00
3238,00	1643,00	70281,00	991,00	592,00	81054,01	2122,00	1071,50	113787,00
Makespan, Labor intensity			979,00	612,00	82772,00	Labor intensity, Energy		
2478,00	955,00	93309,00	668,00	668,00	116639,00	4731,00	1017,00	71306,00
1315,00	1050,00	102145,00	976,00	652,00	79886,00	5847,00	1101,50	58975,00
1401,00	1012,00	103352,00	Labor intensity, Energy					
1283,00	1159,00	104578,00	4979,00	677,50	56411,00			
Labor intensity, Energy			1641,00	562,00	72256,00			
5787,00	1420,00	65619,00	4584,00	635,25	56785,00			
2478,00	955,00	93309,00						

5651,00	1198,00	67809,00						
5588,00	1038,75	73252,00						
5585,00	1325,50	65895,00						
ateliergitare4.xlsx			ateliergitare5.xlsx			ateliergitare6.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
7975,00	2380,00	70073,00	7238,00	1284,50	65311,00	3882,00	762,50	76698,00
4002,00	1323,00	118009,00	2268,00	1016,75	117657,00	1571,00	593,25	90848,00
1792,00	1649,48	134821,02	1182,00	1178,00	130842,99	947,00	797,00	121146,00
2593,00	1728,83	87432,00	1385,00	1201,25	110865,00	1270,00	693,25	87699,00
1816,00	1622,00	142356,00	2390,00	1423,25	89595,00	1897,00	713,50	81127,00
3028,00	1905,75	80448,00	2565,00	1126,75	80629,00	1293,00	639,00	89950,00
5205,00	1546,00	79036,00	1601,00	1214,00	98194,00	1129,00	700,00	89734,00
5439,00	1478,25	79313,00	1428,00	1173,00	129819,00	1177,00	687,50	94234,00
5155,00	1768,50	75829,00	1298,00	1276,00	112784,00	1150,00	795,00	88433,00
2321,00	1436,84	130112,00	6585,00	1084,25	65980,00	5691,00	626,00	67432,00
1819,00	1614,00	143079,00	1333,00	1101,50	132218,00	4370,00	652,25	65838,00
3507,00	1851,01	77655,00	1314,00	1179,00	127636,00	5795,00	688,00	65493,00
Makespan, Energy			1281,00	1245,00	113558,02	1186,00	641,00	90918,00
7975,00	2380,00	70073,00	3390,00	1266,50	74665,00	1078,00	718,00	93043,00
1792,00	1649,48	134821,02	Makespan, Energy			1087,00	902,00	91317,00
2593,00	1728,83	87432,00	7238,00	1284,50	65311,00	2672,00	794,50	69571,00
3028,00	1905,75	80448,00	1182,00	1178,00	130842,99	Makespan, Energy		
5155,00	1768,50	75829,00	1385,00	1201,25	110865,00	947,00	797,00	121146,00
2321,00	1436,84	130112,00	2390,00	1423,25	89595,00	1270,00	693,25	87699,00
3507,00	1851,01	77655,00	2565,00	1126,75	80629,00	1897,00	713,50	81127,00
Makespan, Labor intensity			1601,00	1214,00	98194,00	1129,00	700,00	89734,00
4002,00	1323,00	118009,00	1298,00	1276,00	112784,00	1150,00	795,00	88433,00
1792,00	1649,48	134821,02	6585,00	1084,25	65980,00	4370,00	652,25	65838,00
1816,00	1622,00	142356,00	1281,00	1245,00	113558,02	5795,00	688,00	65493,00
2321,00	1436,84	130112,00	3390,00	1266,50	74665,00	1078,00	718,00	93043,00
1819,00	1614,00	143079,00	Makespan, Labor intensity			1087,00	902,00	91317,00
Labor intensity, Energy			2268,00	1016,75	117657,00	2672,00	794,50	69571,00
7975,00	2380,00	70073,00	1182,00	1178,00	130842,99	Makespan, Labor intensity		
4002,00	1323,00	118009,00	1333,00	1101,50	132218,00	1571,00	593,25	90848,00
5205,00	1546,00	79036,00	Labor intensity, Energy			947,00	797,00	121146,00
5439,00	1478,25	79313,00	7238,00	1284,50	65311,00	1293,00	639,00	89950,00
5155,00	1768,50	75829,00	2268,00	1016,75	117657,00	1129,00	700,00	89734,00
			6585,00	1084,25	65980,00	1177,00	687,50	94234,00
						1186,00	641,00	90918,00
						1078,00	718,00	93043,00

						Labor intensity, Energy		
						1571,00	593,25	90848,00
						5691,00	626,00	67432,00
						4370,00	652,25	65838,00
						5795,00	688,00	65493,00
ateliergitare7.xlsx			ateliergitare9.xlsx			ateliergitare10.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
1998,00	1138,00	110994,00	3954,00	1651,44	74537,00	5787,00	1420,00	65619,00
1374,00	1374,00	140461,00	4681,00	775,65	109360,00	1297,00	1297,00	109686,00
1680,00	1307,00	92160,00	1094,00	1078,00	107331,00	2146,00	1086,00	85192,00
1380,00	1300,00	115944,02	1335,00	980,00	99835,00	2855,00	1476,50	73395,00
2639,00	1485,25	88659,00	1732,00	1279,00	83976,00	2024,00	992,50	90253,00
1696,00	1172,00	110342,00	1149,00	954,00	100165,00	1754,00	856,50	93171,00
1432,00	1287,00	115924,00	1660,00	1465,00	83571,00	1339,00	962,00	138651,00
1617,00	1453,00	90727,00	4765,00	993,56	76878,00	2292,00	1020,50	85307,00
1786,00	1573,00	89028,00	4619,00	917,14	91555,00	4703,00	981,25	77438,00
Makespan, Energy			4727,00	1056,05	76050,00	5400,00	846,75	78022,00
1374,00	1374,00	140461,00	1314,00	918,44	103684,00	4205,00	1101,50	76732,00
1380,00	1300,00	115944,02	1108,00	1006,00	101908,00	1607,00	895,00	103799,00
2639,00	1485,25	88659,00	2301,00	1729,00	77566,00	3250,00	1172,25	81412,00
1432,00	1287,00	115924,00	Makespan, Energy			Makespan, Energy		
1617,00	1453,00	90727,00	3954,00	1651,44	74537,00	5787,00	1420,00	65619,00
1786,00	1573,00	89028,00	1094,00	1078,00	107331,00	1297,00	1297,00	109686,00
Makespan, Labor intensity			1335,00	980,00	99835,00	2146,00	1086,00	85192,00
1998,00	1138,00	110994,00	1149,00	954,00	100165,00	2855,00	1476,50	73395,00
1374,00	1374,00	140461,00	1660,00	1465,00	83571,00	2024,00	992,50	90253,00
1380,00	1300,00	115944,02	1108,00	1006,00	101908,00	1754,00	856,50	93171,00
1696,00	1172,00	110342,00	2301,00	1729,00	77566,00	1607,00	895,00	103799,00
1432,00	1287,00	115924,00	Makespan, Labor intensity			Makespan, Labor intensity		
Labor intensity, Energy			4681,00	775,65	109360,00	1297,00	1297,00	109686,00
1998,00	1138,00	110994,00	1094,00	1078,00	107331,00	1754,00	856,50	93171,00
2639,00	1485,25	88659,00	1149,00	954,00	100165,00	1339,00	962,00	138651,00
1696,00	1172,00	110342,00	4619,00	917,14	91555,00	5400,00	846,75	78022,00
			1314,00	918,44	103684,00	1607,00	895,00	103799,00
			1108,00	1006,00	101908,00	Labor intensity, Energy		
			Labor intensity, Energy			5787,00	1420,00	65619,00
			3954,00	1651,44	74537,00	4703,00	981,25	77438,00
			4681,00	775,65	109360,00	5400,00	846,75	78022,00
			4765,00	993,56	76878,00	4205,00	1101,50	76732,00
			4619,00	917,14	91555,00			

			4727,00	1056,05	76050,00			
ateliergguitare11.xlsx			ateliercouture1.xlsx			ateliercouture2.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
6336,00	1258,50	61223,00	1285,00	762,01	34050,00	1388,00	669,30	26902,00
3268,00	958,50	103823,00	1058,00	254,52	41391,00	1020,00	275,00	36361,00
1290,00	1261,00	131111,00	651,00	352,12	35028,00	513,00	477,00	49319,00
2653,00	1033,00	88531,00	608,00	314,00	37657,00	666,00	347,96	32954,00
3371,00	1190,00	73331,00	576,00	316,00	36693,00	775,00	341,00	29542,00
1744,00	1190,00	103014,00	1036,00	338,00	34710,00	754,00	346,00	31199,00
2503,00	1431,00	87526,00	1202,00	286,00	36500,00	715,00	360,00	31001,00
6347,00	1146,50	61738,00	1168,00	331,38	34847,00	593,00	347,00	36553,00
5637,00	1111,00	69200,00	608,00	282,92	38064,00	753,00	360,00	29776,00
6419,00	1169,00	61226,00	499,00	375,00	38134,00	1247,00	391,49	27233,00
1381,00	1028,00	126349,00	530,00	388,00	36397,00	1082,00	348,49	28483,00
1322,00	1089,00	131910,00	934,00	452,00	34330,00	1169,00	391,49	27500,00
1836,00	1171,00	103307,00	Makespan, Energy			676,00	298,50	34964,00
4452,00	1144,50	67962,00	1285,00	762,01	34050,00	569,00	376,00	39205,00
Makespan, Energy			651,00	352,12	35028,00	588,00	420,00	35208,00
6336,00	1258,50	61223,00	499,00	375,00	38134,00	871,00	535,55	27554,00
1290,00	1261,00	131111,00	530,00	388,00	36397,00	Makespan, Energy		
3371,00	1190,00	73331,00	934,00	452,00	34330,00	1388,00	669,30	26902,00
1744,00	1190,00	103014,00	Makespan, Labor intensity			513,00	477,00	49319,00
2503,00	1431,00	87526,00	1058,00	254,52	41391,00	666,00	347,96	32954,00
1381,00	1028,00	126349,00	576,00	316,00	36693,00	775,00	341,00	29542,00
4452,00	1144,50	67962,00	608,00	282,92	38064,00	715,00	360,00	31001,00
Makespan, Labor intensity			499,00	375,00	38134,00	753,00	360,00	29776,00
3268,00	958,50	103823,00	Labor intensity, Energy			1247,00	391,49	27233,00
1290,00	1261,00	131111,00	1285,00	762,01	34050,00	1169,00	391,49	27500,00
1381,00	1028,00	126349,00	1058,00	254,52	41391,00	569,00	376,00	39205,00
1322,00	1089,00	131910,00	1036,00	338,00	34710,00	588,00	420,00	35208,00
Labor intensity, Energy			1202,00	286,00	36500,00	871,00	535,55	27554,00
3268,00	958,50	103823,00	1168,00	331,38	34847,00	Makespan, Labor intensity		
2653,00	1033,00	88531,00	608,00	282,92	38064,00	1020,00	275,00	36361,00
6347,00	1146,50	61738,00	934,00	452,00	34330,00	513,00	477,00	49319,00
5637,00	1111,00	69200,00				593,00	347,00	36553,00
6419,00	1169,00	61226,00				676,00	298,50	34964,00
4452,00	1144,50	67962,00				569,00	376,00	39205,00
						Labor intensity, Energy		
						1388,00	669,30	26902,00
						1020,00	275,00	36361,00

