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Workforce scheduling and job rotation by considering ergonomic factors (Presentation of the Sequencing Generalized Assignment Problem) : application to production and home healthcare systems

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THÈSE DE DOCTORAT DE L'ÉTABLISSEMENT UNIVERSITÉ BOURGOGNE FRANCHE-COMTÉ

PRÉPARÉE À L'UNIVERSITÉ DE TECHNOLOGIE DE BELFORT-MONTBÉLIARD

École doctorale n°37

Sciences Pour l'Ingénieur et Microtechniques

Doctorat de Science pour l'ingénieur

par

SEYED-ESMAEIL MOUSSAVI

Workforce scheduling and job rotation by considering ergonomic factors: Application to production and home healthcare systems

(Presentation of the Sequencing Generalized Assignment Problem)

Thèse présentée et soutenue à Belfort, le 30 Août 2018

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SPIM
école doctorale **sciences pour l'ingénieur et microtechniques**

Titre : Workforce scheduling and job rotation by considering ergonomic factors: Application to production and home healthcare systems

Mots-clés : problème de planification du personnel, Rotation des tâches, Approaches d'optimisation

Résumé :

Cette thèse porte sur la planification du personnel en accordant une attention particulière à l'aspect humain et aux facteurs ergonomiques dans le domaine de la production. Un certain nombre de modèles mathématiques sont présentés pour formuler les problèmes d'ordonnancement et de planification du personnel étudiée. Dans les modèles de planification, la productivité du système de fabrication et le bien-être des travailleurs sont ciblés. De cette manière, une approche d'affectation des travailleurs est présentée pour réduire le temps de production et une approche d'ordonnancement des rotations des tâches est présentée pour équilibrer les charges de travail sur les opérateurs. A cet effet, une analyse ergonomique est effectuée sur les postes de travail du système de production étudié. Cette analyse aboutit à l'évaluation des postes du travail par rapport du feu de circulation, c'est-à-dire que les postes sont classés dans les niveaux de charge faible, moyen et élevé qui sont présentés respectivement par les couleurs verte, jaune et rouge. Une approche mathématique est développée pour convertir ces sorties en valeurs numériques, car les paramètres quantitatifs sont plus applicables pour l'optimisation de la planification. Une programmation multi-objectifs est proposée pour optimiser deux objectifs mentionnés du problème d'ordonnancement de tounée du personnel étudiée. Les méthodes d'agrégation linéaire et de contrainte epsilon sont appliquées pour résoudre ce modèle d'optimisation. En outre, cette thèse présente une nouvelle variante du problème d'affectation appelé problème d'affectation généralisée de séquençage qui est défini pour la planification du personnel dans un système combiné constitué des postes de travail en série et en parallèle. Il est prouvé que ce problème d'optimisation combinatoire est NP-hard et les méthodes exactes ne sont pas capables de résoudre les instances à grande échelle. Ainsi, trois méthodes approximatives composées de deux approches matheusistiques et une heuristiques hybrides sont développées pour résoudre ce problème. Les méthodes matheuristiques sont basées sur la décomposition de la formulation pour décomposer et simplifier le modèle principal en deux ou plusieurs modèles plus petits. La troisième méthode est une avide heuristique combinée à une recherche locale. En outre, dans la dernière étape de cette thèse, la planification des ressources humaines pour un système de soins à domicile est formulée mathématiquement. Selon la structure du système, une intégration des problèmes d'affectation et de tournées de véhicules est présentée. Enfin, une approche matheuristique en trois étapes est proposée pour résoudre ce problème d'optimisation combinatoire.

Title: Workforce scheduling and job rotation by considering ergonomic factors: Application to production and home healthcare systems

Keywords: Human resource planning, Job rotation scheduling, Heuristic and matheuristic optimization

Abstract:

This thesis concerns the human resource planning by paying a special attention to the human aspect and ergonomic factors in the manufacturing domain. A number of mathematical models are presented to formulate the studied workforce scheduling and planning problems. In the planning models, the productivity of the manufacturing system and the well-being of the workers are targeted. In this way, a worker assignment approach is presented to reduce the production time and a job rotation scheduling approach is presented to balance the workloads on the operators. For this purpose, an ergonomic analysis is carried out on the jobs of the studied production system. This analysis results in the traffic light evaluation for the jobs, i.e., the jobs are categorized into the low, medium and high workload levels which are presented respectively by the green, yellow and red colors. A mathematical approach is developed to convert these outputs to the numerical values, because the quantitative parameters are more applicable for the optimization of the planning. A multi-objective programming is proposed to optimize two mentioned objectives of the studied workforce scheduling problem. Both linear aggregation and epsilon-constraint methods are applied to solve this optimization model. Furthermore, this thesis presents a novel variant of the assignment problem called sequencing generalized assignment problem which is defined for workforce scheduling in a combined system consisting of the jobs in series and in parallel. It is proved that this combinatorial optimization problem is NP-hard and the exact methods are not able to solve the large-scale instances. Hence, three approximate methods consisting of two matheuristic and a hybrid heuristic approaches are developed to solve that. The matheuristic methods are based on the decomposition of the formulation to break down and simplify the main model into two or more smaller models. The third method is a greedy heuristic combined with a local search. The efficiency of three mentioned methods is evaluated by various instances of different sizes. Moreover, in the last step of this thesis, the human resource planning for a home healthcare system is formulated mathematically. According to the structure of the system, an integration of the worker assignment and vehicle routing problems is presented. Finally, a three-steps matheuristic approach is proposed to solve this combinatorial optimization problem.

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Contents

1 General introduction **3**

2 State of the art **7**
2.1 Introduction . . . 7
2.2 Ergonomics in the worker assignment . . . 8
2.2.1 Ergonomic considerations in the workforce scheduling . . . 8
2.2.2 Ergonomics and risk factors in the manufacturing . . . 9
2.2.3 Multi-objective approach in the workforce scheduling . . . 11
2.3 Worker assignment based on the GAP . . . 12
2.4 Human resource planning in the home healthcare systems . . . 15
2.5 Combinatorial optimization problems for manpower planning . . . 17
2.6 Conclusion . . . 19

I Ergonomic workforce scheduling **21**

3 Ergonomic worker assignment for productivity improvement **23**
3.1 Introduction . . . 23
3.2 Methodology . . . 23
3.2.1 Ergonomic analysis on the jobs and the workers . . . 24
3.2.2 Determination of the adequation level between workers and jobs . . . 25
3.2.3 Worker assignment to the jobs based on the adequation level . . . 26
3.3 Problem description . . . 26
3.4 Mathematical model . . . 27
3.4.1 Components of the model . . . 27
3.4.2 Model Formulation . . . 28
3.5 Application on the case study . . . 30
3.6 Conclusion . . . 32

4 Job rotation scheduling for workload balancing **33**
4.1 Studied system and physical workload analysis . . . 33
4.1.1 Current job rotation schedule . . . 33
4.1.2 Ergonomic analysis of workstations by SES method . . . 33
4.1.3 Numerical evaluation of workloads . . . 35
4.2 Modelization of the job rotation problem . . . 37
4.2.1 Components of the mathematical model . . . 38
4.2.2 Model formulation . . . 39
4.3 Numerical application . . . 40
4.4 Discussion . . . 44
4.5 Conclusion . . . 46

5 Multi-objective job rotation by ergonomic considerations **47**

5.1 Multi-objective approach in human resource planning . . . 47
5.1.1 Introduction . . . 47
5.1.2 Problem description . . . 47
5.2 Multi-objective programming for job rotation scheduling . . . 49
5.2.1 Indices, parameters, and variables . . . 49
5.2.2 Objective functions . . . 50
5.2.3 Constraints and required calculations . . . 51
5.2.3.1 Assignment constraints . . . 51
5.2.3.2 Job rotation and worker's capability constraints . . . 52
5.2.3.3 Ergonomic constraints . . . 52
5.2.3.4 Makespan calculations . . . 53
5.3 Numerical application and computational results . . . 53
5.4 Conclusion . . . 56

II Workforce scheduling based on the SGAP 57

6 SGAP formulation for workforce scheduling 59
6.1 Introduction . . . 59
6.1.1 Generalized Assignment Problem (GAP) . . . 60
6.1.2 Definition of the Sequencing Generalized assignment problem (SGAP) . . . 60
6.2 Problem description . . . 62
6.3 Primal mathematical modelalization based on the SGAP . . . 64
6.3.1 Parameters . . . 64
6.3.2 Variables . . . 64
6.3.3 Model formulation . . . 65
6.4 Improved mathematical model . . . 67
6.4.1 Parameters . . . 67
6.4.2 Variables . . . 68
6.4.3 Objective function . . . 68
6.4.4 Assignment constraints . . . 68
6.4.5 Scheduling constraints . . . 69
6.5 Conclusion . . . 70

7 Solution methods for SGAP 71
7.1 Two-phases matheuristic approach . . . 71
7.1.1 First step based on the transportation model . . . 71
7.1.2 Second step based on the scheduling model . . . 72
7.2 Sequencing matheuristic approach : Presentation of the sequencing assignment . . . 73
7.3 Hybrid heuristic algorithm . . . 74
7.3.1 Selecting the best solution . . . 74
7.3.2 Moving towards feasibility . . . 76
7.3.3 Two-exchange neighbourhood to improve the solution . . . 76
7.3.4 Developing the algorithm for the multiple (sequencing) assignments 77
7.4 Discussion . . . 78

8 Numerical application for SGAP's solution methods 81
8.1 Case study of two matheuristic approaches . . . 81

8.1.1 Computational results 82
8.1.2 Production results 84
8.1.3 Analysis of the parameters and solving approaches 86
8.2 Case study of hybrid heuristic approach 88
8.3 Conclusion 89

III Integration of worker assignment and vehicle routing problems : Application to home healthcare scheduling 91

9 Home healthcare routing and scheduling problem 93
9.1 Introduction 93
9.2 Objectives and Problem description 94
9.3 United MIP model to integrate AP and VRP 95
9.3.1 Indices, parameters, and sets 96
9.3.2 Decision variables 97
9.3.3 Objective functions 97
9.3.4 Constraints 98
9.4 Discussion 100

10 Matheuristic approach to integrate AP and VRP : Decomposition of the formulation 103
10.1 Introduction 103
10.2 Step 1 : Determination of the number of needed staffs 104
10.2.1 Additional parameters 104
10.2.2 Variables 104
10.2.3 Model Formulation 105
10.3 Step 2 : Creation of the packages of services 106
10.3.1 Additional parameters 106
10.3.2 Additional sets 106
10.3.3 Additional variables 107
10.3.4 Model formulation 107
10.4 Step 3 : Assignment of the packages to the staff members 109
10.4.1 Additional parameters 109
10.4.2 Additional variables 109
10.4.3 Model formulation 110
10.5 Discussion 111

11 Numerical experiments for the HHC planning problem 113
11.1 Case study 114
11.1.1 Planning for the staff members 114
11.1.2 Analysis of the solutions 115
11.2 Computational results 116
11.3 Statistical analysis 117
11.4 Comparison of solution methods 119
11.5 Conclusion 123

IV Conclusion and perspectives 125

LIST OF FIGURES

1.1 Classical Assignment Problem 4

2.1 Assembly line containing workstations in series and jobs/Workers in parallel 8
2.2 A shift-based job rotation approach 10
2.3 Generalized assignment problem for 3 workers and 6 jobs 12
2.4 Human resource planning for a home healthcare system 16

3.1 Utility function of height for workstation 2 26
3.2 Production cycle time in D6 31

4.1 Comparison of dispersion of the workload by and without job rotation 42

6.1 Sequencing Generalized Assignment Problem 61
6.2 Generalized assignment for the assembly line 63

7.1 Two phases matheuristic approach 72
7.2 Sequencing assignment for multi-period generalized assignment problem . 73
7.4 Selecting the best solution of the assignment matrix 74
7.3 The procedure of the heuristic algorithm 75
7.5 Penalty matrix for replacing a multi-job worker by the vailable workers . . . 76
7.6 Two-Exchange neighbourhoud for the assignment problem 77
7.7 Synchronization of the availability of the workers after each assignment . . 78
7.8 Synchronization of the assignment matrix according to the availability . . . 78

8.1 Production cycle time 85
8.2 Evaluation of the Gurobi computational times as a function of the different parameters of the problem. 85
8.3 Evaluation of the deviations of "two phases" and "sequential" solving approaches in comparison with the optimal solutions obtained by Gurobi. . . . 87

10.1 Matheuristic approach for the home healthcare planning 103

11.1 Variation of the computational times depending on the planning duration . . 120
11.2 Variation of the computational times depending on the number of patients . 121
11.3 Variation of the computational times depending on the number of staffs . . 122

LIST OF TABLES

3.1 Ergonomic characteristics needed by the jobs 24
3.2 Operators' Characterizations 25
3.3 Global utility level of the workers in different workstations 26
3.4 Workstations' properties and Processing times 30
3.5 Weekly workforce schedule 31
3.6 Computational results 32

4.1 Ergonomic parameters measured 34
4.2 Prioritization of risk factors and workloads 34
4.3 Numerical evaluation of the jobs and worker assignment without job rotation 37
4.4 Workforce schedule by Group Job Rotation 41
4.5 Capability of the workers 42
4.6 Statistical analysis of the impact of the rotation 43
4.7 Proposed optimal job rotation in comparison with the best random rotation . 43
4.8 Workforce schedule by Classical Job Rotation 45

5.1 Physical Workload Evaluation of the Jobs 48
5.2 Workers' Operating Time 48
5.3 Workers' Capability 49
5.4 Worker Assignment and Job Rotation based on the Workload Levels of the jobs 54
5.5 Worker Assignment and Job Rotation based on the Operating Times of the workers 55
5.6 Multi-Objective Analysis (Linear aggregation) 56

8.1 Most important factors of the sequencing generalized assignment 82
8.2 Computational results : Application of matheuristic methods to solve SGAP 83
8.3 Production results 84
8.4 Manpower planning and production time for the first period 88
8.5 Gurobi vs Heuristic for solving generalized assignment problem 89

9.1 Raw data for the required services by the patients during a specified day . . 94
9.2 Structured daily services required by the patients 95

10.1 Matrix INT vs matrix SI 104
10.2 Matrix SI vs matrix SIN 106

11.1 Variation domain for the simulation parameters 113
11.2 Planning of 4 home healthcare staffs to cover 10 patients during a given day 114
11.3 The distances between every pair of patients 115
11.4 Numerical results of the case study 115
11.5 Computational results 117
11.6 Proportion of optimal solutions obtained 118

11.7 Percentage of best computational time obtained over all instances 118

LIST OF DEFINITIONS

1 Definition : Sequencing Generalized Assignment Problem (SGAP) 61

LIST OF PUBLICATIONS

INTERNATIONAL JOURNALS

— **Productivity improvement through a sequencing generalized assignment in an assembly line system**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"International Journal of Production Research", 55 (24), 7509-7523.
DOI : https ://doi.org/10.1080/00207543.2017.1378828

— **Balancing high operator's workload through a new job rotation approach : Application to an automotive assembly line**
Moussavi, S.E., ZARE, M., Mahdjoub, M. and Grunder, O.,
"International Journal of Industrial Ergonomics" , Under Review from Mar 2018.

— **A matheuristic approach for the integration of worker assignment and vehicle routing problems : Application to home healthcare scheduling**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"Expert systems with applications", Submitted.