						775,00	341,00	29542,00
						1247,00	391,49	27233,00
						1082,00	348,49	28483,00
						676,00	298,50	34964,00
ateliercouture3.xlsx			ateliercouture4.xlsx			ateliercouture5.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
3012,00	949,73	33100,00	1042,00	384,00	28766,00	1091,00	433,44	39526,00
3240,00	429,37	50498,00	1248,00	192,78	35943,00	662,00	661,00	36374,00
937,00	815,00	73366,00	421,00	405,01	46212,00	767,00	582,00	30976,00
1348,00	688,00	41262,00	520,00	337,00	32506,00	807,00	514,00	32400,01
2063,00	686,25	35120,00	659,00	296,00	31125,00	737,00	558,01	32011,00
1471,00	637,37	44246,00	532,00	289,00	33897,00	712,00	558,01	35849,96
1382,00	652,00	44272,00	538,00	294,00	33753,00	1078,00	433,44	39858,00
1110,00	678,00	63144,00	512,00	289,00	35099,00	671,00	602,00	35753,99
1535,00	796,80	39107,00	607,00	607,00	29975,00	739,00	626,00	30863,00
4303,00	483,25	33813,00	1696,00	246,88	28587,00	Makespan, Energy		
4318,00	460,61	34043,00	1628,00	221,84	29331,00	662,00	661,00	36374,00
2566,00	601,41	36092,00	622,00	244,30	38159,00	737,00	558,01	32011,00
1629,00	622,00	51688,00	431,00	345,80	37856,00	671,00	602,00	35753,99
972,00	739,00	75863,00	473,00	430,00	33345,00	739,00	626,00	30863,00
1223,00	788,00	47965,00	646,00	604,00	29748,00	Makespan, Labor intensity		
1680,00	816,00	37493,00	Makespan, Energy			662,00	661,00	36374,00
Makespan, Energy			1042,00	384,00	28766,00	807,00	514,00	32400,01
3012,00	949,73	33100,00	421,00	405,01	46212,00	712,00	558,01	35849,96
937,00	815,00	73366,00	520,00	337,00	32506,00	1078,00	433,44	39858,00
1348,00	688,00	41262,00	607,00	607,00	29975,00	671,00	602,00	35753,99
2063,00	686,25	35120,00	1696,00	246,88	28587,00	Labor intensity, Energy		
1110,00	678,00	63144,00	431,00	345,80	37856,00	1091,00	433,44	39526,00
1535,00	796,80	39107,00	473,00	430,00	33345,00	807,00	514,00	32400,01
1223,00	788,00	47965,00	646,00	604,00	29748,00			
1680,00	816,00	37493,00	Makespan, Labor intensity					
Makespan, Labor intensity			1248,00	192,78	35943,00			
3240,00	429,37	50498,00	421,00	405,01	46212,00			
937,00	815,00	73366,00	512,00	289,00	35099,00			
1471,00	637,37	44246,00	622,00	244,30	38159,00			
1382,00	652,00	44272,00	431,00	345,80	37856,00			
1110,00	678,00	63144,00	Labor intensity, Energy					
2566,00	601,41	36092,00	1248,00	192,78	35943,00			
1629,00	622,00	51688,00	1696,00	246,88	28587,00			
972,00	739,00	75863,00	1628,00	221,84	29331,00			

Labor intensity, Energy								
3012,00	949,73	33100,00						
3240,00	429,37	50498,00						
4303,00	483,25	33813,00						
4318,00	460,61	34043,00						
ateliercouture6.xlsx			ateliercouture7.xlsx			ateliercouture8.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
1408,00	729,00	33311,00	704,00	669,00	66750,00	4549,00	1565,20	38514,00
1866,00	228,36	42944,00	1614,00	600,50	39013,00	2766,00	991,20	52632,00
491,00	450,00	58248,99	1120,00	540,00	44467,00	2322,00	1156,46	43209,00
948,00	305,45	39778,00	989,00	668,00	44104,00	2337,00	1247,41	42692,00
759,00	384,00	40526,00	908,00	535,00	52966,00	1547,00	1172,90	84693,00
530,00	354,12	56496,00	1032,00	668,00	43172,00	3572,00	1158,52	40146,00
1972,00	317,00	35025,00	1704,00	539,50	39866,00	2968,00	1089,45	44504,00
1881,00	251,00	38055,00	783,00	618,00	56753,00	2350,00	1195,92	40177,00
1976,00	380,61	34191,00	820,00	812,00	53780,00	1886,00	1098,45	81490,00
669,00	323,99	47894,00	1404,00	740,00	39683,00	1464,00	1128,00	88303,00
506,00	405,00	53531,00	Makespan, Energy			2170,00	1333,60	52744,00
669,00	489,00	46125,00	704,00	669,00	66750,00	2478,00	1367,64	40120,00
Makespan, Energy			1614,00	600,50	39013,00	Makespan, Energy		
1408,00	729,00	33311,00	989,00	668,00	44104,00	4549,00	1565,20	38514,00
491,00	450,00	58248,99	908,00	535,00	52966,00	2322,00	1156,46	43209,00
948,00	305,45	39778,00	1032,00	668,00	43172,00	2337,00	1247,41	42692,00
759,00	384,00	40526,00	783,00	618,00	56753,00	1547,00	1172,90	84693,00
506,00	405,00	53531,00	820,00	812,00	53780,00	2350,00	1195,92	40177,00
669,00	489,00	46125,00	1404,00	740,00	39683,00	1886,00	1098,45	81490,00
Makespan, Labor intensity			Makespan, Labor intensity			1464,00	1128,00	88303,00
1866,00	228,36	42944,00	704,00	669,00	66750,00	2170,00	1333,60	52744,00
491,00	450,00	58248,99	908,00	535,00	52966,00	2478,00	1367,64	40120,00
948,00	305,45	39778,00	783,00	618,00	56753,00	Makespan, Labor intensity		
530,00	354,12	56496,00	Labor intensity, Energy			2766,00	991,20	52632,00
669,00	323,99	47894,00	1704,00	539,50	39866,00	1886,00	1098,45	81490,00
506,00	405,00	53531,00				1464,00	1128,00	88303,00
Labor intensity, Energy						Labor intensity, Energy		
1408,00	729,00	33311,00				4549,00	1565,20	38514,00
1866,00	228,36	42944,00				2766,00	991,20	52632,00
1972,00	317,00	35025,00				2322,00	1156,46	43209,00
1881,00	251,00	38055,00				3572,00	1158,52	40146,00
1976,00	380,61	34191,00				2968,00	1089,45	44504,00
						2478,00	1367,64	40120,00

ateliercouture9.xlsx			ateliercouture10.xlsx			atelierpeinture1.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
2537,00	785,15	27192,00	3224,00	1587,45	31357,00	7365,00	2584,00	76094,00
1635,00	278,65	48528,00	2351,00	856,92	51424,00	6518,00	1970,50	85422,00
623,00	570,96	51970,00	1921,00	976,53	34388,00	7115,00	1981,50	77767,00
901,00	393,00	37154,00	1866,00	1015,24	34472,00	3809,00	2363,50	120488,00
1072,00	394,27	35672,00	1859,00	927,29	35067,00	2430,00	2430,00	159268,00
1040,00	407,00	36714,00	1635,00	1102,74	41083,00	4568,00	3013,50	98983,00
750,00	532,27	37375,00	1177,00	970,00	69141,00	3834,00	1994,00	136317,00
683,00	383,64	51576,00	1992,00	1111,57	32843,00	2547,00	2418,00	149852,00
1383,00	373,77	35377,00	2564,00	1006,20	32580,00	2598,00	2455,00	142673,00
1462,00	341,30	36162,00	1921,00	911,21	35333,00	7052,00	2007,00	76986,00
1649,00	550,99	27945,00	2934,00	1032,24	32245,00	Makespan, Energy		
891,00	308,00	48400,00	1137,00	930,84	72785,00	7365,00	2584,00	76094,00
639,00	453,77	43054,00	1065,00	1051,00	75114,00	6518,00	1970,50	85422,00
699,00	484,00	40334,00	1448,00	1137,92	45858,00	3809,00	2363,50	120488,00
1189,00	602,63	28614,00	1953,00	1103,08	32895,00	2430,00	2430,00	159268,00
Makespan, Energy			Makespan, Energy			4568,00	3013,50	98983,00
2537,00	785,15	27192,00	3224,00	1587,45	31357,00	2547,00	2418,00	149852,00
623,00	570,96	51970,00	1921,00	976,53	34388,00	2598,00	2455,00	142673,00
901,00	393,00	37154,00	1866,00	1015,24	34472,00	7052,00	2007,00	76986,00
1072,00	394,27	35672,00	1859,00	927,29	35067,00	Makespan, Labor intensity		
1040,00	407,00	36714,00	1635,00	1102,74	41083,00	6518,00	1970,50	85422,00
750,00	532,27	37375,00	1177,00	970,00	69141,00	3809,00	2363,50	120488,00
1649,00	550,99	27945,00	1992,00	1111,57	32843,00	2430,00	2430,00	159268,00
639,00	453,77	43054,00	2564,00	1006,20	32580,00	3834,00	1994,00	136317,00
699,00	484,00	40334,00	2934,00	1032,24	32245,00	2547,00	2418,00	149852,00
1189,00	602,63	28614,00	1137,00	930,84	72785,00	Labor intensity, Energy		
Makespan, Labor intensity			1065,00	1051,00	75114,00	7365,00	2584,00	76094,00
1635,00	278,65	48528,00	1448,00	1137,92	45858,00	6518,00	1970,50	85422,00
623,00	570,96	51970,00	1953,00	1103,08	32895,00	7115,00	1981,50	77767,00
683,00	383,64	51576,00	Makespan, Labor intensity					
891,00	308,00	48400,00	2351,00	856,92	51424,00			
639,00	453,77	43054,00	1859,00	927,29	35067,00			
Labor intensity, Energy			1921,00	911,21	35333,00			
2537,00	785,15	27192,00	1137,00	930,84	72785,00			
1635,00	278,65	48528,00	1065,00	1051,00	75114,00			
1383,00	373,77	35377,00	Labor intensity, Energy					
1462,00	341,30	36162,00	3224,00	1587,45	31357,00			
1649,00	550,99	27945,00	2351,00	856,92	51424,00			

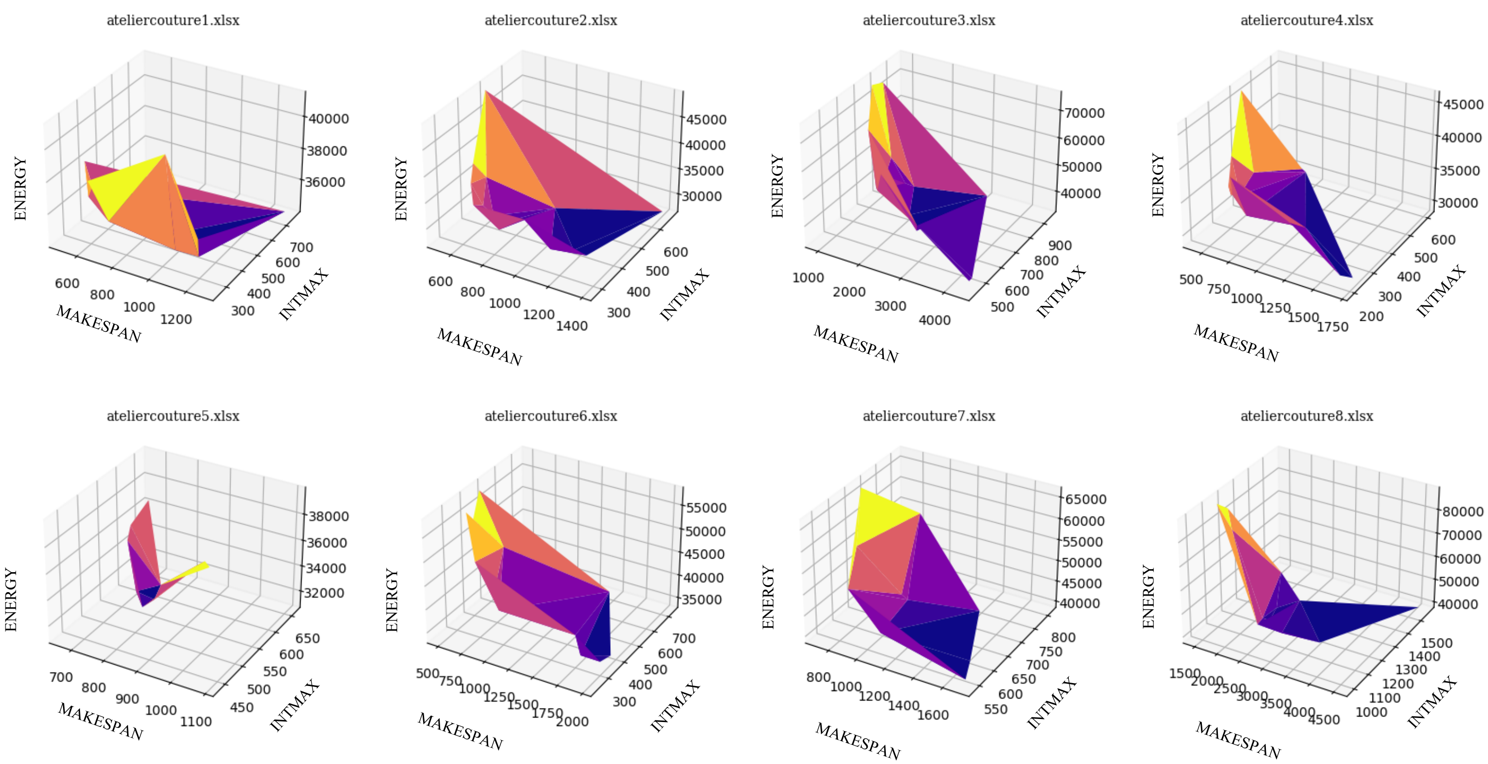
891,00	308,00	48400,00	1921,00	976,53	34388,00			
			1859,00	927,29	35067,00			
			2564,00	1006,20	32580,00			
			1921,00	911,21	35333,00			
			2934,00	1032,24	32245,00			
atelierpeinture2.xlsx			atelierpeinture4.xlsx			atelierpeinture5.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
6489,00	2493,50	89556,00	4507,00	3514,00	98824,00	4945,00	3323,00	194331,00
5037,00	2107,50	97902,00	3542,00	2495,00	119142,00	3811,00	3654,00	148880,00
2341,00	2341,00	169750,00	2637,00	2633,00	161906,72	3795,00	3785,00	146983,00
3540,00	2449,50	101805,00	4396,00	2788,00	99942,00	3798,00	3664,00	147446,00
4691,00	2401,50	91697,00	2675,00	2598,00	158050,00	3680,00	3680,00	151312,00
4218,00	2265,50	98332,00	2797,00	2797,00	122284,00	3927,00	3759,00	146380,00
2960,00	2517,50	111658,00	3479,00	3195,00	101607,97	4425,00	3564,00	145602,00
2500,00	2209,00	161146,00	Makespan, Energy			3773,00	3773,00	148731,00
3490,93	3190,50	97571,99	4507,00	3514,00	98824,00	4059,00	4015,00	145331,00
5281,00	2184,00	90953,00	2637,00	2633,00	161906,72	Makespan, Energy		
2698,00	2158,00	161364,00	4396,00	2788,00	99942,00	3795,00	3785,00	146983,00
2752,00	2517,50	117527,00	2675,00	2598,00	158050,00	3680,00	3680,00	151312,00
4011,00	2900,00	94120,00	2797,00	2797,00	122284,00	3927,00	3759,00	146380,00
Makespan, Energy			3479,00	3195,00	101607,97	3773,00	3773,00	148731,00
6489,00	2493,50	89556,00	Makespan, Labor intensity			4059,00	4015,00	145331,00
2341,00	2341,00	169750,00	3542,00	2495,00	119142,00	Makespan, Labor intensity		
4691,00	2401,50	91697,00	2675,00	2598,00	158050,00	4945,00	3323,00	194331,00
2960,00	2517,50	111658,00	Labor intensity, Energy			Labor intensity, Energy		
2500,00	2209,00	161146,00	4507,00	3514,00	98824,00	4945,00	3323,00	194331,00
3490,93	3190,50	97571,99	3542,00	2495,00	119142,00	4425,00	3564,00	145602,00
5281,00	2184,00	90953,00	4396,00	2788,00	99942,00			
2752,00	2517,50	117527,00						
4011,00	2900,00	94120,00						
Makespan, Labor intensity								
5037,00	2107,50	97902,00						
2341,00	2341,00	169750,00						
2500,00	2209,00	161146,00						
2698,00	2158,00	161364,00						
Labor intensity, Energy								
6489,00	2493,50	89556,00						
5037,00	2107,50	97902,00						
5281,00	2184,00	90953,00						
atelierpeinture6.xlsx			atelierpeinture7.xlsx			atelierpeinture8.xlsx		