INTERNATIONAL CONFERENCES

— **A Multi-Objective Programming Approach to Develop an Ergonomic Job Rotation in a Manufacturing System**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"IFAC-PapersOnLine - Elsevier", (Information Control Problems in Manufacturing - 16th INCOM June 2018 – Bergamo, Italy)

— **A hybrid heuristic algorithm for the sequencing generalized assignment problem in an assembly line**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"IFAC-PapersOnLine - Elsevier", 51(2), pp.695-700. (Mathematical Modelling - 9th MATHMOD Feb 2018 – Vienna, Austria),
DOI : https ://doi.org/10.1016/j.ifacol.2018.03.118

— **Reducing production cycle time by ergonomic workforce scheduling**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"IFAC-PapersOnLine - Elsevier" 49(12), pp.419-424. (Manufacturing Modelling, Management, and Control, 8th MIM Aug 2016 – Troyes, France),
DOI : https ://doi.org/10.1016/j.ifacol.2016.07.642

— **Ergonomic job assignment by using utility functions**
Moussavi, S.E., Mahdjoub, M. and Grunder, O.,
"17ème Conférence Recherche Opérationnelle et d'Aide à la Décision (ROADEF)", 10-12 Février 2016, Compiègne, France.

1

General introduction

The human aspect is an important factor in the analysis of the productivity and efficiency of a production or service system. In the manufacturing, the efficiency of the workers and their capacities cause the uncertain executing time for the production tasks. In the real cases, the efficiency of the workers varies from a task to another, so that the best worker for a task is not necessarily the best for another task. Hence, assigning the best worker to each task can significantly improve the productivity of the system. Thus, the human resource planning in a production system could be considered as a specific version of the Assignment Problem (AP). Moreover, the job rotation scheduling also plays an important role in the workforce planning domain as well, particularly where the ergonomic issues are considered as the objectives or constraints in the planning. Actually, reducing musculoskeletal disorders (MSD), risk factors and monotony of the work are the main reasons that persuade a manufacturing industry to apply job rotation in the manpower planning. Many various objectives can be targeted in the manpower planning of a system. In the production domain, improving the productivity, reducing the production cycle time or manpower costs... are the economical objectives and workload balancing, reducing the ergonomic risks, MSDs, and occupational disease are the ergonomic objectives of the workforce planning. In a service system, for instance a home delivery system, the objective of the planning can be minimizing the distance travelled by the staff members, reducing the travel costs, ...

In the last decades, the Operational Research's (OR) approaches have been employed to manage and optimize the human resource planning in diverse domains. The mixed-integer programming (MIP), linear programming (LP), mixed-integer linear programming (MILP), ... are the optimization approaches which have been widely applied to formulate mathematically a human resource planning problem. In this way, various operational research's problems were developed. For instance Assignment Problem (AP), Travel Salesman Problem (TSP), and Vehicle Routing Problem (VRP) are some well-known problems for the operations and personnel management. In the personnel management domain, the assignment problem is frequently used as the basis to formulate the problem mathematically. The classical assignment problem concerns a number of agents and a number of tasks. Any agent can be assigned to perform any task with an operating time that may vary depending on the agent-task assignment. A simple example of the classical assignment problem is shown in figure 1.1.

This thesis is composed of three parts. The first part concerns a human resource planning in a continuous manufacturing system in which the ergonomic considerations play the important roles. At the first step of this part, the ergonomic criteria are considered to

	Job 1	Job 2	Job 3	Job 4
Worker A	5	9	2	6
Worker B	8	7	5	4
Worker C	6	5	7	9
Worker D	4	8	8	3

Worker A takes 6 units of time to finish Job 4.

Worker/Job assignment problem for four workers and four jobs. The red values show optimal assignment that is Worker A is assigned to Job 3, Worker B to Job 4, Worker C to Job 2 and Worker D to Job 1.

FIGURE 1.1 – Classical Assignment Problem

develop a worker assignment by the aim of improving the productivity. It is proved that the ergonomic adequation level between worker and job has an impact on the efficiency of the worker. Thus, the operating time of the workers vary according to their ergonomic adequation level with the job. In this way, an integer linear mathematical model based on the assignment problem is proposed to reduce the daily production cycle time by an ergonomic workforce scheduling. The worker assignment in this part of research is not directly based on the ergonomic criteria but that is based on the workers' operating times where the operating times are depended on the ergonomic adequation between worker and job.

At the second step of the first part, the ergonomic factors are directly considered in the workforce planning. In the same production system, various ergonomic criteria are taken into account to calculate the workloads of each job. This analysis shows that the workload level largely varies from a job to another. Hence, a job rotation approach is proposed by the aim of balancing the daily workloads among the workers. This optimization problem is also formulated mathematically by using mixed-integer programming. Finally, at the third and last step of this part, both studied objectives (productivity improvement and workload balancing) are integrated in the same problem. A multi-objective optimization approach is proposed to implement an ergonomic worker assignment and job rotation schedule in the studied production line. This approach improves the productivity and balances the operators' workloads simultaneously.

Three presented models in the first part do not follow a well-known problem formulation in the OR domain. According to the structure of the studied system, in the second part of this thesis, the Generalized Assignment Problem (GAP) is used as the basis of the formulation for the manpower planning models. The GAP is an enlarged version of the classical assignment problem in which the assignment of several tasks to an agent is possible. The only restriction that can limit the assignment of the tasks to the agents is the capacity of the agent. In this part, the manpower planning in the studied assembly line is modelled as a GAP. The considered assembly line consists of a number of workstations in series where each workstation contains several jobs in parallel. The presented optimization model in this part seeks to assign the best operator to the jobs in order to minimize the processing time in each workstation and in the whole of the system. The generalized assignment formulation is adapted to this case. Moreover, the objective is to perform an

efficient human resource planning for a specified horizon consisting of several periods. Hence, we present an extension of the generalized assignment problem, consisting of a set of GAPs (one for each planning period) in which each GAP depends on previous ones. A mixed integer mathematical model is presented for this sequencing assignment problem.

It is proved that the problem is NP-hard and solving the medium and large size instances is not possible by the exact algorithms. Hence, three approximate solution methods are presented for this novel optimization problem : Two matheuristic approaches based on the disaggregated formulation of GAP and also a heuristic algorithm. The first matheuristic approach solves the problem through two sub-problems as the transportation formulation and assignment formulation. The second matheuristic approach solves the problem by decomposition of the problem into several classical GAPs. The heuristic algorithm is a greedy heuristic combined with a local search.

In some cases, the modelization of the human resource planning problem by using only assignment problem formulation is not possible. For instance, the manpower planning in a home delivery service deals with two different OR aspects. The first is the Assignment Problem (AP) and the second is a variant of the Vehicle Routing Problem (VRP). In the last years, the home health care planning problem has been widely studied as a novel OR problem in the human resource planning domain. The third and last part of this thesis concerns the workforce planning in a home health care system, which is a special type of the home delivery service. Both assignment and vehicle routing formulations are used to model this combinatorial optimization problem. To model a home healthcare planning problem by classical VRP and AP formulation, the dimensions of the problem are : 1. The staffs, 2. The patients, 3. The routes (sequence of the patients for each staff).

In this thesis, we present an extension of the home healthcare planning problem by adding an extra dimension of time so that the staffs are not only assigned to the patients, but they are also assigned to the daily periods. The horizon of the planning problem contains multiple days in which the patients' needed services vary from one day to another. Hence, the problem concerns a sequence of plannings (one planning for each day) for the staff members. This variant of the home healthcare planning problem is modelled mathematically by employing the sequencing generalized assignment formulation which is presented in part two. Considering that, the studied combinatorial optimization problem is NP-complete, a matheuristic approach based on the decomposition of the formulation is proposed in this research to simplify the mathematical model and reduce the computational time needed to solve the problem. Actually, in this part of thesis, two mathematical programming approaches are presented to integrate the generalized assignment and vehicle routing problems.

2

STATE OF THE ART

2.1/ INTRODUCTION

Human and machine factors are two considerable agents which have the important impact on the productivity in the manufacturing environment. Because of being various difficulties in modelling the human issues, this aspect has not been greatly considered in the previous researches. Nevertheless, it is a substantial factor in the production not only for its influence on the productivity but also to control the ergonomic risks which play the important role in such systems. Nowadays, work-related musculoskeletal disorders (WMSDs) and ergonomic risks have received a considerable amount of attention in the manufacturing.

In various researches, job rotation is defined as a solution to balance workloads and reduce the ergonomic risks among operators. Moreover, considering the ergonomic aspect in the job assignment procedure may decrease WSMDs and its associated risks in manufacturing lines. The job assignment and job rotation, as the two main branches of the workforce scheduling problem (WSP), have been widely studied in the literature.

This thesis concerns the human resource planning for two different systems : 1. A manufacturing system (figure 2.1) ; 2. A home healthcare system. For the first system, the objective is to improve the productivity, while the ergonomic factors have been considered for the worker assignment. Then, a job rotation approach has been proposed to balance the workloads to which the workers are exposed. In the next step, a multi-objective approach has been proposed to combine two mentioned objectives by aiming to improve the productivity and reduce the ergonomic risks simultaneously. In the next step, the human resource planning for this manufacturing system is formulated based on the Generalized Assignment Problem (GAP).

The human resource planning in a home healthcare system is a combinatorial optimization problem, because the staffs are not only assigned to the services (jobs) but they must also move from a patient to another. Therefore, this problem deals with both assignment and vehicle routing problems. A state of the art is presented for all aforementioned aspects of this thesis as follows.

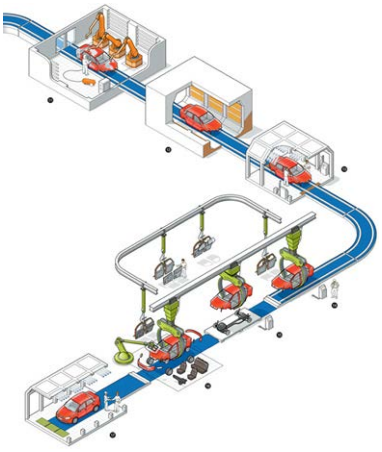


FIGURE 2.1 – Assembly line containing workstations in series and jobs/Workers in parallel

2.2/ ERGONOMICS IN THE WORKER ASSIGNMENT

2.2.1/ ERGONOMIC CONSIDERATIONS IN THE WORKFORCE SCHEDULING

In the two last decades, diverse objectives have been purposed for the workforce scheduling problems. For instance, Alfares (2002) proposed an optimal job allocation to the employees such that minimize the number workers by regarding the successive work-days and also the successive off-days. Total labor cost is another objective which is targeted in a paper published by Elshafei et al. (2008). Seçkiner et al. (2008) and Michalos et al. (2010) published papers on workforce scheduling domain by modelling the job rotation. Their works are aimed at, respectively, minimizing the workload of jobs and balancing workload in the automotive assembly line.

Personal features of the worker are another considerable aspect for assessment of human factor in the manufacturing. In this way, Costa et al. (2009) proposed a metric to evaluate the efficiency of job rotation in the case of disabling workers. Their objective was to minimize the number of different jobs which are performed by each worker. Othman et al. (2012) developed a multi-objective mixed integer model on the workforce scheduling by considering human aspects and worker differences such as skills, fatigue, and personalities. The objective of their model consists of productivity and economic aspects. After that, Moreira et al. (2013) published another paper on the job rotation problem with paying specific attention to the personality, body and mental characterizations of workers. They proposed a hybrid algorithm for selecting the appropriate schedules from a pool of solutions at each period. Smoothing the workload among the heterogeneous workers was their objective.

In the above-mentioned studies, the researchers have not directly addressed the ergonomic aspect in their job rotation and assignment problems whereas in two last decades divers papers have been published on the workforce scheduling with significant ergonomic considerations as the main issues. Rattanamanee et al. (2013) proposed an ergonomic job assignment for a production system. Ergonomic aspect was depicted as daily hazard caused by working in the different workstations. The objective was to minimize the number of employees for the planning period such that the daily hazard does not exceed an allowable limit for each worker. Ergonomic risks were targeted in another paper published

by Otto et al. (2013), in which a model was presented for balancing the ergonomic risk among workers using job rotation scheduling. A comprehensive evaluation of workstation was performed with the aim of risk assessment in different tasks of an automotive production line. These two studies did not consider the difference between the personal characterization of workers.

Very few researches have considered the ergonomic aspect of jobs together with personal features and capacities of each operator, in the workforce scheduling. For example, Azizi et al. (2010) presented a dynamic model for job rotation. In their model, job rotation has a negative effect on the efficiency of workers because of the skill forgetting ; And has a positive effect thanks to the raising the motivation level. Their principle objective was to determine the optimal interval for rotation the tasks by considering the mental personal factors of workers. In another research developed by Huang et al. (2014), anthropometry, which is a physical factor in the ergonomic domain, is considered in their job rotation approach. Reducing the average risk and decreasing the number of workers who experience the high level of risk, are their objectives. They performed a risk assessment according to the difference between the anthropometry of the operator and what needed by the job. Furthermore, Van den Bergh et al. (2013) reviewed comprehensively the literature on workforce scheduling and classified them according to their objectives, constraints, considerations, assumptions, and applications. They identified different perspectives such as demand forecasting, hiring and firing, machine scheduling. Next section presents a state of the art on the different ergonomic risks and criteria which can be considered for human resource planning in the manufacturing domain.

2.2.2/ Ergonomics and risk factors in the manufacturing

Work-related musculoskeletal disorders (WR-MSDs) develop due to exposure to risk factors and represent one third of all diagnosed work-related diseases in the manufacturing domain in many countries (Chiasson et al. (2012)). They have significant financial and social consequences which result in more than 40% of occupational costs (Speklé et al. (2010)). Many industries in France have experienced increases in the number of workers' compensation claims in recent decades due to WR-MSDs risk factors (Rivière et al. (2014) ; Roquelaure et al. (2006)). Repetitive tasks, work posture, lifting and material handling, energy consumption, and tooling are common WR-MSDs risk factors in various industries (Falck et al. (2014)). There are other factors such as the frequency of actions, duration of repetitive tasks over a day and lack of recovery time that intensify the impact of these risk factors (Berlin et al. (2009)). An ergonomic approach including the assessment of risk factors, engineering and administrative strategies need to improve the workplace situation in order to provide the positive effects on system and human performance (Côté et al. (2013) ; Fuller et al. (2009) ; Widanarko et al. (2015)).

Job rotation as an organizational approach is used by manufacturing industries aimed at mitigating exposure to high physical workload and monotony. Figure 2.2 shows a simple example of the shift-based job rotation approach. Researchers often recommend to reduce exposure to risk factors using job rotation (Fallentin et al. (2000) ; Wells et al. (2007)). This rotation allows transmission of workload to other muscles and increases utilization of different body region. For instance, Mathiassen (2006) suggested that more physical variation may be an effective act against MSDs for the repetitive jobs. Furthermore, job rotation strategy has been frequently applied by engineers following the implementation

of lean management, because of the need for more workers with autonomy (Padula et al. (2017)). However, efficiency of a job rotation strategy depends on identifying workloads, evaluating exposure level, and proper planning and schedule of job rotation (Otto et al. (2013)).

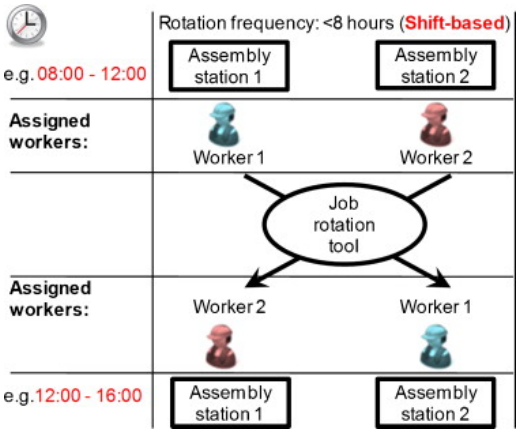


FIGURE 2.2 – A shift-based job rotation approach

To develop a job rotation strategy, previous studies have considered different types of ergonomic parameters to characterize physical workload. Various methods such as direct measurement tools (Jonsson (1988) ; Balogh et al. (2006)), NIOSH lifting equation, Rapid Upper Limb Assessment, Occupational Repetitive Actions (Asensio-Cuesta et al. (2012)), Rapid Entire Body Assessment (Triggs et al. (2000) ; Yoon et al. (2016)), Occupational Repetitive Actions (Otto et al. (2011)) and checklists have been frequently used to assess physical workloads. However, few studies have integrated various biomechanical parameters such as repetition, postures, force, material handlings and energy consumption into a mathematical model for job rotation. Frazer et al. (2003) suggested integrating several risk factors such as force and repetition to effectively reduce physical workload. Their paper is an experimental study on the effect of job rotation on risk predictions of reporting low back pain, using the two approaches Low Back Pain Reporting (LBPR) and Time Weighted Average (TWA). In another research, Leider et al. (2015) showed that knowledge about exposure to physical workload at organizational and individual levels could facilitate the implementation of job rotation as a useful or easy to use ergonomic intervention.

Furthermore, the impact of the job rotation approach on the biomechanical factors and well-being of workers are analysed by Aptel et al. (2008). They concluded that a job rotation schedule must consider all the dimensions of the work particularly biomechanical parameters. Yoon et al. (2016) proposed a job rotation schedule in a production assembly line that successfully reduce cumulative workloads on the same body region. However, physical workloads were identified and assessed by REBA tool which focus on whole body postural analysis. Furthermore, learning aspect and its cost/time were ignored in this mathematical model. de Oliveira Sato et al. (2009) found a great variability in the pattern of exposure to physical workloads when workers rotate between workstations. Thus, appropriate indicators must consider to evaluate physical workloads and to be sensitive to the effects of work variability. In order that practitioners could apply the theoretical achievement in the real industrial settings, Otto et al. (2013) confirmed that a comprehensive analysis of physical workloads closer and applicable to the real settings is required to define the parameters and the objective functions of the mathematical model for job ro-

tation schedules. In fact, their paper illustrates a binary linear program for the ergonomic job rotation scheduling problem (EJRSP) which uses period-specific ergonomic points (EP) from the EAWS for the definition of the risk exposures and of the objective function. Then, a smoothing heuristic solution method is proposed. In this way, Moussavi et al. (2016) proposed a job rotation model to perform a workforce scheduling in a real setting assembly line. They analyzed some ergonomic factors on the operators and on the jobs to assign the most appropriate worker to each job.

Application of job rotation schedules developed in various studies to the real settings has been less considered in the literature. Learning-forgetting effect and its related time/cost have been often neglected in the developed job rotation model such that these theoretical model could not be applied to the real settings (Azizi et al. (2010)). All aforementioned researches are the mono-objective job rotation problems. They considered whether productivity or ergonomic factors as the objective function. In the next section a state of the art is presented on the multi-objective job rotation scheduling problems.

2.2.3/ Multi-objective approach in the workforce scheduling

As mentioned before, various objectives have been targeted in the human resource planning domain. In the classical assignment problem the economical objectives are often considered, but in the classical job rotation, the ergonomic factors are usually taken into account. Moreover, there are the researches that consider the productivity in the job rotation models. According to the divers origins and domains of the objectives of job rotation, a main objective is mostly purposed and the other aspects are often ignored or are analyzed very slightly. A few studies have considered a multi-criteria optimization in the job rotation, worker assignment and human factors in the production domain. In this way, Costa et al. (2009) studied a job rotation, worker assignment problem in an assembly line. They only considered the disabled workers and training aspect in their job rotation model. The optimization of the human factors in the production is considered in the research by Grosse et al. (2017). They studied the state of art of the incorporating human factors in the production and logistics. The work-related musculoskeletal disorders were considered in the job rotation model presented by Botti et al. (2017). Their objective was to reduce the ergonomic risks and assigning the skilled workers to each jobs . They proposed a bi-objective mathematical model for their job rotation strategy. In other multi-criteria researches, Rossi et al. (2013) proposed an AHP approach to evaluate various scenarios containning humain factor and productivity considerations. Two multi-criteria optimizations, one in job rotation and another in worker assignment proposed by respectively Diego-Mas et al. (2009) and Hussin et al. (2017).

Line Balancing and it's related problems are the well-known optimization problems in the production systems. The human factors, ergonomic risks, productivity and multi-criteria optimization were largey considered in this domain in the last years. In this way, Battini et al. (2016a) presented a novel extension of the line balancing problem and they proposed a mixed-integer model by considering the ergonomic factors. They have shown that how their proposed optimization approach reduce the inventories and the fatigue of workers. Moussavi et al. (2017) and Moussavi et al. (2018) proposed a new extension of assignment problem and job rotation for worker assignment in the production. The ergonomic aspect was considered in the line balancing in the research by Sgarbossa et al. (2016) where a multi-objective programming approach was presented to incorporate the

ergonomics criteria and the assembly line balancing problem. Apart from the ergonomic criteria, the energy expenditure is also studied in their work. In this way, Battini et al. (2016b) in another research proposed a multi-objective model containing four different objectives to evaluate the impact of the ergonomic criteria on the line balancing performance. They used the energy expenditure to obtain the level of the ergonomics.

Another domain of application for the optimization by ergonomic criteria in the production is cell formation problem. Niakan et al. (2014) proposed a multi-objective mixed integer model to the cellular manufacturing system that considers social factors together with the economic criteria and they proposed a hybrid genetic algorithm to solve their model. The problem studied by Akyol et al. (2016) is a integration of the worker assignment and line balancing problems. They analyzed the ergonomic risks in their problem as the main consideration. A heuristic solving approach was proposed for their problem.

Actually, this thesis aims at obtaining the optimal assignment of the appropriate operators to the workstations. Considering the structure of the studied assembly line that consists of the workstations which are in series (flowshop system) and each workstation is composed of several jobs. In a workstation, as there are no precedence relationships between jobs, they can be processed in parallel. Consequently, several workers are assigned to the same workstation. Therefore, the studied problem can be regarded as a special type of the generalized assignment problem (GAP) which is a combinatorial optimization problem. The presented worker assignment researches in the previous sections are not based on a particular well-known problem formulation. In the next section, a state of the art on the workers assignment formulation based on the GAP is presented.

2.3/ WORKER ASSIGNMENT BASED ON THE GAP

For the first time, the term generalized assignment problem is introduced by Ross et al. (1975) as multiple assignments of tasks to agents which are limited by some resource available to the agents. Figure 2.3 shows a simple example of the GAP containing three workers and 6 jobs with a capacity of two jobs for each worker.

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
A	5	9	2	6	8	5
B	8	7	5	4	3	7
C	6	5	7	9	8	4

Generalized Assignment with the capacity of 2 jobs for each worker.

FIGURE 2.3 – Generalized assignment problem for 3 workers and 6 jobs

For the GAP, Ross et al. (1975) Proposed a branch and bound algorithm and compared that with two other algorithms named IPNETG presented by Klingman et al. (1974) and also a zero-one algorithm presented by De Maio et al. (1971). They demonstrated the advantages of their algorithm in the computational time and precision of the solution by

examining the different size of the problem. Another exact method which has been employed to solve the classical GAP is the Lagrangian relaxation approach in the researches by Jörnsten et al. (1986) and Fisher et al. (1986) . After that Cattrysse et al. (1992) presented a survey on the different relaxation algorithms which had been proposed for the generalized assignment problem. Various extension of the GAP such as bottleneck generalized assignment problem (BGAP) and non-linear capacity constraints (NLGAP) were presented in their research. In this way, Savelsbergh (1997) proposed an exact algorithm by using the column generation and branch and bound approaches for this kind of problems.

Apart from the exact algorithms, divers approximation algorithms have been presented for the GAP. In the literature, there exist the heuristics, metaheuristics and hyper-heuristics approaches. Shmoys et al. (1993) adapted a generalized assignment problem to the scheduling of the parallel machines and proposed a polynomial-time algorithm, as an approximation method, to solve this problem. Tabu search has been employed by many researchers for the various extensions of the GAP. Laguna et al. (1995) presented the multilevel generalized assignment problem (MGAP), as an extension of the GAP, in which the efficiency of the agents depend on the number of tasks assigned to those. They proposed a tabu search algorithm with the ejection chain for the neighborhoods definition. Another tabu search heuristic for the GAP is proposed by Dıaz et al. (2001) in which a dynamic adjustment for the feasibility violation penalty is defined by using a medium-term memory. A hybrid of the heuristic strategy of tabu search with the exact branch and bound approach is proposed by Woodcock et al. (2010) to solving the generalized assignment problem . They validated their method by benchmark instances and comparison with other heuristic approaches in the literature. Among the metaheuristic approaches, the genetic algorithm has been also employed for the generalized assignment problem. For instance, Chu et al. (1997) and Wilson (1997) illustrated the advantages of this method for such problems in comparison with earlier works.

In fact, Chu et al. (1997) proved that the generalized assignment problem is an NP-complete combinatorial optimization and the existing exact methods are practical only for certain instances where there are no additional constraints. Therefore, they proposed a genetic algorithm which is able to solve the GAPs with more constraints. They also compared their adaptive genetic algorithm with various existing approaches, for instance, tabu search and simulated annealing which were adapted for the GAP by Osman (1995). They presented the results of the genetic algorithm for different instances and demonstrated that the results are extremely near to the optimal solution which is obtained by CPLEX mixed integer solver.

Thereafter, various heuristic and meta-heuristic approaches have been proposed for the generalized assignment problem. For instance, Osorio et al. (2003) and Dıaz et al. (2001) considered the generalized assignment problems as the subproblems in their studies and they added more details and assumptions to the classical GAP. They prove that these type of problems are much more complicated than classical GAP to solve and proposed the tabu search and logic cuts in a branch and bound algorithm for solving such problems. In this way, Tasgetiren et al. (2009) presented a continuous optimization algorithm based on differential evolution for the GAP and they hybridized their algorithm by employing variable neighborhood search to improve the quality of the solutions. Moccia et al. (2009) proposed a column generation algorithm to compute a lower bound by linear relaxation and find a feasible integer solution for the dynamic GAP. Posta et al. (2012) presented an exact algorithm based on the decomposition of the GAP formulation by fixing certain

variables.

The uncertainty considerations were also studied in the more recent researches as an extension of the GAP. In this domain, an approximation algorithm based on the combinatorial local search has been presented for the GAP by Cohen et al. (2006) . Kiraz et al. (2010) proposed another combinatorial algorithm for an extension of the GAP. They presented a dynamic GAP and proposed an integration of the hyper-heuristic with the memory-search algorithm to solve such problems. Subtil et al. (2010) also proposed an adapted version of the genetic algorithm by considering non-dominated sorting for another extension of the GAP. Their extension was the multi-objective consideration. In this way, a fuzzy multiple objective extension for the generalized assignment problem is presented by Tapkan et al. (2013) . For solving this problem, a combinatorial approach consisting of the fuzzy ranking and and bees algorithm was proposed. Additionally, in the uncertainty extensions, the stochastic consideration has been import into the GAP as another extension, for instance, Alaei et al. (2013) presented an online stochastic GAP. Sadykov et al. (2015) also presented a combinatorial method consisting of the column generation, diving heuristic and dual stabilization for the classical GAP. Özbakir et al. (2010) proposed a heuristic composed of a meta-heuristic (bees algorithm) and a ejection chain heuristic for such problems.

In recent years, the literature has been more focused on different extensions of the GAP. In this way, for the Generalized Quadratic Assignment Problem (GQAP), as an extension of the GAP, McKendall et al. (2017) proposed a meta-heuristic tabu search algorithm. They applied GQAP formulation to solve a location problem and assign the machines to different locations. Location/Allocation consideration was studied in the GAP by Ghoniem et al. (2016b). They developed a heuristic algorithm based large-scale neighborhood search for this problem. Ghoniem et al. (2016a) in another research presented an exact algorithm based on the branch and bound algorithm for their extended version of the GAP. In this year, Sethanan et al. (2016) developed a hybrid algorithm composed of three local search techniques which are added to the differential evolution (DE) to solve the classical GAP. Furthermore, the generalized quadratic assignment problem (GQAP) is presented by Mateus et al. (2011) and a combined heuristic integrating the GRASP with path-relinking was proposed.

In fact, all mentioned works consider the generalized task assignments but without considering several consecutive periods of assignment, which has an impact on human factors like working days of the operators. Therefore, the GAP model and corresponding solving methods cannot be applied directly to this problem. An important contribution of this part of our research is the consideration of the availability of the workers and possibility of job rotation in the worker assignment problem. In this way, Alfares (2002) and Elshafei et al. (2008) studied the availability of the workers and they considered the restrictions on the working-days and off-days in their workforce scheduling model. Alfares tried to minimize the number of worker regarding the successive working-days and successive off-day for the workers in his research. Then Elshafei and Alfares developed a dynamic model for labor assignment by aiming to minimize the labor costs.

On the other hand, this research can be regarded as a line balancing strategy by the optimal manpower planning. The classical assembly line balancing problem is about the assignment of tasks to the stations of an assembly line, whereas this research is concerned with the assignment of non-identical tasks to heterogeneous workers. Recently various researchers have considered the human resource planning in the line balancing

domain. The integration of the assignment problem with the line balancing problem has been introduced by Miralles et al. (2007) as an extension of the assembly line balancing problem. In this way, in a research by Vilà et al. (2014), worker assignment is considered in the line balancing problem in which the efficiency of the workers is the main parameter of assignment. The objective of their research is to minimize the cycle time by reducing the idle time of the stations. Zacharia et al. (2016), presented an assembly line balancing problem containing worker assignment. They have proposed a bi-objective model for their combinatorial optimisation problem. A multi-objective evolutionary algorithm (MOEA) has been presented as the solving method. Worker assignment is considered in another assembly line balancing research by Manavizadeh et al. (2013) in which the workers with different efficiency were classified into four categories. They assumed two type of operators, permanent and temporary, who work in regular and overtime periods. They proposed a simulated annealing approach to solve the line balancing and worker assignment in different steps.

In this way, an integration of the worker assignment and assembly line sequencing and balancing could be seen in the research carried out by Cortez et al. (2015). In their work, a sequencing model assembly line was studied in which task execution time depends on the workers. They considered the heterogeneous workers by different skill level and efficiency and also the disabled in their sequencing and assignment model to manage studied assembly line. Minimizing the number of workers in an assembly line balancing problem was targeted in the research by Roshani et al. (2017). The same skill level and efficiency have been assumed for all workers and subsequently, the task execution times are not worker dependant.

Furthermore, the human aspect have been imposed to the assembly line balancing problem in the research by Chiang et al. (2016) in which the tasks duration were assumed to be stochastic because of the worker's efficiency variation. In this manner, the assumption of non-deterministic task execution time depending on skill level of the workers have been taken into account in the research by Zeltzer et al. (2017). Note that, the objective of their research was the levelling and balancing of the workload among the workstations.

In comparison with our research in this thesis, all aforementioned literature did not consider the availability of the workers (working-days and off-days) and also they consider one operator for each station whereas, in the research presented in this thesis, we deal with several workers working in parallel in each station. Another contribution of the research carried out in this thesis is the proposed matheuristic solving approaches for multi-period worker assignment in an assembly line.