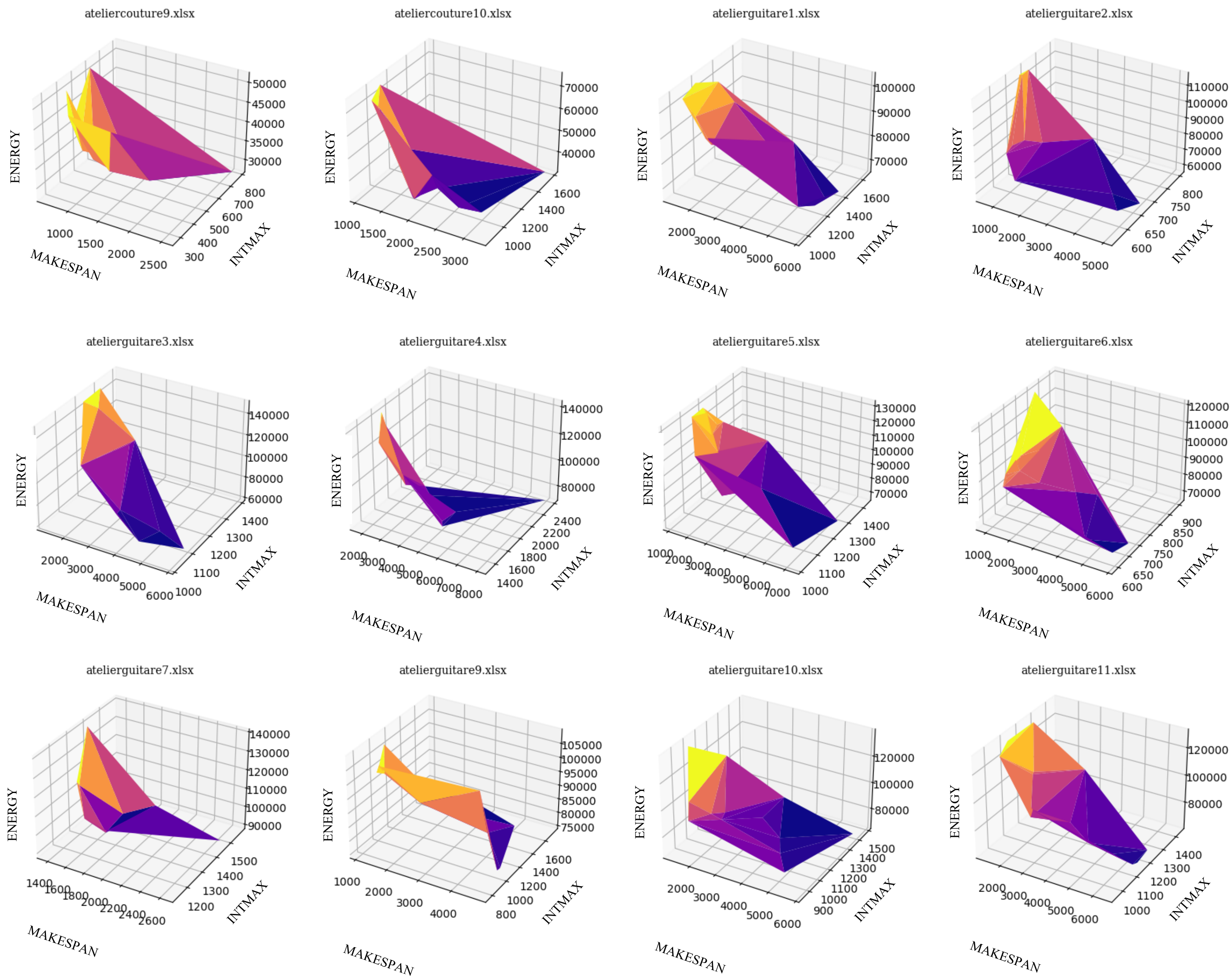
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
2779,00	1247,00	88924,00	4041,00	860,25	69725,00	4437,00	1276,75	100618,99
1823,00	674,00	96478,00	2326,00	675,00	73242,00	2271,00	1026,00	144296,00
989,00	955,00	127191,00	1390,00	1390,00	142730,00	1568,00	1338,00	133660,01
1199,00	827,50	94126,00	3519,00	683,75	70688,00	1887,00	1102,00	108153,01
1737,00	796,00	91576,00	3160,00	674,75	71405,00	4382,00	1116,00	102115,00
1350,00	765,50	95092,00	3344,00	721,00	70257,00	3890,00	1074,00	103104,00
1168,00	833,50	94132,00	1619,00	996,00	92608,00	4094,00	1146,75	101324,00
1139,00	833,50	94993,00	1915,00	722,00	72502,00	1860,00	1075,00	109356,00
2717,00	717,00	91003,00	Makespan, Energy			1578,00	1434,00	129728,00
2679,00	674,00	92468,00	4041,00	860,25	69725,00	1751,00	1408,25	107422,00
2883,00	780,75	89541,00	1390,00	1390,00	142730,00	Makespan, Energy		
1370,00	746,50	94911,00	3160,00	674,75	71405,00	4437,00	1276,75	100618,99
1150,00	805,00	97622,00	3344,00	721,00	70257,00	1568,00	1338,00	133660,01
1387,00	1142,00	92301,00	1619,00	996,00	92608,00	3890,00	1074,00	103104,00
Makespan, Energy			1915,00	722,00	72502,00	4094,00	1146,75	101324,00
2779,00	1247,00	88924,00	Makespan, Labor intensity			1578,00	1434,00	129728,00
989,00	955,00	127191,00	2326,00	675,00	73242,00	1751,00	1408,25	107422,00
1737,00	796,00	91576,00	1390,00	1390,00	142730,00	Makespan, Labor intensity		
1168,00	833,50	94132,00	3160,00	674,75	71405,00	2271,00	1026,00	144296,00
1139,00	833,50	94993,00	1619,00	996,00	92608,00	1568,00	1338,00	133660,01
2717,00	717,00	91003,00	1915,00	722,00	72502,00	1860,00	1075,00	109356,00
1387,00	1142,00	92301,00	Labor intensity, Energy			Labor intensity, Energy		
Makespan, Labor intensity			4041,00	860,25	69725,00	4437,00	1276,75	100618,99
1823,00	674,00	96478,00	3519,00	683,75	70688,00	2271,00	1026,00	144296,00
989,00	955,00	127191,00	3160,00	674,75	71405,00	4382,00	1116,00	102115,00
1350,00	765,50	95092,00	3344,00	721,00	70257,00	3890,00	1074,00	103104,00
1139,00	833,50	94993,00				4094,00	1146,75	101324,00
1370,00	746,50	94911,00						
1150,00	805,00	97622,00						
Labor intensity, Energy								
2779,00	1247,00	88924,00						
2717,00	717,00	91003,00						
2679,00	674,00	92468,00						
2883,00	780,75	89541,00						
atelierpeinture9.xlsx			atelierpeinture10.xlsx			atelierpeinture12.xlsx		
Cmax	Intmax	Total energy	Cmax	Intmax	Total energy	Cmax	Intmax	Total energy
Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy			Makespan, Labor intensity, Energy		
4681,00	3176,00	88430,00	4186,00	1414,00	107328,00	3622,00	1712,00	146606,00
2642,00	2642,00	109987,00	4234,00	1506,00	99533,00	1919,00	1919,00	200250,00

4708,00	2476,00	90208,00	4341,00	1466,00	101664,00	2904,00	2101,00	118168,00
4788,00	2524,00	89767,00	4144,00	1597,00	98185,00	1957,00	1957,00	164467,00
2707,00	2481,00	103410,00	1647,00	1552,00	148718,00	3342,00	2390,00	110659,00
Makespan, Energy			1629,00	1583,00	145378,00	5386,00	1816,00	115153,00
4681,00	3176,00	88430,00	2196,00	1776,00	114293,00	4026,00	2185,00	105212,00
2642,00	2642,00	109987,00	Makespan, Energy			2089,00	1859,00	161156,00
Makespan, Labor intensity			1629,00	1583,00	145378,00	2136,00	2136,00	143543,00
2642,00	2642,00	109987,00	2196,00	1776,00	114293,00	Makespan, Energy		
Labor intensity, Energy			Makespan, Labor intensity			1919,00	1919,00	200250,00
4681,00	3176,00	88430,00	4186,00	1414,00	107328,00	2904,00	2101,00	118168,00
4708,00	2476,00	90208,00	1647,00	1552,00	148718,00	1957,00	1957,00	164467,00
4788,00	2524,00	89767,00	Labor intensity, Energy			3342,00	2390,00	110659,00
			4186,00	1414,00	107328,00	2089,00	1859,00	161156,00
			4234,00	1506,00	99533,00	2136,00	2136,00	143543,00
			4341,00	1466,00	101664,00	Makespan, Labor intensity		
			4144,00	1597,00	98185,00	3622,00	1712,00	146606,00
						1919,00	1919,00	200250,00
						2089,00	1859,00	161156,00
						Labor intensity, Energy		
						3622,00	1712,00	146606,00
						5386,00	1816,00	115153,00
						4026,00	2185,00	105212,00

APPENDIX E

FIGURES REPRESENTING THE RELATIONSHIP BETWEEN MAKESPAN, ENERGY AND LABOR INTENSITY FOR EACH INSTANCE

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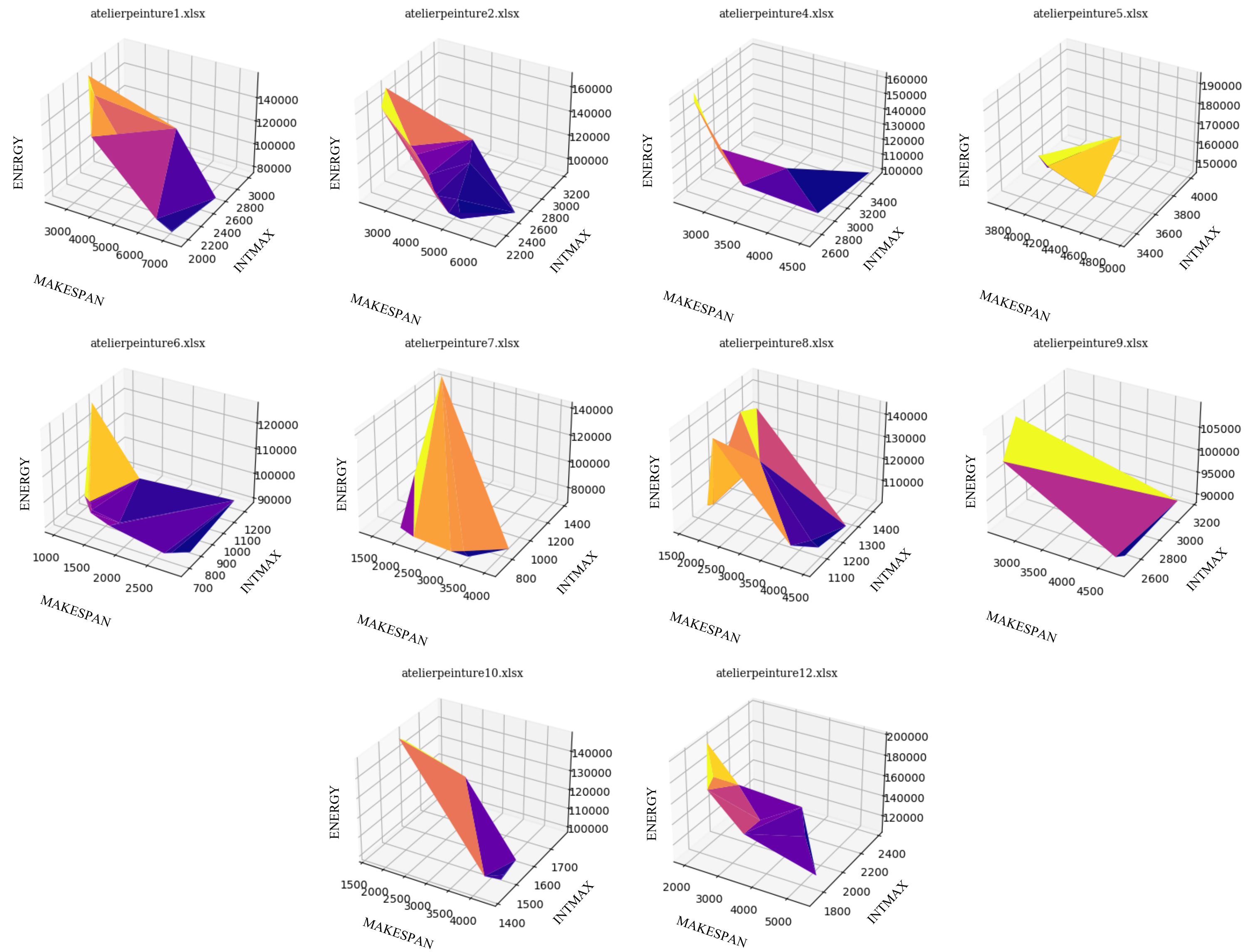
atelierguitare2.xlsx
atelierguitare3.xlsx
atelierguitare4.xlsx
atelierguitare5.xlsx
atelierguitare6.xlsx
atelierguitare7.xlsx
atelierguitare9.xlsx
atelierguitare10.xlsx
atelierguitare11.xlsx
ENERGY
MAKESPAN
INTMAX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80000
3000
4000
5000
6000
7000
MAKESPAN
3000
2800
2600
2400
2200
2000
INTMAX
atelierpeinture2.xlsx
ENERGY
160000
140000
120000
100000
3000
4000
5000
6000
MAKESPAN
3200
3000
2800
2600
2400
2200
INTMAX
atelierpeinture4.xlsx
ENERGY
160000
150000
140000
130000
120000
110000
100000
3000
3500
4000
4500
MAKESPAN
3400
3200
3000
2800
2600
INTMAX
atelierpeinture5.xlsx
ENERGY
190000
180000
170000
160000
150000
3800
4000
4200
4400
4600
4800
5000
MAKESPAN
4000
3800
3600
3400
INTMAX
atelierpeinture6.xlsx
ENERGY
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110000
100000
90000
1000
1500
2000
2500
MAKESPAN
1200
1100
1000
900
800
700
INTMAX
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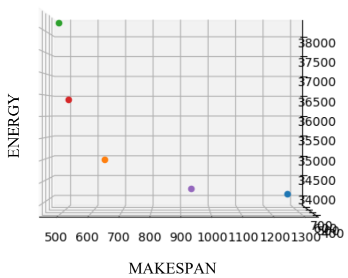
ENERGY
140000
120000
100000
80000
1500
2000
2500
3000
3500
4000
MAKESPAN
1400
1200
1000
800
INTMAX
atelierpeinture8.xlsx
ENERGY
140000
130000
120000
110000
1500
2000
2500
3000
3500
4000
4500
MAKESPAN
1400
1300
1200
1100
INTMAX
atelierpeinture9.xlsx
ENERGY
105000
100000
95000
90000
3000
3500
4000
4500
MAKESPAN
3200
3000
2800
2600
INTMAX
atelierpeinture10.xlsx
ENERGY
140000
130000
120000
110000
100000
1500
2000
2500
3000
3500
4000
MAKESPAN
1700
1600
1500
1400
INTMAX
atelierpeinture12.xlsx
ENERGY
200000
180000
160000
140000
120000
2000
3000
4000
5000
MAKESPAN
2400
2200
2000
1800
INTMAX

APPENDIX F

FIGURES REPRESENTING THE RELATIONSHIP BETWEEN MAKESPAN AND ENERGY FOR EACH INSTANCE

ateliercouture1.xlsx



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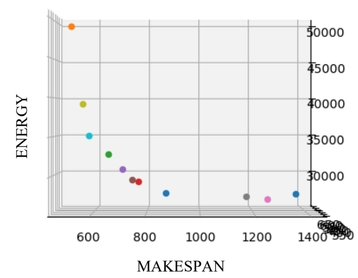

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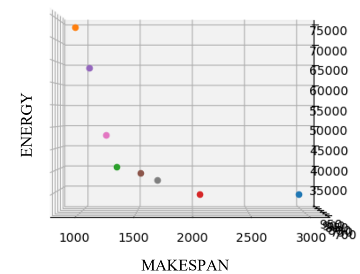
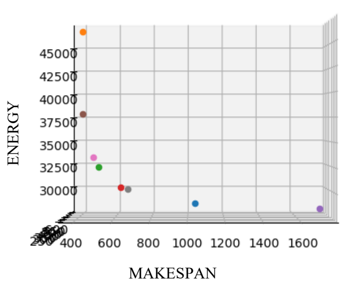


ateliercouture4.xlsx



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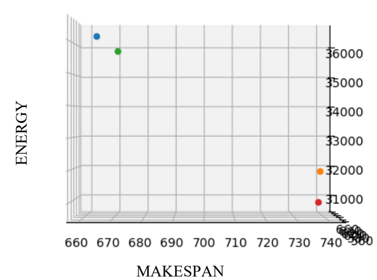

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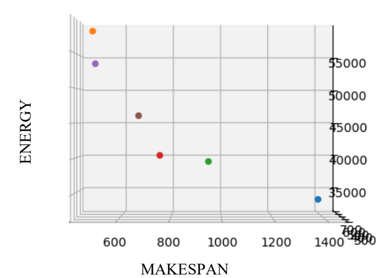

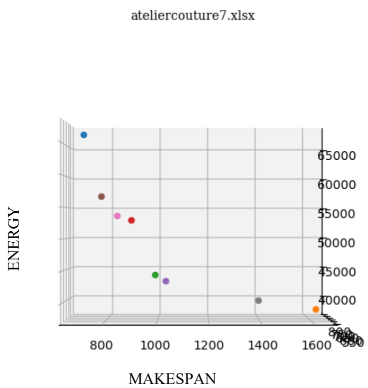
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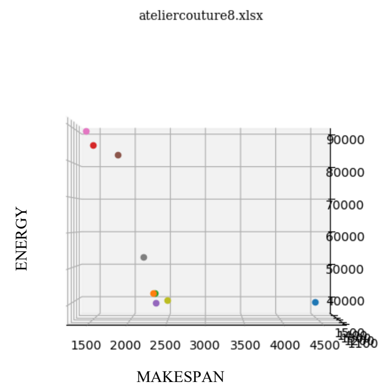
MAKESPAN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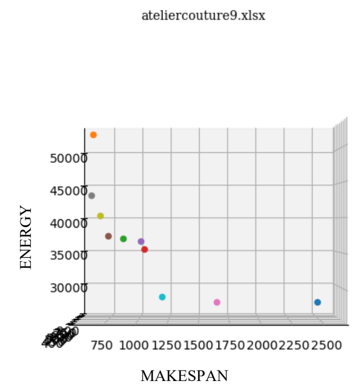
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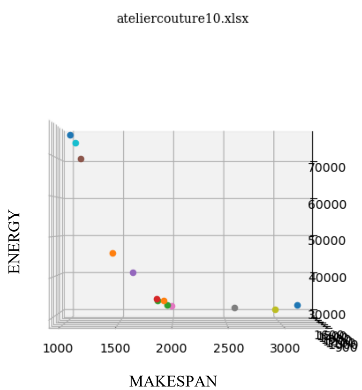
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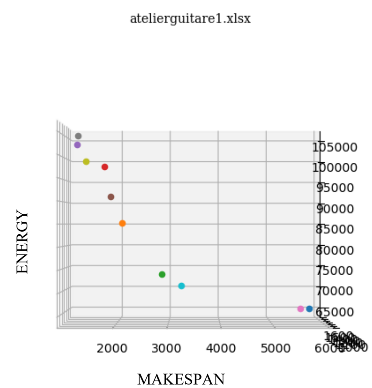
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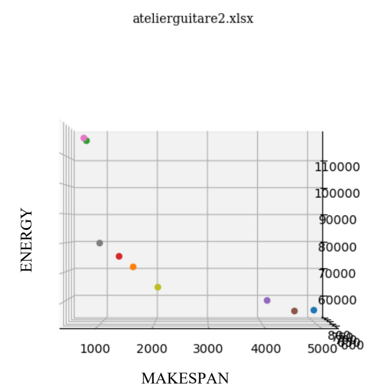
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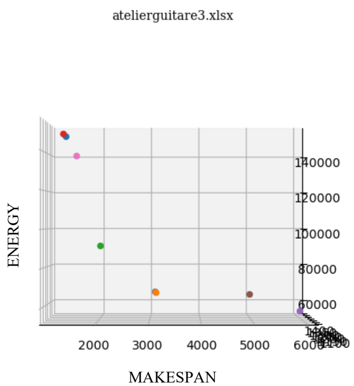
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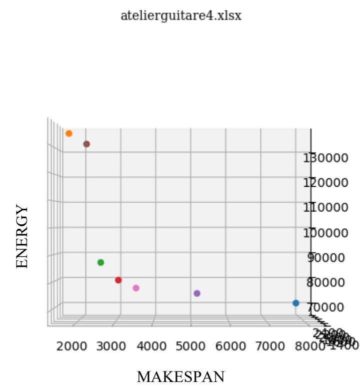
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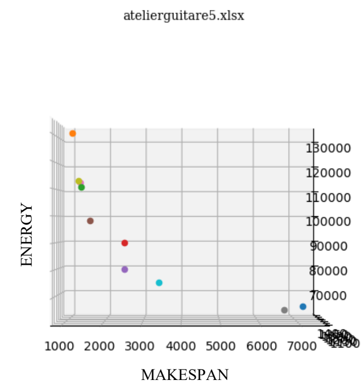
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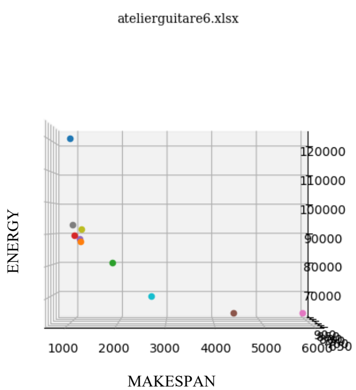
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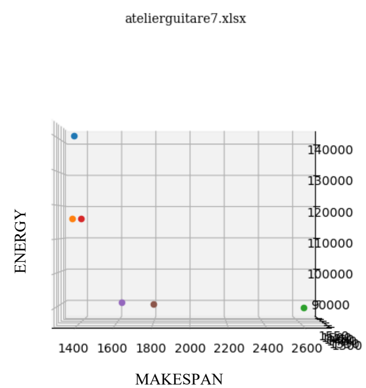
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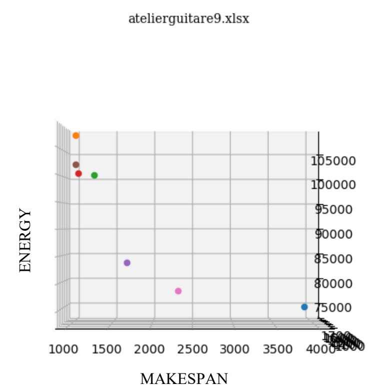
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ateliergguitare10.xlsx
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MAKESPAN
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100000
90000
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70000
2000 3000 4000 5000 6000
atelierguitare11.xlsx
ENERGY
MAKESPAN
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110000
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60000
2000 3000 4000 5000 6000
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3000 4000 5000 6000 7000
atelierpeinture2.xlsx
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120000
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100000
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atelierpeinture5.xlsx
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146000
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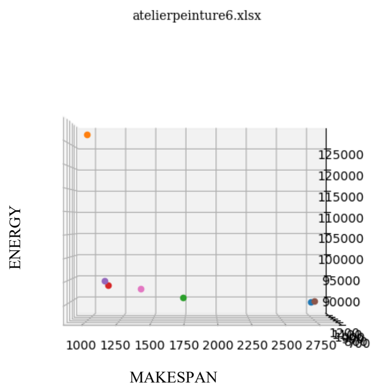
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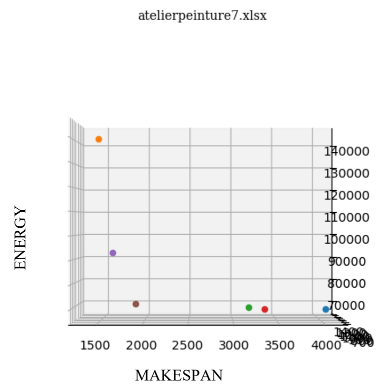
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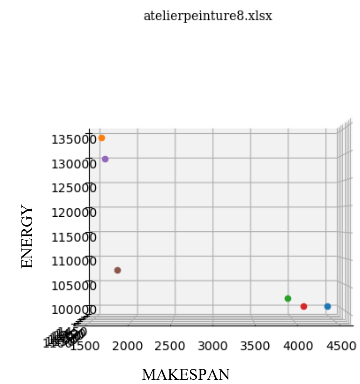
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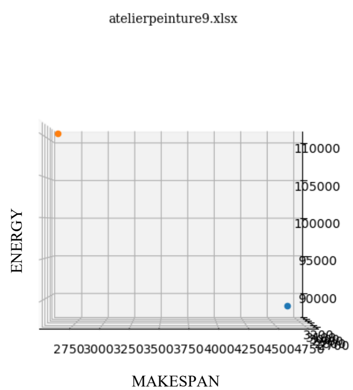
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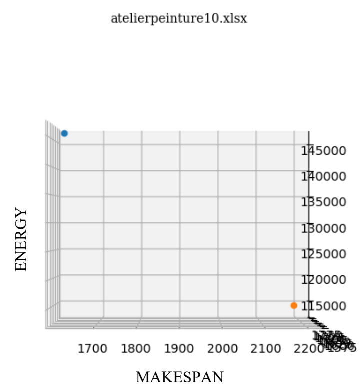
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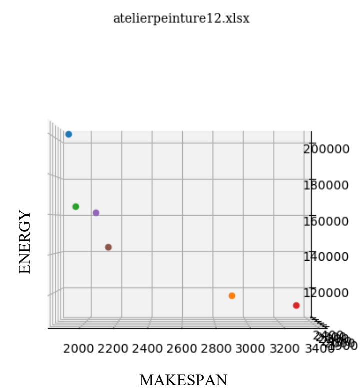
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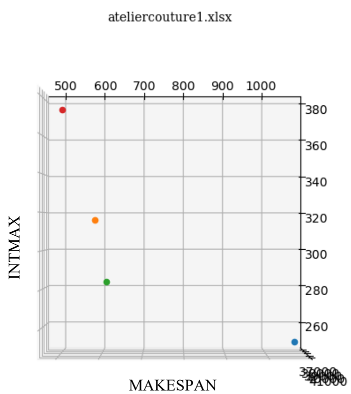
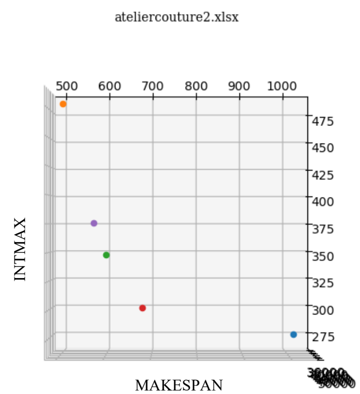
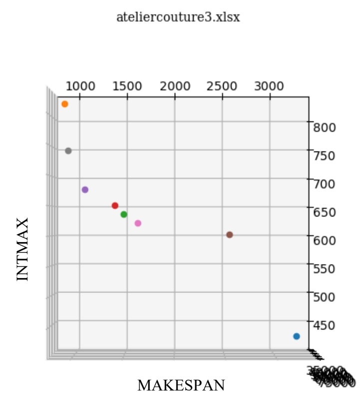
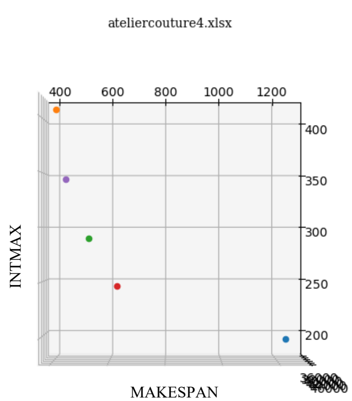
APPENDIX G