2.4/ Human resource planning in the home healthcare systems

Apart from the manufacturing system, the human resource planning in the home healthcare system has also been studied in this thesis. Home healthcare system, as a particular type of the home delivery service systems, is a growing scope of application in the operational research domain. The novelty and complexity of home healthcare operations planning makes it an interesting problem for planning support by Operations Research techniques, particularly the related routing and scheduling problem (Rasmussen et al.

(2012)). Figure 2.4 shows a home healthcare planning problem which can be viewed as an integration of the worker assignment and vehicle routing problems.

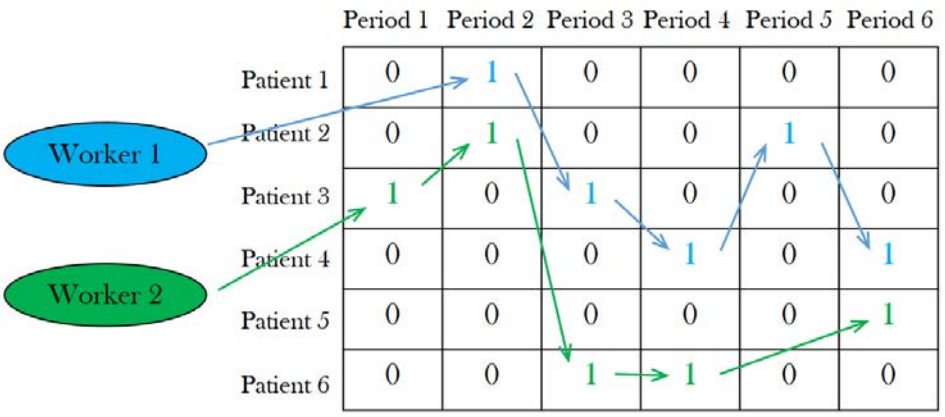


FIGURE 2.4 – Human resource planning for a home healthcare system

Many various researchers in the optimization domain have worked on such case studies to develop their optimization approaches by taking into account various characteristics and considerations. For instance, Allaoua et al. (2013) proposed an integer linear model and a matheuristic approach with a lower bound restriction for the home health-care problem. They studied both aspects of the problem which are routing and assignment concerns, but they did not consider the time dimension. Hence, their model results in a staff assignment to the health-care services for one period of time. En-nahli et al. (2015) developed a multi-objective mixed-integer linear model for the home healthcare planning problem. The preferences of the patients and staffs together with the skill constraints are the considerations which were studied in their research. Cost, workload level, satisfaction level and waiting time are the objectives of their multi-objective model. In their paper the daily needed services are considered to be the same in all of the days. Therefore, the working-days dimension, i.e., the diversity of the needed services in different days is not considered. It was assumed that the resulted planning can be repeated everyday. En-nahli et al. (2016) modeled the home healthcare routing problem as a Vehicle Routing Problem (VRP), and proposed a combined heuristic algorithm to solve that. Their algorithm consists of an initial heuristic to find a primal solution and a local search with a perturbation operator to improve the solution. Synchronization and tie windows constraints are the main issues which were considered in their study. The home healthcare routing and scheduling problem with synchronized visit and time windows is studied in another research by Frifita et al. (2017) in which an extension of the Variable Neighborhood Search (VNS) algorithm was proposed to solve such problems.

Additionally, Fikar et al. (2017) and Cissé et al. (2017) presented two overviews of the recent researches on the home healthcare scheduling and routing problem. The objectives, considerations, constraints, and the solution methods are the different aspects which are investigated in their review. The current studies in this field are well classified based on the planning horizon (single or multi-period). In another similar research, Lin et al. (2016) introduced a model for the therapist assignment problem (TAP) in the home healthcare structure by considering the diversity and the workload of the cares, the priority of the patients and the skills of the staff members. They classified the patients and the therapists and proposed a mixed-integer programming model to this assignment problem to maximize the satisfaction rate of demand while meeting the patients' and therapists'

preferences. The learning effect and the uncertainty of the care times are two considerations which were taken into account in the HHC model of Errarhout et al. (2016), where they proposed a stochastic model for the nurse assignment in a HHC structure. The learning effect was added to the model by the reducing time resource consumption during the care through the planning horizon while the experiences gained by giving the cares to the patients. The uncertainty was studied on the resource consumption and their objective was to balance the workload exposed to the nurses by preventing the excessive assignments. Braekers et al. (2016) developed a metaheuristic algorithm based on local search heuristic for the daily home care worker routing and scheduling problem. They proposed a bi-objective model for the studied problem : Minimization of the overtime and travel costs and minimization of the patients inconveniences. The preferences of the patients and the time windows for the cares are the additional considerations in their problem. They indicated that the route schedules have an impact on the both objectives. The routes influence the overtime and the total cost in consequence, they also influence the amount of satisfied time preferences and the level of inconvenience in consequence.

The home healthcare system is a particular type of the home delivery service system in which the services are the healthcare services. For the workforce planning in this domain, Ehmke et al. (2015) considered time windows in their home delivery service problem which was modeled as a vehicle routing problem with time windows. They proposed an approach to guarantee the service levels given to all customers while the objective of the problem is the classical VRP objective which is traditional routing costs. Another issue which has been studied in their paper is the stochastic travel times consideration. Goel et al. (2013) considered a human resource planning for a home delivery service system where both routing and scheduling aspects in their workforce planning for the staff members of the electricity network maintenance. Additionally, the home healthcare routing and scheduling problem can be formulated very similar to other optimization problem named "goods assignment and routing planning" in the supply chain management domain where the care services can be regarded as the goods to be assigned and the staffs members can be considered as the vehicles. For such problems, Kuo et al. (2009) developed a model that considers both assignment and routing aspects to minimize the travel times of a distribution system.

2.5/ Combinatorial optimization problems for manpower planning

Considering that the HHPP is a problem composed of both assignment and routing problems, this part of our research can be viewed as an application of the combinatotial optimization problems. In this domain, many researchers have combined the well-known Operations Research (OR) problems to formulate their studied problems into a mathematical programming model. For instance, Hassanzadeh et al. (2017) have modeled a problem of minimization of the resource consumption as an integration of the resource allocation and vehicle routing problems. In the home healthcare domain, Zhang et al. (2017) proposed a combinatorial model to formulate home healthcare problem as a combination of VRP and manpower allocation. Their allocation problem assigns the healthcare vehicles (non-emergency ambulances) to the patients and the VRP part of their model defines the routes for the vehicles. The staff members were regarded as identical and a variable neighborhood search (VNS) algorithm was proposed to solve this optimization

problem. Yalçındağ et al. (2016) modeled the human resource planning in home healthcare services as a combination of the assignment (for the assignment of patients to the staff members), scheduling (for the staff members to visit the assigned patients) and routing (to define the sequence of the visits for each staff member) problems. They proposed a decomposition technique to solve their optimization problem by analyzing various scenarios.

Our problem studied in this part is a variant of the multi-period human resource planning problem in which the assignment of one period has an impact on the next period's assignments. In this domain, Chen et al. (2017) provide a stochastic model for the multi-period technician scheduling in which the learning effect and experience of the service workers have been taken into account to assign the tasks of the stochastic costumers to the service workers (technicians) by aiming to minimize the sum of service time and the expected service time for the next period. They formulated this problem based on the markov decision process and solved by employing an approximate approach based on the dynamic programming method. In the multi-period worker assignment domain, Moussavi et al. (2017) also proposed a sequencing assignment model for weekly human resource planning in which an assignment was attributed to a day and depended to the previous ones. They proposed two matheuristic approaches to solve their Sequencing Generalized Assignment Problem (SGAP).

The combination of vehicle routing and assignment problems was widely studied in the supply chain and production domain which can be adapted to our service delivery system (home healthcare scheduling). For example, in a research made by Vidal et al. (2014), a multi-depot VRP was presented and enriched by the sequencing choices and depot assignments. For this combinatorial optimization problem, they proposed two metaheuristic approaches, a hybrid genetic algorithm and an iterative local search. Enderer et al. (2017) also developed a model to integrate the vehicle routing and assignment problems in a cross-docking optimization problem in which a assignment of the trucks to the doors of cross-dock terminals is combined with the designing of the routes for the vehicles. The objective of their model was to minimize the material handling and transportation costs which are the classical objectives of the VRP. They proposed a column generation algorithm to solve this combinatorial optimization problem. In this domain, a combination of the VRP and scheduling problem with synchronization and precedence considerations was proposed by Bredström et al. (2008). For the integration of the vehicle routing and scheduling problems in the production domain, Moons et al. (2017) provided a review and classification study on the existing literature. The characteristics and considerations of the models and the proposed objective functions were reviewed in their research. In this domain, Corréa et al. (2007) proposed a hybrid method consisting of a constraint and mixed-integer programming to solve an integrated model composed of the scheduling, assignment and vehicle routing problems. Another variant of the VRP which is very close to the HHS problem is presented by Spliet et al. (2015) as the discrete time window assignment vehicle routing problem (DTWAVRP) in the distribution networks. The assignment part of their problem aims to assign a time window to each customer, and the VRP part is to construct the vehicle routes by satisfying the assigned time windows. They proposed a two stage stochastic approach to optimize this problem.

About the solution approaches for such problems (VRP with time windows), many researchers developed different heuristics, metaheuristics and exacts approaches. For instance, Miranda et al. (2016) proposed a metaheuristic based on an iterative local search algorithm by aiming to minimize travel and operating costs. Dalmeijer et al. (2018) de-

veloped a branch and cut approach by considering two optimization aspects : assigning time windows and routes planning for the vehicles. Baker et al. (1999) proposed a heuristic approach based on the generalized assignment formulation to solve the vehicle routing problem. They decomposed the VRP model to the generalized assignment problem (GAP) and the travel salesman problem (TSP) and employed the generalized assignment heuristic presented by Fisher et al. (1981) to solve the first part of their approach.

Another consideration of the studied problem is the number of working-days and off-days restrictions for the staff members which has been taken into account for the various workforce scheduling models in the literature (Özgüven et al. (2013), Narasimhan (1997)). This issue is considered in another model on the workforce scheduling problem presented by Moussavi et al. (2016) where the adequateness level of the heterogeneous workers (the efficiency of the workers) on different tasks is the basis of the assignment. The objective of their model was to minimize the total task time.

2.6/ CONCLUSION

In this section of the thesis, a state of the art for the different aspects of the studied problem has been presented. The next sections present the studied problems, methodology, mathematical models and the proposed algorithms together with the numerical applications and experimental and computational results.

The rest of this thesis is organized as follows : in the first part, a human resource planning by ergonomic considerations in a manufacturing system is modelized mathematically. According to the structure of the studied system, the manpower planning is formulated by applying the generalized assignment problem in the second part. A novel variant of this well-known operations research problem is introduced in this part. A hybrid heuristic and two matheuristic approaches are proposed in this thesis to solve the GAPs. In the third part, human resource planning by using GAP formulation is developed for a home healthcare system. Another contribution of the GAP is presented in this part where an integration of the GAP with the Vehicle Routing Problem (VRP) is developed. A matheuristic approach is proposed to solve this combined optimization problem.

I

Ergonomic workforce scheduling

3

Ergonomic worker assignment for productivity improvement

3.1/ Introduction

Considering the ergonomic factors in the worker assignment and job rotation planning, may be an effective strategy to increase the worker satisfaction and motivation as well as the efficiency of the workers. Most of the recent researches in this domain focus on the on the minimizing the ergonomic risk and hazard, whereas the characteristics of the workers were not sufficiently considered. As an ergonomic research, in this study, the worker assignment is performed according to the ergonomic adequation between characteristics of jobs and operators features. In this way, all of the workstations are analysed to determine the ergonomic requirements of jobs. On the other hand, the operators characterization are explored. There are various criteria in the ergonomic analysis of job and operator but in this study, four commune ergonomic factors are concurrently considered to compare the job requirement and worker capacity and measuring the adequation level between them.

It is not possible to obtain an exact value for some ergonomic factors because of being qualitative. For this reason, they must be estimated by fuzzy, probabilities or other uncertain approaches. In this research utility function is applied to determine the adequation level between jobs and operators. These values might be used as efficiency index of operators for performing each job. In an experimental research, we proved that this efficiency index affects the operation time of the job. In this part of our research, we intend to reduce the production cycle time by an effective job assignment considering the ergonomic criteria and adequation between workstations and workers. Note that this assignment is not constant for all of the planning days. The workers positions may be changed from one day to another. This approach is applied to a part of a automotive assembly line consists of 5 workstations with 9 daily required workers and 13 available workers.

3.2/ Methodology

A novel approach based on ergonomic criteria is proposed for evaluation of the jobs and operators to estimate the ergonomic adequation level between work and worker. For this, we consider 4 essential ergonomic factors to analyse. Comparison of job requirement

and operator capacity is done for each factor by using the utility function. As a result, 4 utility functions is achieved and in the next step by determination an importance weight for each criterion, a global utility function is obtained for estimating the conformity level. Job assignment is realized by considering these accumulated values as the performance indices. Note that, in the experimental sampling, it has been proved that these values have a relationship with the operation times.

3.2.1/ Ergonomic analysis on the jobs and the workers

There exist many various ergonomic factors in the manufacturing. In one of the most commune categorization, they are classified into three general types as following :

- Cognitive : Intellectual workload, skill level in decision-making, learning and forgetting...
- Physical : Anthropometry and other features relevant to the physical activities such as force.
- Organizational : Capacity of teamwork and communication, management the quality and resources...

In this study, according to the case study and from the point of view of the experts, 4 most relevant criteria are analysed in a manufacturing system. 1.Height, which is one of the most important anthropometric criteria, 2.Age. Most of the ergonomic factors have a relationship with that. 3.skill level, which is related to the both of the cognitive and organizational aspects. and 4.experience level, that is almost an organizational factor of ergonomics. At the beginning, an ergonomic evaluation must be done on the workstations. Two following questions must be answered after this evaluation.

Which criteria have a significant impact on the performance and productivity of process ?

What level of each criterion is required for performing the tasks ?

In our case, this assessment is performed by analysing the working place, questionnaire and also using the classified information from the experts. Consequently, a table of jobs requirements for the system under study (consisting of 5 workstation), is achieved (table 3.1). Note that for skill level criterion, there exists an evaluation test for each job, with a score between 0 and 10, and the experience level is evaluated based on the number of years of experience.

Ergonomic characteristics needed by the jobs					
Ergo factor	*WS1*	*WS2*	*WS3*	*WS4*	*WS5*
Height (cm)	-	$172 \leq H \leq 183$	$H \geq 170$	-	$165 \leq H \leq 178$
Age (year)	-	$25 \leq A \leq 35$	-	$A \geq 30$	$28 \leq A \leq 45$
Skill level (score)	$A \geq 8$	$A \geq 5$	$A \geq 6$	$A \geq 8$	$A \geq 5$
Experience level (year)	$E \geq 5$	-	$E \geq 3$	$E \geq 7$	$E \geq 4$

TABLE 3.1 – Ergonomic characteristics needed by the jobs

In the next step of this work, the characterizations of the workers must be discovered. For the skill level, each operator have to pass an examination test for each job. The experience level is the number of years that the workers have already worked on the

same or similar jobs. Table 3.2 shows the result of the evaluation of the 4 operators in 5 different workstations. In this table WS denote the workstations. For example “WS1 :2” in the skill level row, shows that the score of the operator in the evaluation test of workstation 1 is 2/10.

Operators’ Characterizations				
Ergo factor	*Operator1*	*Operator2*	*Operator3*	*Operator4*
Height (cm)	171	183	175	178
Age (year)	33	40	42	26
Skill level	WS1 :5 WS2 :8 WS3 :3 WS4 :2 WS5 :5	WS1 :2 WS2 :3 WS3 :7 WS4 :9 WS5 :8	WS1 :10 WS2 :4 WS3 :5 WS4 :1 WS5 :7	WS1 :5 WS2 :6 WS3 :2 WS4 :5 WS5 :2
Experience level	WS1 :2 WS2 :5 WS3 :0 WS4 :0 WS5 :1	WS1 :0 WS2 :0 WS3 :4 WS4 :8 WS5 :3	WS1 :6 WS2 :2 WS3 :1 WS4 :0 WS5 :4	WS1 :1 WS2 :3 WS3 :0 WS4 :1 WS5 :0

TABLE 3.2 – Operators’ Characterizations

According to this table, as an example, operator 1 with 33 years old and 171cm height, has a skill level of 5 for workstation 1 and 2 years experiences in this or other similar jobs.

3.2.2/ DETERMINATION OF THE ADEQUATION LEVEL BETWEEN WORKERS AND JOBS

After evaluation of the jobs and operators, separately, we have to define a systematic approach to determine the adequation level between two above mentioned tables (3.1,3.2). Adequation values, as a performance index, denotes the conformity of each operator in each job. Subsequently, by using the information from the experts, a linear utility function is defined for each ergonomic factor. Linear utility function is a simplified model of quasi-concave utility function. In this way, 3 intervals is determined for each parameter : 1.forbidden, 2.acceptable and 3.excellent intervals. Utility functions (U) of “Height” at workstation 2 $(172 \leq H \leq 183)$,as an example, is defined as follows :

$$U(h) = \begin{cases} 0 & \text{if } h < 168 \; or \; h \geq 190 \\ 1 - \frac{172-h}{172-168} & \text{if } 168 \leq h < 172 \\ 1 & \text{if } 172 \leq h < 183 \\ 1 - \frac{h-183}{190-183} & \text{if } 183 \leq h < 190 \end{cases} \tag{3.1}$$

As shown in figure 3.1, by applying the utility function, the conformity level of the operators for each job is calculated. This figure is corresponded to only “height” parameter. Similarly, for 3 other factors, the relevant functions are defined. As a result, in each factor for each operator a conformity value at each job is determined.

Now for making a decision about the conformity between operators and jobs, All four analysed parameters must be combined. This will be possible by assigning the weights to the parameters. Defining an accumulated function (equation 3.2) on the utility values obtained in the previous section, realizes the global conformity level. Table (3.3) shows the result of this mixed utility function by considering the same weights for all the criteria.

$$U_{ij}^{total} = W_h U_{ij}^h + W_a U_{ij}^a + W_s U_{ij}^s + W_e U_{ij}^e \tag{3.2}$$

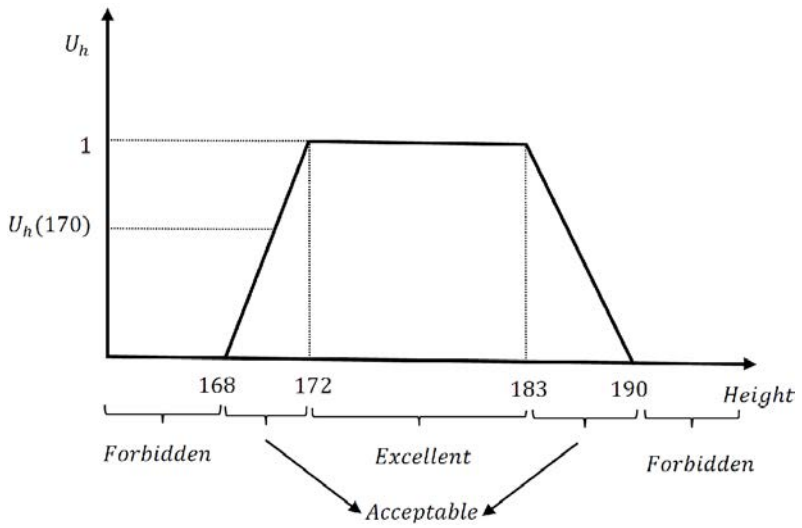


FIGURE 3.1 – Utility function of height for workstation 2

In this function, W_h, W_a, W_s, W_e denote the weights of the parameters, and $U_{ij}^h, U_{ij}^a, U_{ij}^s, U_{ij}^e, U_{ij}^{total}$, indicate, respectively, the utility value of "height", "age", "skill level", "experience level" and "global utility value" of operator i for workstation j.

Global utility level					
	Operator1	*Operator2*	*Operator3*	*Operator4*	*Operator5*
WS1	0.68	0.38	0.85	0.40	0.44
WS2	0.79	0.47	0.41	0.71	0.76
WS3	0.31	0.63	0.55	0.27	0.95
WS4	0.25	0.92	0.33	0.62	0.59
WS5	0.49	0.76	0.70	0.18	0.34

TABLE 3.3 – Global utility level of the workers in different workstations

3.2.3/ WORKER ASSIGNMENT TO THE JOBS BASED ON THE ADEQUATION LEVEL

Final step of the proposed approach, is the assignment of jobs to the operators. This assignment is not directly based on the utility values ; whereas it is based on the operation times of operators on the workstations. For evaluation of the impact of utility value on the operation times, we applied the simple random sampling method in a production line. Afterwards, linear regression has been used to estimate the function of operation times based on the utility values. The objective is to minimize the production cycle time by an efficient ergonomic job assignment. In the next section, a mixed integer mathematical model is presented to solve this allocation problem.

3.3/ PROBLEM DESCRIPTION

Ergonomic worker assignment problem focuses on the evaluation of the jobs (requirements) and the operators features to assign the jobs to the workers according to the most

adequation between jobs and persons from the ergonomic point of view. In a system that works all of the days in a week and with the workers who works 4 or 5 days per week, workforce size must be more than the daily number of required workers. The number of available workers for weekly job assignment in this system is predetermined. By regarding to the ergonomic efficiency index of the workers in different workstations (using 4 popular ergonomic factors in manufacturing), the jobs are assigned to the operators.

This allocation is not a static one because of workday limitation of the workers (4 or 5 days per week) and industrial workday requirement (7 days per week). Thus, in the production planning, the positions of the workers are changed regarding to their availability.

On the other hand, the ergonomic efficiency index have a considerable impact on the operation time of the jobs ; The main objective is to reduce the production cycle time by most adequate assignment (ergonomically) of jobs to the workers. Because of dynamic in the model (position of the workers), the production cycle time in different days, will be different. Thus the output of the model is optimum weekly workforce schedule, such that the total daily production cycle time in a week would be minimized. Indirect aim of the problem is to maximize the number of production units per week.

3.4/ MATHEMATICAL MODEL

Mixed integer linear programming can be a competent approach to formulate the ergonomic job allocation problems. The objective of the model is the minimization of the daily production cycle time in a week through an effective job assignment by satisfying the process and operations schedules and ergonomic limitations of the workstations. The other conditions of the problem is as the following :

- Each worker can be assigned to only one job in each day.
- Each worker must be assigned to work for a limit number of days in planning period.
- The number of required workers for each workstation must be satisfied every day.
- The jobs can be started once all of the workers in the preceding workstation complete their tasks.
- A worker can be assigned to a job if his efficiency for the job would be more than the permissible limit.

The assumptions of the model are as the following :

- The number of operators required by different workstations are not necessarily equal.
- The number of available workers for assignment is predetermined.
- The number of days that the operators can work, are either 4 or 5 days per week and manager (system) decides about that.
- The starting times for all operators in a workstation are simultaneously .

3.4.1/ COMPONENTS OF THE MODEL

The Parameters of the model are as the following :

- D_{max} maximum number of days that operators are authorized to work in a week ;

- D_{min} minimum number of days that operators have to work in a week ;
- n number of available workers ;$I = \{1, ..., n\}$
- m number of workstations ; $J = \{1, ..., m\}$
- k number of days in planning period ; $D = \{1, ..., k\}$
- A_j minimum operation time in workstation j ;
- B_j maximum operation time in workstation j ;
- N_j number of workers required in workstation j ;
- E_j^{omin} permissible limit for efficiency of individuals to work in workstation j ;
- E_j^{wmin} permissible limit for average efficiency of workers who work simultaneously in workstation j ;
- E_{ij} efficiency of worker i in workstation j ;

And the variables of the model are :

- C : sum of the daily production cycle time in a planning period ;
- $X_{ij}^d = 0 - 1$ binary value where $X_{ij}^d = 1$ if operator i is assigned to the workstation j in the workday d, and 0 otherwise ;
- Z_i = the number of day that operator i works ;
- O_{ij}^d = the operation time of operator i in the workstation j in the workday d ; where $O_{ij}^d = 0$ if $X_{ij}^d = 0$, and $O_{ij}^d > 0$ if $X_{ij}^d = 1$.
- S_j^d = starting time of the workstation j in day d ;
- P_j^d = processing time of workstation j in day d ;
- F_j^d = ending time of workstation j in workday d ;
- C^d = production cycle time in workday d ;

3.4.2/ Model Formulation

A linear minimization objective is formulated for the problem and the constraints which must be respected are presented as follows.

$$Minimize \quad C = \sum_{d=1}^{k} C^d \tag{3.3}$$

subject to :

$$\sum_{j=1}^{m} X_{ij}^d \leq 1 \qquad \forall i \in I, d \in D \tag{3.4}$$

$$Z_i = \sum_{j=1}^{m} \sum_{d=1}^{k} X_{ij}^d \qquad \forall i \in I \tag{3.5}$$

$$\sum_{i=1}^{n} Z_i \leq D_{max} \qquad \forall i \in I \tag{3.6}$$

$$\sum_{i=1}^{n} Z_i \geq D_{min} \qquad \forall i \in I \tag{3.7}$$

$$\sum_{i=1}^{n} X_{ij}^{d} = N_j \qquad \forall j \in J, d \in D \tag{3.8}$$

$$O_{ij}^{d} = \left(B_j - E_{ij}\left(B_j - A_j\right)\right) X_{ij}^{d} \qquad \forall i \in I, j \in J, d \in D \tag{3.9}$$

$$O_{ij}^{d} \leq P_j^{d} \qquad \forall i \in I, j \in J, d \in D \tag{3.10}$$

$$F_j^{d} = S_j^{d} + P_j^{d} \qquad \forall j \in J, d \in D \tag{3.11}$$

$$S_{j+1}^{d} \geq F_j^{d} \qquad \forall j \in J, d \in D \tag{3.12}$$

$$C^{d} \geq F_j^{d} \qquad \forall j \in J, d \in D \tag{3.13}$$

$$\left(E_{ij} - E_j^{omin}\right) X_{ij} \geq 0 \qquad \forall i \in I, j \in J \tag{3.14}$$

$$\sum_{i=1}^{n} E_{ij} X_{ij}^{d} \geq N_j E_j^{wmin} \qquad \forall i \in I, j \in J, d \in D \tag{3.15}$$

$$X_{ij}^{d} \in \{0, 1\}, \qquad Y_{ij}, Z_i \geq 0 \; integer \tag{3.16}$$

$$S_j^{d}, W_j^{d}, F_j^{d}, K_{ij}^{d} \in \mathbb{R}^{+} \tag{3.17}$$

The objective of the model is to minimize the sum of the daily production cycle time in the planning period. In the model, workforce schedules are determined by X_{ij}^{d} decision variables, which are binary. They show whether operator i is assigned to workstation j in workday d, ($X_{ij}^{d} = 1$), or not ($X_{ij}^{d} = 0$). The first set of constraints (3.4) ensure that each operator is assigned to maximum one workstation in each workday. Equation (3.5) shows the total number of days that each operator works during the planning period, while (3.6 and 3.7) indicate that each worker has to work 4 or 5 days per week. Constraints (3.8) define the number of workers required for each workstation. Constraints (3.9) calculate the operation time of each worker (for producing one product) which is depended on his efficiency in the workstation in which he works ; where it takes a positive value if mentioned worker is assigned to the intended position, otherwise its value would be zero. Constraints (3.10) describe the relationship between operation time of each worker and the processing time of the workstation which is the maximum operation times of the workers who work in the considered workstation. Constraints (3.11) define the relationship between starting, processing and ending times of a production cycle time in each day, where the precedences necessities between workstations are provided by constraints (3.12). By constraints (3.13) the production cycle time in each day can be calculated which is the maximum values of the ending time of the jobs. Two set of constraints (3.14) ensure that the efficiency of the individuals who work in the workstations are more than the individual

permissible limits. Note that, according to the constraints (3.15), the average efficiency of the operators who work simultaneously in the same workstation in the same day must not be less than permissible limit.

3.5/ APPLICATION ON THE CASE STUDY

An assembly line consisting of 5 workstations (WS1,...,WS5) is considered as a numerical application. This system must work seven days a week (D1,...,D7). The number of required workers at different workstations are not identical. The system has 13 available operators (O1,...,O13) and each one has a specific utility level at each workstation (like table 3 but for 13 operators). The procedure of the calculation of these values was explained in section 3.2.

The operation times at certain workstations (WS2, WS3, WS5) depend on the utility level of the operator who performs them. Whereas other workstations (WS1, WS4), the performance of the worker does not affect on the processing time (for example, an automated workstation). The processing time and number of required workers at different workstations are presented in table 3.4. The operators must work four or five days in a week. The planning is defined for a duration of one week. In this workforce scheduling each operator is able to change his job from a day to another. But they are not authorized to change that during a workday.

The case study is a continuous production system in which all of the operators in the same workstation, start their works simultaneously, once the latest worker of the preceding station completes his task. Note that, the operation time of the operators at the workstations in which the processing times are changeable (WS2, WS3, WS5), is linearly varied based on the performance of the operator (as shown in table 3.4).

Workstations' properties and Processing times					
	No. of operators	Processing times			
		Type	WorstU_{ij}	BestU_{ij}	Relevant linear Function
WS1	1	constant	5 mins	5 mins	$F(U_{i1}) = 5$
WS2	3	changeable	10 mins	6 mins	$F(U_{i2}) = 10 - (4 * U_{i2})$
WS3	2	changeable	6 mins	3 mins	$F(U_{i3}) = 6 - (3 * U_{i3})$
WS4	1	constant	4 mins	4mins	$F(U_{i4}) = 4$
WS5	2	changeable	7 mins	5 mins	$F(U_{i5}) = 7 - (2 * U_{i5})$

TABLE 3.4 – Workstations' properties and Processing times

In table 3.4, U_{ij} and $F(U_{ij})$ denote, respectively, the performance (utility) and the processing time of worker i working at workstation j. As a result we obtain a table similar to the table 3.3 which shows the operation time of each operator in different workstations. By using the values of this table, the workers are assigned to the workstations with the aim of reducing total processing time (makespan).