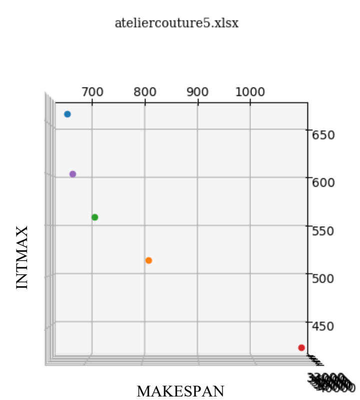
FIGURES REPRESENTING THE RELATIONSHIP BETWEEN MAKESPAN AND LABOR INTENSITY PER INSTANCE

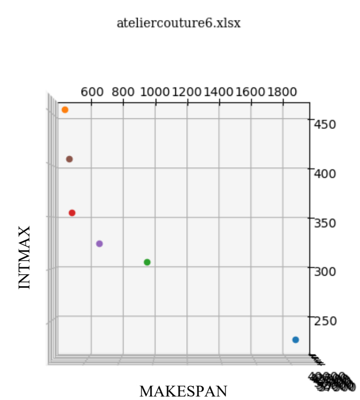


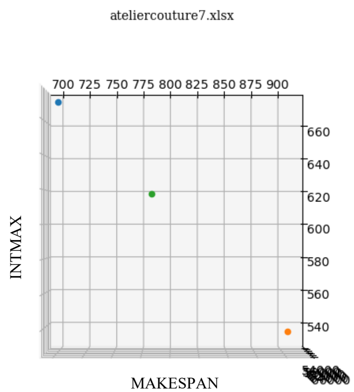








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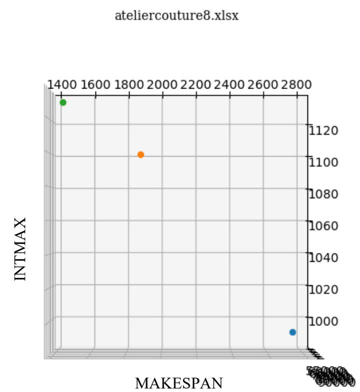
MAKESPAN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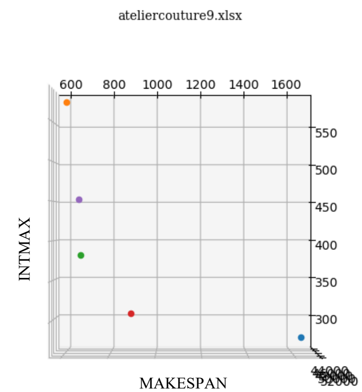
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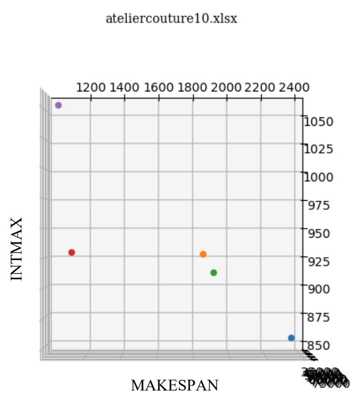
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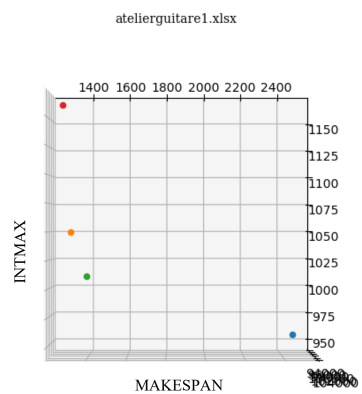
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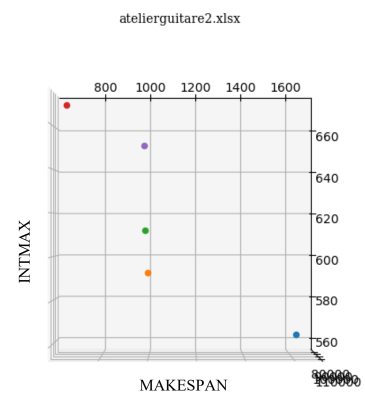
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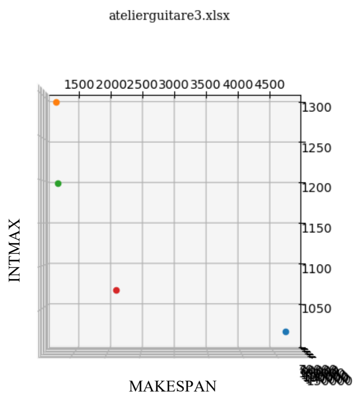
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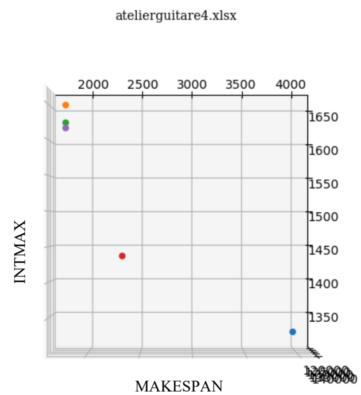
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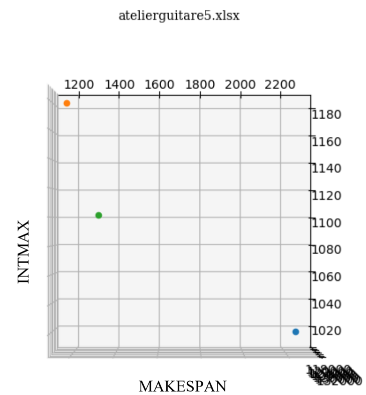
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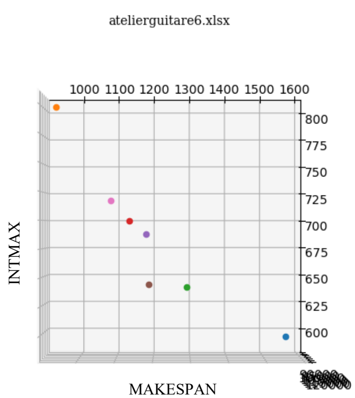
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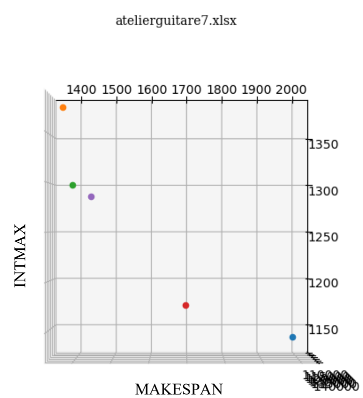
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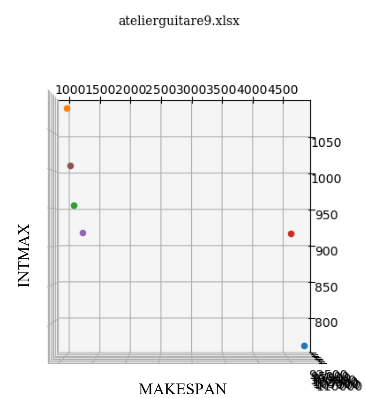
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INTMAX
MAKESPAN