For solving this assignment problem, a mixed integer mathematical model, as explained in detail in section 3, is proposed. An optimization software named GUROBI has been employed to solve the problem. The optimal workforce schedules for a weekly production

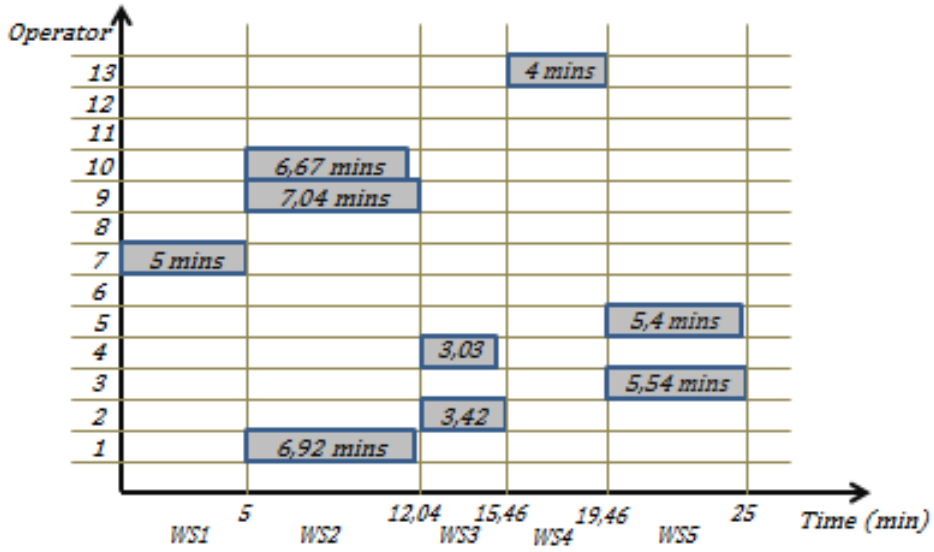


FIGURE 3.2 – Production cycle time in D6

planning is shown in table 3.5 (PCT : production cycle time). As can be seen, the assignment of the workers, varies from a day to another. It happens because of the limitation on the number of workdays for the operators (they must work only 4 or 5 days in a week).

Weekly workforce schedule								
	D1	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*Avg ET*
WS1	O11	O6	O13	O7	O11	O7	O7	5
WS2	O1/O9/O10	O1/O9/O12	O2/O10/O12	O1/O9/O12	O1/O9/O12	O1/O9/O10	O2/O10/O12	11.96
WS3	O2/O8	O5/O8	O5/O8	O8/O10	O2/O4	O2/O4	O5/O8	15.61
WS4	O13	O13	O11	O6	O13	O13	O11	19.61
WS5	O6/O7	O3/O4	O3/O4	O3/O5	O6/O7	O3/O5	O3/O4	25.39
PCT	26.16	25.33	25.04	25.33	25.86	25	25.04	25.39

TABLE 3.5 – Weekly workforce schedule

As an example, figure 3.2 illustrates the job assignment to the workers in the sixth workday (D6). The workers assigned to different workstations and their operation times are shown in this figure. The result of the optimal solution, in comparison with an random assignment, reduces largely the production cycle time in each workday. The proposed approach has been tested for 20 simulated instances consisting of 5 to 9 workstations and the computational results is shown in table 3.6.

Computational results				
No of WS	*No of OP per day*	*No of OP per week*	*Avg* $\sum Cmax$	*Computing time*
5	9	13	180.31	17s
6	10	14	208.76	38s
7	11	16	234.71	95s
8	14	20	272.34	730s
9	16	23	-	$> 10^5$s

TABLE 3.6 – Computational results

Specific contributions of presented research in comparison with most related literature such as Otto and Scholl (2013), Rattanamanee and Nanthavanij (2013) and Mossa et al. (2016) are the basis of the decision about dynamic job assignment which is ergonomic adequation level between job and worker as well as the basis of the job rotation which is the availability of workers. Besides, the objective is to minimize the sum of the daily makespan and proposed approach has been applied in a combined system consisting of the parallel and consecutive tasks.

3.6/ CONCLUSION

This chapter proposes an approach for ergonomic job assignment by determination of the ergonomic adequation level between workers and workstations in a manufacturing system. For this purpose, a mixed integer mathematical model is presented and solved. Its objective is to minimize the average of daily production cycle times for a given planning period by an appropriate job assignment. The model generates the optimal daily rotating workforce schedules during the planning period by respecting all of the operator limitations and workstation and production constraints. On the other side, for determination of adequation level, the personal capacities of the workers and also workstations requirements is considered. Ergonomic factors are applied for evaluation of the workstations and operators and linear utility functions are employed for determination of efficiency the operators in the jobs.

The numerical application illustrates that the ergonomic considerations in the job assignment has an important impact on the production cycle time. Additionally, the results of the presented strategy in workstation and operator evaluation phases, show that the processing times at the workstations are highly depended on the ergonomic capacities of the operators. Consequently, ergonomic operator characterizations give us more benefits for an efficient job assignment. As a result an ergonomic workforce schedule consisting of job assignment and rotation for a planning period is constructed. It determines which worker performs which job in which workday in an optimum manner. The idle times and ergonomic risks can be considered as the futures works of the proposed approach.

4

JOB ROTATION SCHEDULING FOR WORKLOAD BALANCING

4.1/ STUDIED SYSTEM AND PHYSICAL WORKLOAD ANALYSIS

4.1.1/ CURRENT JOB ROTATION SCHEDULE

In the automotive assembly line, there are generally several sectors which is considered as a small factory including numerous workstations. A sector is then divided into several team that is a small organizational unit consisted of 4-7 members. Similarly, the jobs are grouped into several workstations and a team is assigned to a workstation. Each team has its own team leader who plan the rotations of the operators. The team members rotate between jobs within a workstation. Job rotations were scheduled because the assembly line required high flexibility as the operators have to be qualified to work at any job. Team rotation schedules were performed manually by the team leader without considering workloads and risk factors for an operator at different jobs. Therefore, the variance in cumulative daily workloads was high between the team members, and an operator might expose to the sequential high workloads by the job rotation. The cycle time to perform all the tasks in a workstation was 6 minutes. There were three pauses during the day and the operators of a team rotate between jobs after each break. This means that each operator works at four different jobs over one work shift.

A distinguishing characteristic of the job rotation in the studied system in comparison with the classical job rotation is as follows : In the classic job rotation all of the workers must be able to perform all the jobs which cause difficulty in term of cost and time for learning an executing model in a system. Whereas, job rotation within a group which consist of a specified number of jobs reduces significantly cost and time spending for learning. The aim of this field study is to develop a mathematical model applicable in a real-world setting to balance the physical workload in a production assembly and to minimize sequential high workloads during a daily job rotation.

4.1.2/ ERGONOMIC ANALYSIS OF WORKSTATIONS BY SES METHOD

An in-house ergonomic method for automotive assembly line, called SCANIA Ergonomic Standard (SES), is employed to analyze the workstations and determined physical workloads (ZARE et al. (2016)). This field method integrates 20 ergonomic parameters (Table

4.1), which are grouped into five categories including repetitiveness, working posture, force, manual handling and energy consumption (ZARE et al. (2016)).

Ergonomic parameters measured	
Main category	*Sub-category Risk factors*
Energy consumption	Tightening torque, hand and power tools Climbing/stepping over Movement
Force	Pushing, pulling with fingers Hand pushing and pulling Whole Body Push /Pull Force
Material handlings	Lifting torque – Two-handed lifts One-handed lifts
Work postures	Wrist posture Shoulder posture Neck posture Back posture Component size Surface area for pressure Hand grip Hand workspace Clearance for hand and finger Access, hidden assembly Occurrence of work posture
Repetition	Performing same repetited actions per hour

TABLE 4.1 – Ergonomic parameters measured

Therefore, the widespread ergonomic factors were measured to define the parameters and the objective functions of the mathematical model for job rotation schedules. Weights of objects, magnitude of forces (dynamometer), and handle diameters (caliper) were also measured. The results were classified according to a traffic light system : the normal or green level indicating an acceptable situation with minimal risk of WR-MSDs ; the yellow level indicating a moderate workload, and the red level corresponding to situations at high workload. After studying each ergonomic criterion for a workstation, the numbers of green, yellow and red criteria determined the final workload of that workstation (Table 4.2).

Prioritization of risk factors and workloads				
Methods	*Evaluation Criteria*	*Green*	*Yellow*	*Red*
Ergonomic Standard method (SES)	Number of Yellows*	$0-8$	$9-16$	≥ 17
	Number of Reds	$0-6$	$7-9$	≥ 10
	Number of Yellows + Reds	$0-16$	-	≥ 17

*The worst colour dictates the final evaluation of the workstation

TABLE 4.2 – Prioritization of risk factors and workloads

This color-coded method is based on Swedish guidelines and it has been used in other observational methods particularly in the car industries (Berlin et al. (2009) ; Törnström

et al. (2008)). Considering 20 ergonomic parameters evaluated by the in-house ergonomic method in a mathematical model provide a complicated model, non-applicable to a real-world setting. We, therefore, developed a method of aggregation which 20 parameters were categorized in five main parameters such as work posture (composed of 11 ergonomic criteria), repetition, force (composed of 3 ergonomic criteria), material handlings (composed of 2 ergonomic criteria), and energy consumption (composed of 3 ergonomic criteria)(MAHMOUDABADI (2015)). Following this logic, the final workload was attributed to the main criteria, and they were considered as the parameters of the mathematical model to make the decision about the job rotation schedules (Table 4.3).

For solving the mathematical model of job rotation, we need a numerical score for each color to be able to balance the global workload among the operators. To obtain the numerical ratio for the workload colors, a statistical analysis is carried out as explained in the following.

4.1.3/ NUMERICAL EVALUATION OF WORKLOADS

The Swedish guideline which is presented in table 4.2 is employed to translate the traffic light level (green, yellow, red) into numerical values. In this way, a mathematical analysis is undertaken as follows.

The parameters of this analysis is presented as :

WL_j : The global workload level of job j.

G, Y, R : If the global workload evaluation of the job results in a respectively, green, yellow or red level of workload.

$S(G)$, $S(Y)$, $S(R)$: The severity scores of the workload colors.

$n(g)$, $n(y)$, $n(r)$: The number of analyzed criteria in each job with respectively, green, yellow and red workload. Note that twenty ergonomic criteria are analyzed to evaluate the workload of each job ($n(g) + n(y) + n(r) = 20$).

As shown at the first line of the table 4.2 (number of yellows), the relevant equation is as :

$$WL_j = \begin{cases} if \quad n(y) \leq 8 \Longrightarrow & G \\ elseif \quad 9 \leq n(y) \leq 16 \Rightarrow & Y \\ else \quad (n(y) \geq 17) \Longrightarrow & R \end{cases} \tag{4.1}$$

And in the second line of the table (number of reds) we have :

$$WL_j = \begin{cases} if \quad n(r) \leq 6 \Longrightarrow & G \\ elseif \quad 7 \leq n(r) \leq 9 \Rightarrow & Y \\ else \quad (n(r) \geq 10) \Longrightarrow & R \end{cases} \tag{4.2}$$

Finally, the third line (number of reds + number of yellows) can be presented as :

$$WL_j = \begin{cases} if \quad n(y) + n(r) \leq 16 \Longrightarrow & G \\ else \quad (n(y) + n(r) \geq 17) \Longrightarrow & R \end{cases} \tag{4.3}$$

According to the third line of the first equation, once we meet $17th$ yellow criteria, the red color is attributed to the job as the global workload level instead of yellow. Similarly, in the third line of the second equation, the yellow color is replaced by the red while the $10th$ red criteria is met. It can be concluded that 17 yellow criteria have the same impact as 10 red criteria. Therefore, the ratio of the severity of the red to yellow workload can be estimated as follows :

$$17 \times S(Y) \simeq 10 \times S(R) \quad \Longrightarrow \quad \frac{S(R)}{S(Y)} = \frac{17}{10} = 1.7 \tag{4.4}$$

Hence, the red workload is 1.7 times more severe than the yellow color.

To calculate the severity ratio of the green workload, a normalization is required because the parameters are dependent on each other. By considering that more than 90% of the analyzed jobs contain at least four green criteria, it is assumed that the number of green criteria at all of the jobs are equal or greater than 4 ($n(g) \geq 4$). Therefore, according to the equations (4.1, 4.2, 4.3) :

$$If\ n(g) \geq 11 \Rightarrow \begin{cases} n(y) \\ n(r) \\ n(y) + n(r) \end{cases} \leq 9 \quad \Longrightarrow \quad WL_j \neq R\ (WL_j = \{G\ or\ Y\}) \tag{4.5}$$

This condition formula signifies that at least 11 green criteria are needed to ensure that the workload color of the job is not red. On the other hand, the proposed normalization ($n(g) \geq 4$) implies :

$$If\ n(y) \geq 7 \Rightarrow \begin{cases} n(r) \leq 9 \\ n(y) + n(r) \leq 16 \end{cases} \quad \Longrightarrow \quad WL_j \neq R\ (WL_j = \{G\ or\ Y\}) \tag{4.6}$$

As a consequence of the above mathematical analysis, 7 yellow criteria are needed to be sure that the red workload is not assigned to the job. Therefore, seven yellow criteria have the same impact as eleven green criteria to prevent the red workload being attributed to a job. It means that :

$$11 \times S(G) \simeq 7 \times S(Y) \quad \Longrightarrow \quad \frac{S(Y)}{S(G)} = \frac{11}{7} = 1.57 \tag{4.7}$$

In this research, the severity of the green color as the basis of the workload amount is considered to be 1. As a result :

$$\begin{cases} \frac{S(Y)}{S(G)} = 1.57 \\ \frac{S(R)}{S(G)} = \frac{S(R)}{S(Y)} \times \frac{S(Y)}{S(G)} = 1.7 \times 1.57 = 2.67 \end{cases} \quad \Longrightarrow \quad \begin{cases} S(G) = 1 \\ S(Y) = 1.57 \\ S(R) = 2.67 \end{cases} \tag{4.8}$$

A severity score is calculated for each workload color by above mathematical analysis. It must be noted that, this analysis has been validated and proved by the engineers and the experts of the studied company.

The proposed calculations are to attribute a numerical score to the workload severity of a criterion in a job. For the global workload of a job, the severity score is estimated by the sum of the workload scores of the analysed criteria. The numerical daily workload on the operators is estimated by the sum of the workload scores of the jobs to which they are assigned during the day. (table 4.3)

Numerical evaluation of the jobs and worker assignment without job rotation											
Workstation	**Job**	**Physical Workload (general evaluation)**	*Repetition*	*Postures*	*Material Handling*	*Force*	*Energy Consumption*	**Workload Score per period (WL)**	**Assigned worker**	**Number of periods during a day (P)**	**Daily Workload (WL*P)**
1	1	Yellow	1.57	2.67	1.57	1.57	1.57	8.95	OP1	4	35.8
	2	Yellow	1.57	1.57	1.57	1.57	1.57	7.85	OP8	4	31.4
	3	Green	1	2.67	1.57	1.57	1	7.81	OP9	4	31.24
	4	Green	1	1.57	1	1.57	1	6.14	OP14	4	24.56
2	5	Green	1.57	1	2.67	1.57	1	7.81	OP2	4	31.24
	6	Green	1	1	1.57	1	1	5.57	OP3	4	22.28
	7	Green	1	1.57	1.57	2.67	1	7.81	OP5	4	31.24
	8	Green	1	1.57	1.57	1.57	1.57	7.28	OP11	4	29.12
	9	Yellow	1.57	2.67	1.57	1.57	1.57	8.95	OP12	4	35.8
3	10	Red	2.67	1.57	2.67	2.67	1	10.58	OP4	4	42.32
	11	Green	1	1.57	1.57	1.57	1	6.71	OP6	4	26.84
	12	Green	1	1.57	2.67	1.57	1	7.81	OP7	4	31.24
	13	Yellow	1.57	1.57	2.67	1.57	1.57	8.95	OP10	4	35.8
	14	Yellow	1	2.67	2.67	1.57	1	8.91	OP13	4	35.64

TABLE 4.3 – Numerical evaluation of the jobs and worker assignment without job rotation

4.2/ MODELIZATION OF THE JOB ROTATION PROBLEM

The balancing of the daily workload on the workers in an assembly line is targeted in this research. The workers are exposed to the workload by working at the heterogeneous jobs with different workloads. The difference between workload levels of the jobs persuades us to employ job rotation to smooth and minimize the ergonomic risks on the workers. In the case study, the workers are not able to do all of the jobs. They are only skilled for the jobs which are placed in one workstation. Hence, the job rotation is implemented on the workers of the same group. As mentioned above, a group is a number of workers who work at the jobs of the same workstation. In fact, the workers are assigned to the workstations and the job rotation is developed into the workstations. Note that, the workers can not change their workstation (group) during the planning horizon. The planning

horizon is a predefined number of days and each day contains four working periods of two hours (Two periods in the morning and two in the afternoon). The rotations take place during the break time between two periods. To find the optimum job rotation planning on the presented system, the problem is modeled mathematically. Actually, a mixed-integer linear programming is proposed to model the studied job rotation problem. The objective of the model is to minimize the maximum daily workload which is exposed to the workers. The daily workload on a worker is equal to the sum of the workloads of the jobs which are performed by him during the different periods of the day. In the job rotation model, the ergonomic restrictions which must be respected are as the following :

— The assignment of two consecutive high workload jobs to a worker during a day must be prevented.
— The assignment of two jobs, with the high workload in the same criterion, consecutively to a worker during a day must be prevented.