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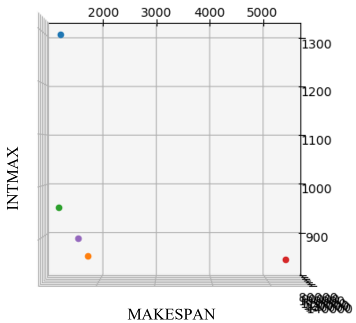

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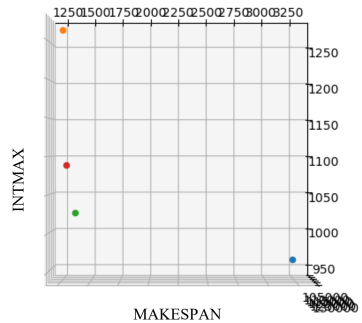

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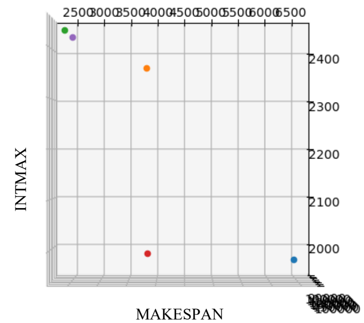

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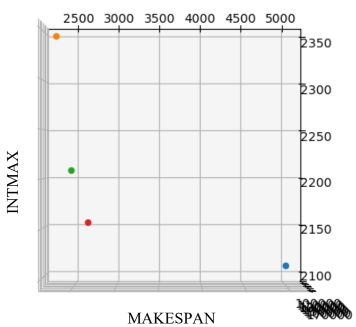

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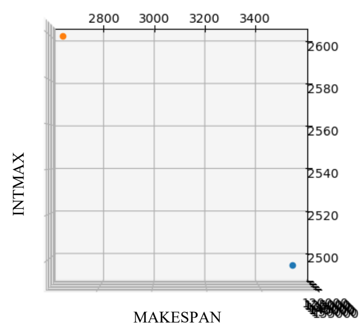

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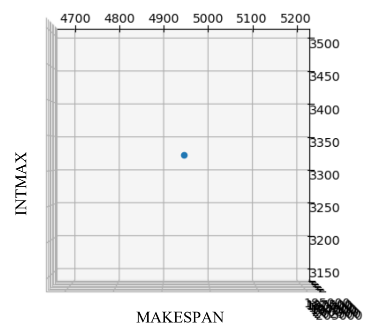

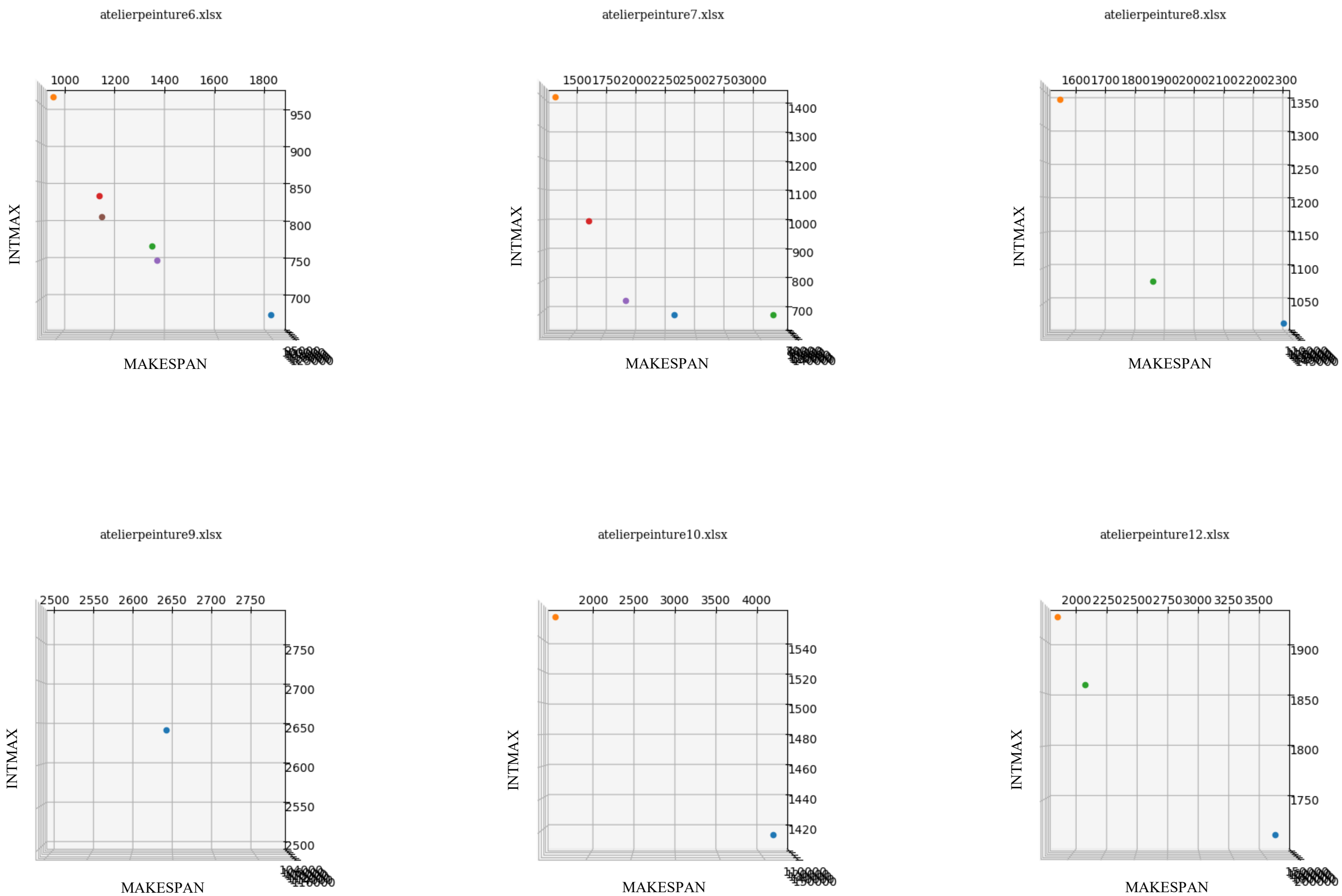
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INTMAX
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MAKESPAN
INTMAX
atelierpeinture8.xlsx
MAKESPAN
INTMAX
atelierpeinture9.xlsx
MAKESPAN
INTMAX
atelierpeinture10.xlsx
MAKESPAN
INTMAX
atelierpeinture12.xlsx
MAKESPAN
INTMAX

APPENDIX H

FIGURES REPRESENTING THE RELATIONSHIP BETWEEN LABOR INTENSITY AND ENERGY PER INSTANCE

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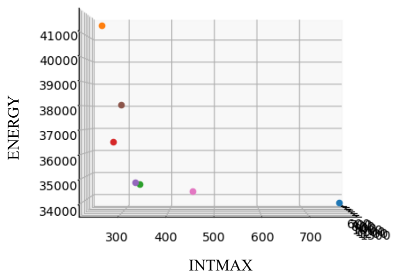

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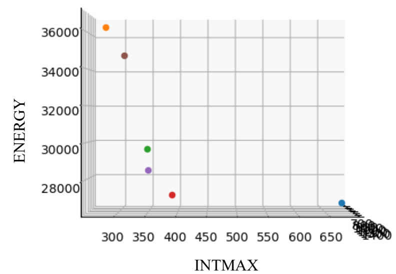

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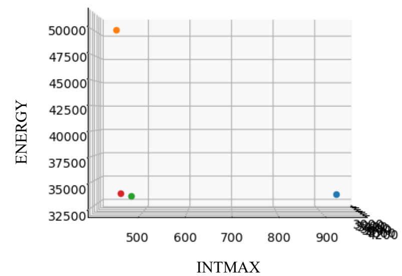

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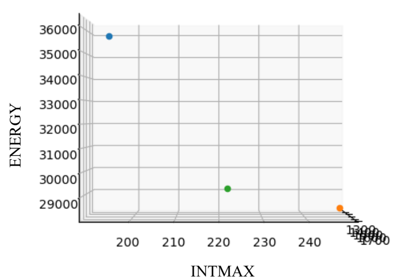

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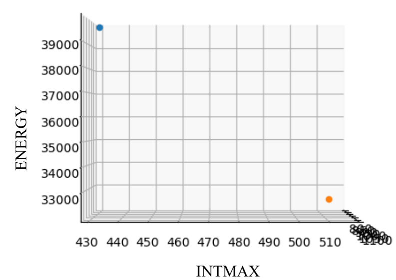

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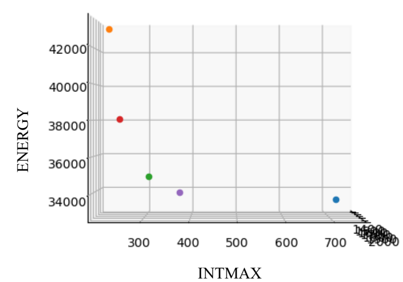