A mathematical model is composed of the parameters and the variables, and it is formulated by the objective function and the constraints. The proposed model for the studied problem is as the following.

4.2.1/ Components of the mathematical model

Parameters

The parameters of the model which must be identified before solving the model, are presented as :

— Q_{jl} : Workload of type l[1] that a worker is exposed by working one period in job j, where $Q_{jl} = 1,\ 1.57\ or\ 2.67$ if job j has a, respectively, Green, Yellow or Red workload of criterion l.
— H_j : Global workload of job j, where $H_j = 1,\ 1.57\ or\ 2.67$ if the global workload of job j is, respectively, Green, Yellow or Red.
— W_l : Coefficient (Impact factor) of criteria l for calculating the global workload of the jobs.
— m : Number of workers to be allocated, $I = \{1,\ ...,\ m\}$;
— n : Number of jobs to be assigned, $J = \{1,\ ...,\ n\}$;
— r : Number of ergonomic criteria which are analyzed in the job evaluation, $L = \{1,\ ...,\ r\}$;
— t : Number of periods during a day, $P = \{1,\ ...,\ t\}$, $P^- = P \setminus \{t\}$;
— s : Number of days during the planning horizon, $D = \{1,\ ...,\ s\}$, $D^- = D \setminus \{s\}$;
— q : Number of workstations in the system, $G = \{1,\ ...,\ q\}$, $G^- = G \setminus \{q\}$;
— K_g : Number of jobs which are placed in workstation g, $\forall g \in G$;
— α, β, γ : Quantitative workload scores for, respectively, high, medium and low level of workload. (In this research : 2,67 , 1,57 and 1)

Variables

The variables are obtained by solving the model, and they identify the objective value and its related outputs. The decision variables of the model are presented as :

1. Workload of type l implies the workload score related to criterion l

— X_{ijpd} : binary, where $X_{ijpd} = 1$ if worker i works at job j in period p of day d, and 0 otherwise ;
— Z_{ilpd}, Y_{ilpd}, V_{ilpd} : binary variables, where $Z_{ilpd} = 1$ if worker i is exposed to the high workload, $Y_{ilpd} = 1$ if worker i is exposed to the medium workload and $V_{ilpd} = 1$ if worker i is exposed to the low workload of type l in period p of day d.
— C_{ipd}, B_{ipd}, A_{ipd} : binary variables, where $C_{ipd} = 1$ if worker i works at a job with the high global workload, $B_{ipd} = 1$ if worker i works at a job with the medium global workload and $A_{ipd} = 1$ if worker i works at a job with the low global workload in period p of day d ;
— F_{id} =Total score of the workloads to which worker i is exposed during day d ;

4.2.2/ MODEL FORMULATION

The formulation of the mathematical model is composed of the objective function and the constraints. The objective function of our model aims to balance the daily workload on the workers and presented as follows :

$$Minimize\, Z = Max_{i,d}\, F_{id} \tag{4.9}$$

The constraints of the proposed model consider the conditions of the assignment problem, job rotation problem, and the capability of the workers with a special attention to the ergonomic aspect. These conditions are presented and explained below.

$$\sum_{i=1}^{m} X_{ijpd} = 1 \qquad \forall\, j \in J,\ p \in P,\ d \in D \tag{4.10}$$

$$\sum_{j=1}^{n} X_{ijpd} = 1 \qquad \forall\, i \in I,\ p \in P,\ d \in D \tag{4.11}$$

$$\sum_{p=1}^{t} \sum_{j=1}^{n} \sum_{l=1}^{r} W_l\, Q_{jl}\, X_{ijpd} = F_{id} \qquad \forall\, i \in I,\ d \in D \tag{4.12}$$

$$Q_{jl}\, X_{ijpd} = \alpha Z_{ilpd} + \beta Y_{ilpd} + \gamma V_{ilpd} \qquad \forall\, i \in I,\ j \in J,\ l \in L,\ p \in P,\ d \in D \tag{4.13}$$

$$Z_{ilpd} + Y_{ilpd} + V_{ilpd} = 1 \quad \forall\, i \in I,\ l \in L,\ p \in P,\ d \in D \tag{4.14}$$

$$Z_{ilpd} - V_{il(p+1)d} \leq 0 \quad \forall\, i \in I,\ l \in L,\ p \in P,\ d \in D \tag{4.15}$$

$$H_j\, X_{ijpd} = \alpha C_{ipd} + \beta B_{ipd} + \gamma A_{ipd} \qquad \forall\, i \in I,\ j \in J,\ p \in P,\ d \in D \tag{4.16}$$

$$C_{ipd} + B_{ipd} + A_{ipd} = 1 \qquad \forall\, i \in I,\ p \in P,\ d \in D \tag{4.17}$$

$$C_{ipd} - B_{i(p+1)d} - A_{i(p+1)d} \leq 0 \quad \forall\, i \in I,\ p \in P,\ d \in D \tag{4.18}$$

$$\sum_{K_g+1}^{K_g+K_{g+1}} X_{ijpd} + \sum_{K_g+1}^{K_g+K_{g+1}} X_{ij(p+1)d} = 0 \qquad \forall\, g \in G^-,\ i \in I,\ j \in J,\ d \in D,\ p \in P^- \tag{4.19}$$

$$\sum_{K_g+1}^{K_g+K_{g+1}} X_{ijpd} + \sum_{K_g+1}^{K_g+K_{g+1}} X_{ijp(d+1)} = 0 \qquad \forall\, g \in G^-,\ i \in I,\ j \in J,\ p \in P,\ d \in D^- \tag{4.20}$$

$$X_{ijpd}, Z_{ilpd}, Y_{ilpd}, V_{ilpd}, C_{ipd}, B_{ipd}, A_{ipd} \in \{0,1\},\ Q_{jl}, H_j \in Integer^+,\ W_l \in R^+ \tag{4.21}$$

Equation (4.9), as the objective function of the model, is to balance the workload by minimization of the maximum daily workload to which each one of the workers is exposed.

The two fist sets of constraints (4.10,4.11) are related to the assignment aspect of the studied problem and ensure respectively that each of the jobs in every period is assigned to the one and only one worker and each one of the workers is allocated to the one and only one job every period. By constraints (4.12), the amount of the daily workload on the workers "F_{id}" is calculated. This score is obtained by the weighted sum of the workload scores of different types which are exposed to the worker during different periods of the day. The two next sets of constraints (4.13,4.14) determine the score of the workloads of different types on the workers where in each period of time, one of the three binary variables Z_{ilpd},Y_{ilpd} or V_{ilpd} is equal to 1 and implies respectively the worker i is exposed to the high, medium or low workload of type l in period p of day d. The constraints (4.15) represent one of the ergonomic conditions which are considered in this problem and ensure that if a worker is exposed to the high workload of type l in a period, in the next period he must be allocated to a job with low workload of type l. By the constraints (4.16,4.17), three binary variables are attributed to the global workload level of the jobs. These variables represent the global workload level that each one of the workers is exposed during a period. Note that, for each worker, in every period only one of the binary variables C_{ipd}, B_{ipd} or A_{ipd} is equal to 1. Another ergonomic condition is imposed on the model by constraints (4.18) where they guarantee non-assignment of two consecutive high workload jobs to the workers. It means a high workload job must be followed by a medium or low workload one for a worker during a day. The two sets of constraints (4.19,4.20) are related to the job rotation inside of the workstations (teams) and ensure that the workstation assigned to the the workers is unchangeable from a period to another and from a day to another.

4.3/ Numerical application

The ergonomic analysis which was presented in section 4.1.2 and 4.1.3, and the proposed job rotation mathematical model (section 4.2) are employed to develop a platform

for the ergonomic job rotation in an automotive assembly line. In this research, a specific part of this production system containing three workstations and fourteen jobs is studied where four jobs are placed in the first workstation and the number of jobs in the second and third workstations is five. As mentioned before, to perform the job rotation inside the workstations, all of the the jobs are analyzed by 20 ergonomic parameters. These parameters are grouped into five main ergonomic criteria as the Repetition, Posture, Material handling, Force and Energy consumption. The job rotation is programmed based on these five criteria. This normalization is performed to simplify the solving of mathematical model.

The results of the ergonomic evaluation of the studied jobs which are shown in table 4.3, are used as the parameters of the job rotation model. In this table, the workload score of each job is estimated by the sum of the workload amounts of the individual criteria. It can be seen that the difference between workloads of the jobs is not negligible. For instance, the estimated score for job 10 is equal to 10.56 where three of five ergonomic criteria have a high workload, whereas the score of job 6 which is 5.57 and it has a low workload in all of the ergonomic criteria. These significant differences persuade us to apply job rotation strategy to reduce the risk of MSDs and occupational diseases on the operators who work at the high workload jobs. Note that, the workload score of the jobs is calculated for an operating duration of two hours. As mentioned before, the working day of the studied system contains four periods of two hours. Therefore, if one operator works at the job number 10 all of four periods during a day, he is exposed to a workload score of 42.32.

The main objective of this research is to minimize (balance) the daily workload score on the operators by employing the proposed job rotation model. Moreover, the mathematical approach avoids the risk of assigning two successive high workload jobs to an operator during a day. This consideration is imposed on the model as an ergonomic constraint. The model is solved for the studied production system by using the parameters presented in table 4.3. The GUROBI solver is employed to solve our mixed-integer model and the results are shown in table 4.4.

Workforce schedule by Group Job Rotation							
Work station	*Worker*	*Sequence of jobs*	*Workload exposed*				*Cumul load*
			P1	*P2*	*P3*	*P4*	
1	op1	$3 \to 4 \to 1 \to 2$	7.81	6.14	8.95	7.85	30.75
	op8	$4 \to 1 \to 2 \to 3$	6.14	8.95	7.85	7.81	30.75
	op9	$2 \to 3 \to 4 \to 1$	7.85	7.81	6.14	8.95	30.75
	op14	$1 \to 2 \to 3 \to 4$	8.95	7.85	7.81	6.14	30.75
2	op2	$6 \to 9 \to 7 \to 8$	5.57	8.95	7.81	7.28	29.61
	op3	$7 \to 6 \to 9 \to 7$	7.81	5.57	8.95	7.81	30.14
	op5	$5 \to 5 \to 6 \to 9$	7.81	7.81	5.57	8.95	30.14
	op11	$9 \to 7 \to 5 \to 6$	8.95	7.81	7.81	5.57	30.14
	op12	$8 \to 8 \to 8 \to 5$	7.28	7.28	7.28	7.81	29.65
3	op4	$12 \to 13 \to 11 \to 10$	7.81	8.95	6.71	10.58	34.05
	op6	$13 \to 14 \to 14 \to 12$	8.95	8.91	8.91	7.81	34.58
	op7	$14 \to 12 \to 13 \to 14$	8.91	7.81	8.95	8.91	34.58
	op10	$10 \to 11 \to 10 \to 11$	10.58	6.71	10.58	6.71	34.58
	op13	$11 \to 10 \to 12 \to 13$	6.71	10.58	7.81	8.95	34.5

TABLE 4.4 – Workforce schedule by Group Job Rotation

In this research, the workers are considered to be identical, but the only difference between them is their skills for working in different workstations. Table 4.5 presents the capability of the workers where worker 1 (op1) is skilled for workstations 1 and 2, worker 2 for only workstation 2 and worker 9 is able to work at all of the workstations.

Capability of the workers														
	op1	*op2*	*op3*	*op4*	*op5*	*op6*	*op7*	*op8*	*op9*	*op10*	*op11*	*op12*	*op13*	*op14*
Skill	ws1							ws1	ws1		ws1	ws1	ws1	ws1
	ws2	ws2	ws2		ws2	ws2			ws2	ws2	ws2	ws2	ws2	
				ws3	ws3	ws3	ws3		ws3	ws3		ws3	ws3	

TABLE 4.5 – Capability of the workers

As shown in table 4.4, the worker assignment and job rotation inside the workstations are developed by considering the capability of the workers. According to this table, four operators are assigned to workstation 1 (operators 1, 8, 9 and 14 for jobs 1, 2, 3 and 4), five operators to workstation 2 (operators 2, 3, 5, 11 and 12 for jobs 5, 6, 7, 8 and 9) and five operators work in workstation 3 (operators 4, 6, 7, 10, 13 for jobs 10, 11, 12, 13 and 14). The results present the optimal worker assignment to the jobs, also the periodic and cumulative workload scores to which each operator is exposed during a day. By applying the proposed worker assignment, the cumulative (daily) workload scores for all workers in workstation 1 are identical and equal to 30.75 ; These scores in workstation 2 vary between 29.61 and 30.14 ; For workstation 3 vary from 34.05 to 34.58. As a result, the physical workload are well propagated among the operators where in each workstation, their variations have been enormously became slight (in comparison with table 4.3). The workload propagation before and after job rotation is presented in figure 4.1.

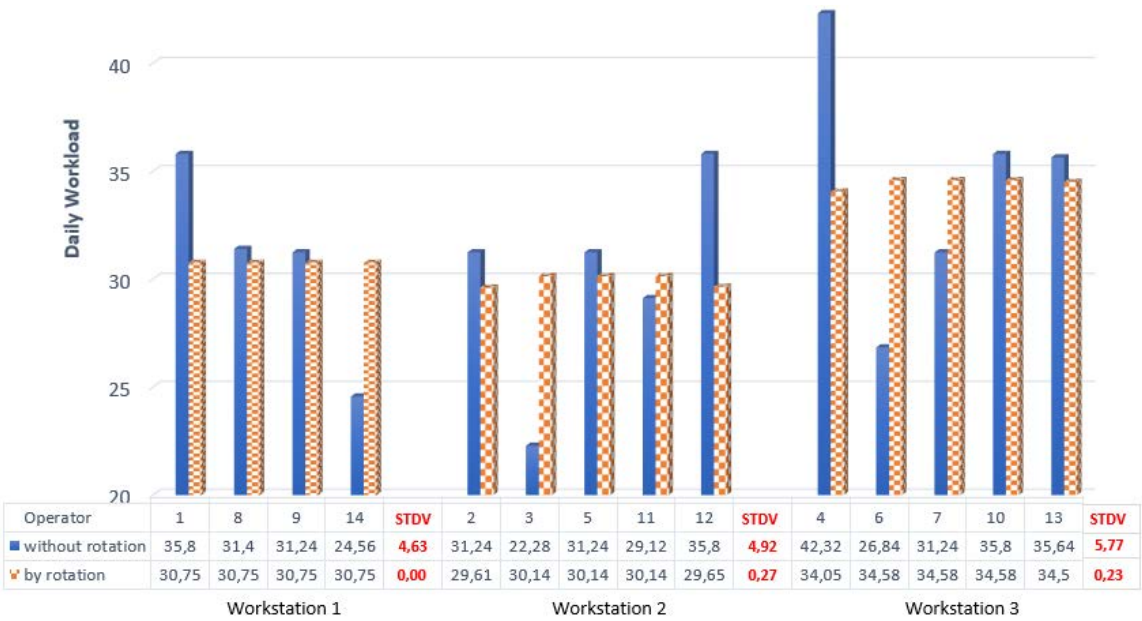


FIGURE 4.1 – Comparison of dispersion of the workload by and without job rotation

In the figure, the color filled bottoms show the physical workload levels before applying job rotation and hatching filled bottoms display the workload levels by applying job rota-

tion inside the workstations. As can be seen, in every workstations, the variation of the workloads between the operators is highly decreased after job rotation.