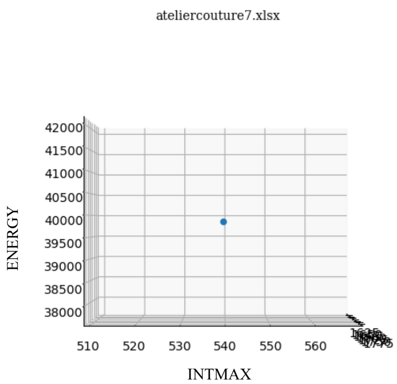
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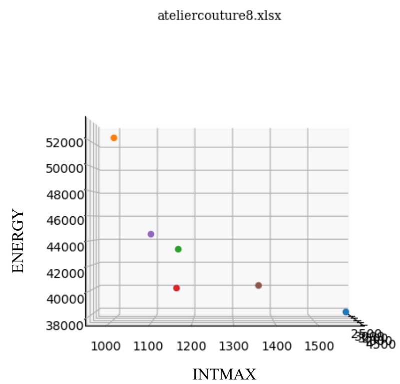
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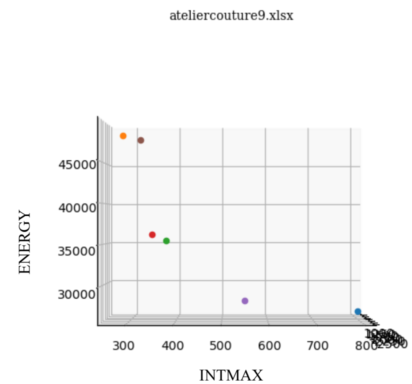
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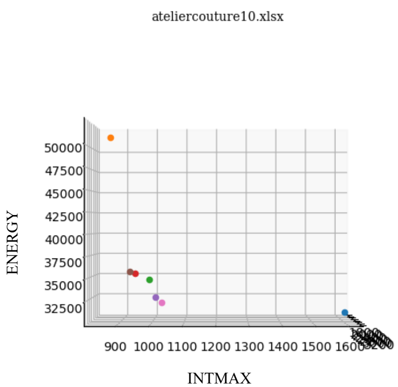
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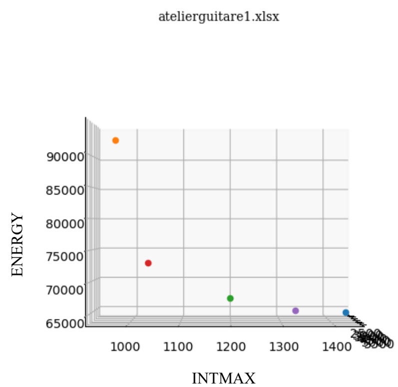
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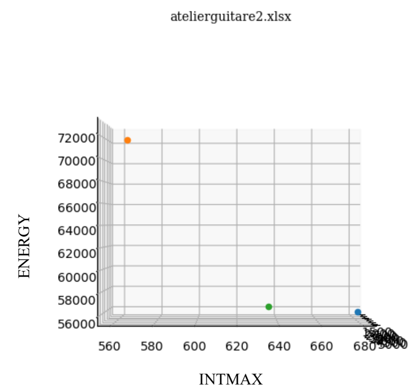
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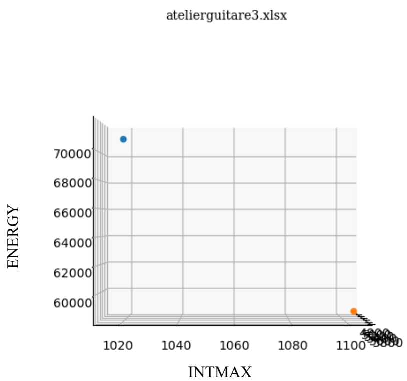
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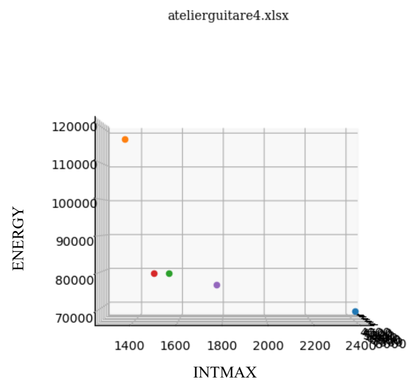
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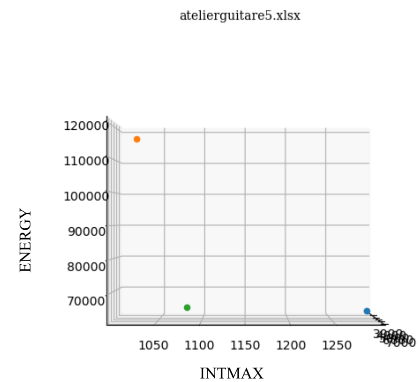
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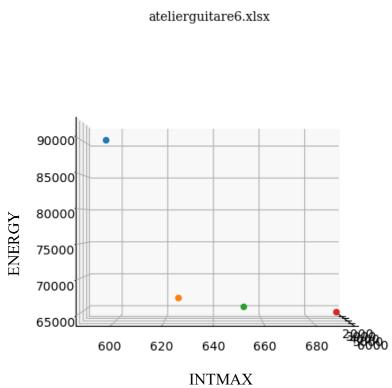
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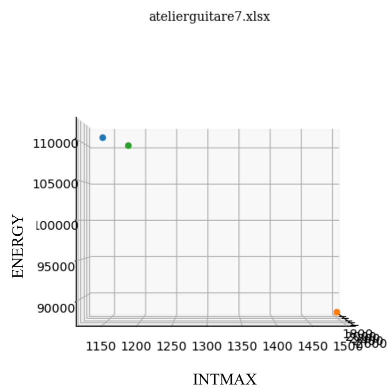
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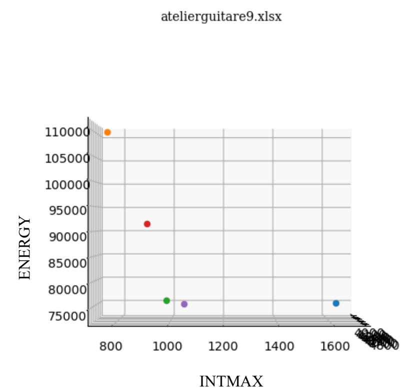
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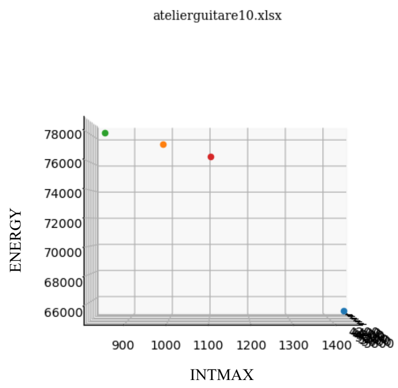
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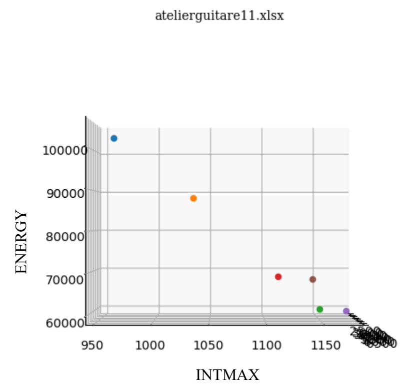
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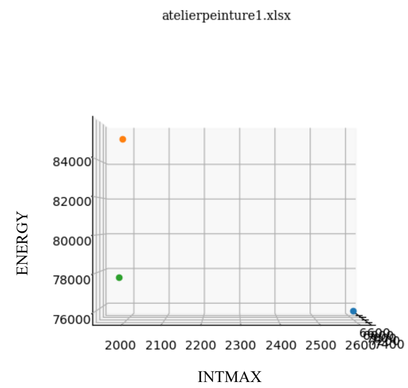
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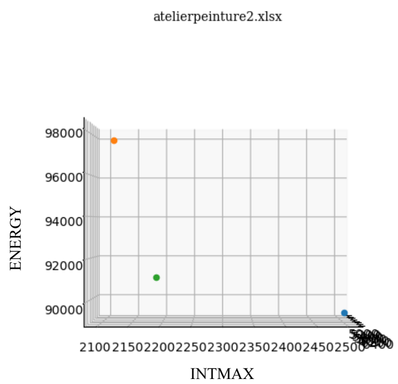
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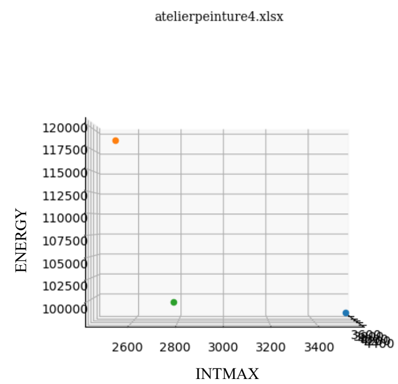
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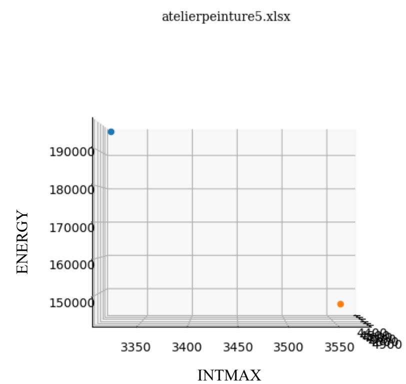
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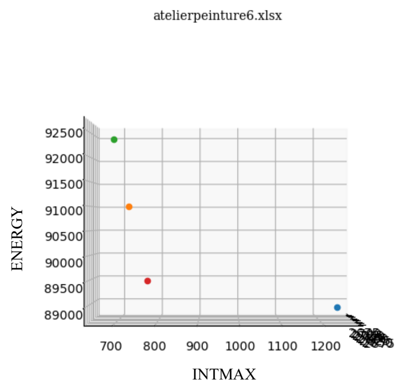
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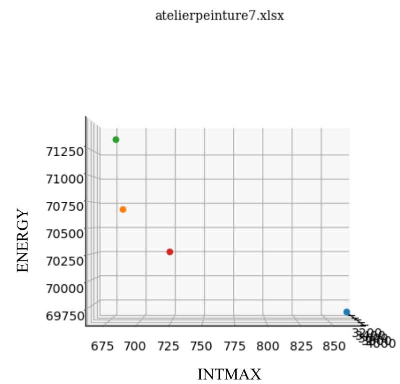
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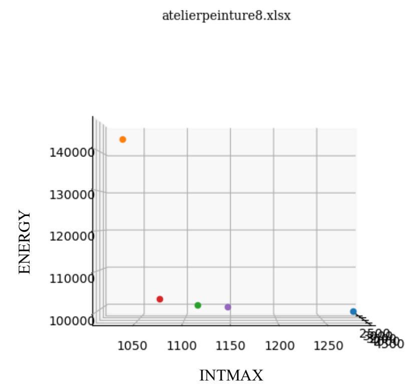
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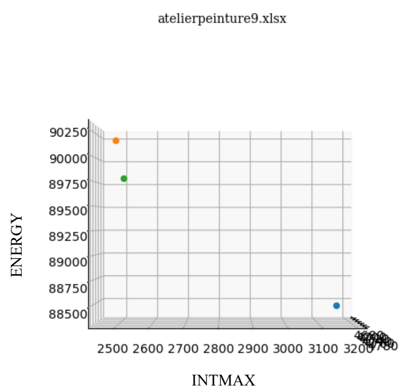
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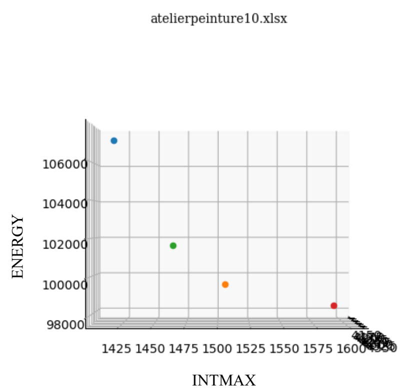
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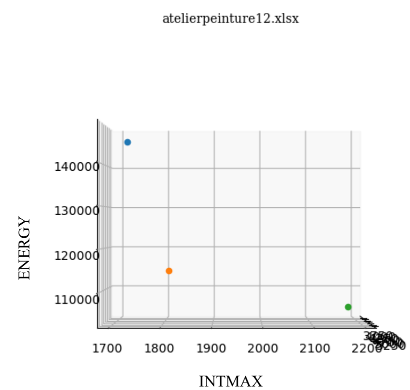
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