Afterwards, a statistical analysis has been performed to obtain the practical information about the dispersion of the workloads . In this analysis, the workload scores are analyzed by employing two most important statistical factors as “mean” and “standard deviation” and the results are shown in table 4.6.

Statistical analysis of the impact of the rotation					
Workstation	*No of data*	*WL Without rotation*		*WL by rotation*	
		Mean	*STDEV*	*Mean*	*STDEV*
1	4	30.75	4.63	30.75	0.00
2	5	32.45	4.92	32.45	0.27
3	5	38.85	5.77	38.85	0.23

TABLE 4.6 – Statistical analysis of the impact of the rotation

As seen in the table, the mean of the workload in each workstation does not vary by job rotation but the standard deviations are greatly decreased.

As an example, the standard deviation (that presents the dispersion of the data) before job rotation in workstation 1 is 4.63 which is decreased to $zero$ by developing job rotation. This significant decrease guarantees the smoothing and balancing the physical workloads among the operators. On the other side, to demonstrate the efficiency of the proposed model and it’s related optimal assignment, we have compared the results of the proposed job rotation with the random rotations. In this way, 10 random job rotations are simulated and the best one is selected to be compared with the proposed rotation. The table 4.7 shows this comparison in detail. The propagation of the different physical workload among the workers and the number of successive high workloads are evaluated to compare these two strategies of job rotation with a fixed job assignment (without rotation).

Proposed optimal job rotation in comparison with the best random rotation													
		Optimal rotation				*Best random rotation*				*Without rotation*			
		Successive high workload			*STDV*	*Successive high workload*			*STDV*	*Successive high workload*			*STDV*
		R-R	*Y-R*	*R-Y**		*R-R*	*Y-R*	*R-Y*		*R-R*	*Y-R*	*R-Y*	
Ergo criteria	Repetition	0	1	0	1.19	1	0	1	1.42	3	0	0	2.56
	Posture	3	8	6	1.54	4	7	7	2.20	12	0	0	3.50
	Material h.	6	5	6	2.79	10	5	5	2.81	15	0	0	3.54
	Force	1	4	4	1.27	1	5	5	1.40	6	0	0	2.60
	Energy cons.	0	0	0	0.62	0	0	0	0.62	0	0	0	1.31
Cumul. Workload		0	0	0	3.11	1	0	0	4.56	3	0	0	7.20

*R-R signifies the number of Red workloads which are followed by another Red.

*Y-R signifies the number of Red workloads which are followed by a Yellow.

*R-Y signifies the number of Yellow workloads which are followed by a Red.

TABLE 4.7 – Proposed optimal job rotation in comparison with the best random rotation

As shown in this table, The number of successive high workload (R-R) has been mini-

mized by the proposed job rotation model. About the cumulative workload, without job rotation, there are three high workloads (Red) which are followed by another high workload whereas by the best random rotation R-R is occurred one time and by the proposed job rotation model, a Red is never followed by another Red. Moreover, for each one of the ergonomic criteria, the number of R-R workloads is decreased by employing the proposed job rotation without the significant increases of the Y-R and R-Y. The columns of the STDV show the dispersion of the different types of workload on the workers. The results of the optimal rotation show an important decrease on the dispersion of the workload criteria. It guarantees a homogeneous workload being exposed to the workers.

4.4/ Discussion

This study presents a job rotation strategy that balances the daily physical workload and avoid the successive high workloads for the operators during a working-day. At the first step of the research, we had to determine how to analyze the jobs, which criteria must be considered and how to obtain the workload level of the jobs in each ergonomic criterion. There are many various ergonomic criteria which could be considered, but the number of criteria is a critical factor for solving the job rotation mathematical model. That is because the computational time for solving the model depends on the number of considered criteria. Hence, each job was evaluated by twenty sub-criteria which were clustered into five principal criteria. The clustering approach helps us to analyze the jobs by maximum number of criteria and enables us to solve the job rotation mathematical model in a reasonable time. The contribution of this research in comparison with the job rotation model presented by Yoon et al. (2016), is the evaluation procedure of the jobs. They have analyzed the physical workload only by the posture, whereas this study has considered various criteria for the physical workload evaluation. On the other hand, the proposed model considers two ergonomic objectives simultaneously. The first one is the daily physical workload to which the operators are exposed where the model aims to balance that among the workers. The second ergonomic factor which is analyzed in our model, is the successive high workloads for a worker. This factor has been also taken into account in the model of Yoon et al. (2016) where they paid a special attention to the posture of the different parts of body. But our model minimizes the successive high workloads of different types including posture, repetition... as well as the high cumulative workload. This consideration (avoiding the successive high workloads) has been imposed to the mathematical model by constraints 4.15 and 4.18. Constraint 4.15 signifies that if a worker has a high workload of posture in current period, in the next period he has to be assigned to a job with a low workload of posture. Similarly, constraint 4.18 implies that if a worker has a high cumulative workload, in the next period he has to be assigned to a job with a medium or low cumulative workload.

Figure 4.1 shows the efficiency of the proposed model on the balancing of the workloads mainly inside the workstations.

The balancing has been proved by employing Standard Deviation (STDV) which is most common index to evaluate the propagation where the results are shown in table 4.6.

A detailed analysis on the STDV for each one of the ergonomic criterion has been performed and the results are presented in table 4.7.

Another job rotation model for balancing the ergonomic factors in the manufacturing domain has been presented by Otto et al. (2011). The first contribution of our research in comparison with theirs is our procedure of the ergonomic evaluation of the jobs. In this way, we have proposed a mathematical approach to obtain the quantitative scores for the level of the physical workloads of different types. Whereas, they estimated the ergonomic risks of the jobs and they considered the potential risks on the workers in their balancing (job rotation) model. Hence, our considered parameters for developing job rotation model are different from their parameters. In fact, they aimed at smoothing the the ergonomic risks but our objective is to balance the different types of the physical workload together with preventing the successive high workloads on the workers. Another additional consideration which is included in our model is capability of the workers and learning costs. In the case study, the workers had been skilled for the particular workstations. The policy of the company was to not invest additional cost and time for learning the operators. Therefore, in this research a new model of job rotation is programmed in which the rotations occur only inside the workstations.

The advantage of the proposed approach in comparison with the classical job rotation, where the workers can be assigned to all of the jobs, is it's learning cost and time and also the complexity of the manpower planning will be reduced. The presented model can be easily converted to a classical job rotation model by neglecting constraints 4.19 and 4.20. To validate this assumption, the model has been employed to simulate a classical job rotation on the studied system. The results of the computational simulation is shows in table 4.8.

Workforce schedule by Classical Job Rotation						
Worker	*Sequence of jobs*	*Workload exposed*				*Cumul. load*
		P1	*P2*	*P3*	*P4*	
op1	$6 \to 12 \to 10 \to 3$	5.57	7.81	10.58	7.81	31.77
op2	$1 \to 6 \to 11 \to 10$	8.95	5.57	6.71	10.58	31.81
op3	$11 \to 10 \to 13 \to 6$	6.71	10.58	8.95	5.57	31.81
op4	$14 \to 4 \to 3 \to 9$	8.91	6.14	7.81	8.95	31.81
op5	$5 \to 1 \to 4 \to 13$	7.81	8.95	6.14	8.95	31.85
op6	$12 \to 11 \to 14 \to 2$	7.81	6.71	8.91	7.85	31.28
op7	$13 \to 14 \to 12 \to 4$	8.95	8.91	7.81	6.14	31.81
op8	$9 \to 8 \to 7 \to 12$	8.95	7.28	7.81	7.81	31.85
op9	$7 \to 3 \to 1 \to 8$	7.81	7.81	8.95	7.28	31.85
op10	$2 \to 9 \to 2 \to 11$	7.85	8.95	7.85	6.71	31.36
op11	$4 \to 2 \to 9 \to 14$	6.14	7.85	8.95	8.91	31.85
op12	$3 \to 13 \to 8 \to 7$	7.81	8.95	7.28	7.81	31.85
op13	$10 \to 5 \to 6 \to 5$	10.58	7.81	5.57	7.81	31.77
op14	$8 \to 7 \to 5 \to 1$	7.28	7.81	7.81	8.95	31.85

TABLE 4.8 – Workforce schedule by Classical Job Rotation

According to the cumulative workload column of this table, the daily workload scores of the operators are well balanced by this strategy. But there is no consideration about the capability of the workers or the learning aspect (cost and time that the operators need to be skilled and adapted to a job). Note that, the presented mathematical model is programmed by GMPL language and is solved by employing the GUROBI solver. Consequently, the term "computational results" in this study implies the results of the GUROBI solver.

4.5/ CONCLUSION

This chapter presented a specific type of job rotation in which the rotations occur only inside the predefined groups. This strategy needs less cost and time for learning the staffs in comparison with the classical job rotation and balances the physical workloads exposed to the operators of each group. At the first step, an ergonomic analysis was carried out for the jobs and its physical workloads were evaluated by different ergonomic criteria. The workload levels were classified into high, medium and low categories. Afterwards, a mixed integer mathematical model was developed to obtain optimal sequences for the group job rotation by aiming to balance the daily physical workloads on the workers. Furthermore, the constraints of the proposed model prevent the operators to face the successive high workloads.

The proposed approach was applied to plan the workforce scheduling for a truck assembly line. The computational results and its related statistical analysis demonstrate that the workload scores are balanced among the operators. The model is well adaptable for other production and service systems to reduce the risks of the WMSDs and occupational diseases. The proposed job rotation method can be favourable for the systems in which the skills required by different jobs are largely different. Considering the productivity factors into the job rotation model combined with the ergonomic issues may be an interesting axis for the future studies. On the other hand, we can consider uncertainty concerns for the estimation of the workload scores by employing the Fuzzy logic or Statistical approaches. The analyzing of the learning-forgetting effect and learning costs can be other ways as the further researches.

5

Multi-objective job rotation by ergonomic considerations

5.1/ Multi-objective approach in human resource planning

5.1.1/ Introduction

Many various objectives have been targeted in the worker assignment and job rotation problems in the production environment. In the classical worker assignment problems, the economic goals are often one of the most important factors to be considered. For the job rotation problems, the nature of the objectives is different and most of the time the ergonomic goals are targeted. By regarding the importance of the musculoskeletal disorders (MSDs) and the occupational disease, which is progressively increasing, the application of the job rotation approach in the manufacturing is growing. Apart from the ergonomic criteria, the job rotation is used in the worker assignment to face unplanned absenteeism and unavailability of the workers.

In this thesis, we present an integration of the worker assignment and job rotation problems as a novel optimization problem in the production domain. A multi-objective mathematical model is proposed for the mentioned problem. Two main objectives of the model are aimed at balancing the physical workload level among the workers and improving the productivity level of the studied assembly line. The mathematical model is applied to a part of a truck assembly line and is solved by using Gurobi solver.

5.1.2/ Problem description

To develop a worker assignment and job rotation platform in a manufacturing system, the workers and the jobs as the basic components must be precisely analyzed. Many various criteria can be considered in this analysis. Depending on the objective and the considerations of the job rotation model, the workers and the jobs are evaluated by different parameters. In this study two main objectives are targeted for the worker assignment and job rotation model. The first one is to balance the physical workload level that the workers are exposed during a day. This is because the jobs of the studied system have not the same level of load. The physical workload level of different jobs is evaluated by a local

standard of the company that gives an integer value between 1, as the minimum and 10, as the maximum workload. In this standard the jobs by a workload level less than or equal to 4 are considered as the low workload jobs. The jobs with a load from 5 to 7 are the medium jobs and the workload level more than or equal to 8 implies a high workload job. As an example, the results of the evaluation of the nine jobs ($J1$ ... $J9$) are shown in the table 5.1.

Physical Workload Evaluation of the Jobs										
		J1	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*
Workload Amount (L)		7	6	7	10	2	8	9	2	6
Workload Level		M	M	M	H	L	H	H	L	M
Binary Parameters	U	0	0	0	0	1	0	0	1	0
	V	1	1	1	0	0	0	0	0	1
	W	0	0	0	1	0	1	1	0	0

TABLE 5.1 – Physical Workload Evaluation of the Jobs

In this table H, M, L signify respectively the High, Medium and Low physical workload level and the the binary parameters are defined to ease the modelization of workload mathematically.

The second objective of the presented worker assignment problem is to minimize the production cycle time of the studied manufacturing system. In this way, the efficiency and also the capability of the workers are evaluated because the workers are heterogeneous. For the efficiency, the operating time of the workers on different jobs is considered. In this part we have made a test on the operators to obtain their operating time on different jobs. The result of the mentioned test for nine operators ($I1$ ... $I9$) on the nine jobs ($J1$ ... $J9$) is shown in the table 5.2. Note that the actual production cycle time of the studied system is 5 minutes. It means that every worker must complete his job before five minutes.

Workers' Operating Time									
	J1	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*
I1	3.5	4.2	4.4	4.1	4.5	4.1	4.4	3.6	4.9
I2	–	–	–	–	5	4.3	3.6	3.6	4.9
I3	3.8	5	3.8	4.8	4.1	3.8	4	4.9	4.4
I4	5	4.5	4.5	3.5	–	–	–	–	–
I5	–	–	–	–	–	–	–	–	–
I6	4.5	4.4	3.6	3.6	4	4	4.2	5	4.1
I7	–	–	–	–	–	–	–	–	–
I8	–	–	–	–	3.9	4.8	3.9	4	4.1
I9	3.5	3.7	4.1	3.6	–	–	–	–	–
	WS1				WS2				

TABLE 5.2 – Workers' Operating Time

As shown in this table, one operator can be very efficient in some jobs but not very efficient in others. The first row the table shows the operating time of the worker one ($I1$). It can be seen that he is the best operator in the jobs one and eight ($J1$, $J8$), but he is not very adequate for the job number nine ($J9$). The nine jobs presented in this table are the

jobs of two workstations ($WS1$, $WS2$). In fact the studied production system composed of different workstations and each workstation composed of divers jobs. According to this table, first workstation incorporates four and the second one incorporates five jobs.

The other consideration of the proposed job rotation model is the capability of the workers. Actually, the problem concerns the mono-skilled and multi-skilled workers. The capability of the workers is evaluated for working to different workstations. The result of this analysis is shown in the table 5.3 by "Y" and "N" that imply respectively "YES" and "NO".

Workers' Capability				
	WS1	*WS2*	*WS3*	*WS4*
I1	Y	Y	N	N
I2	N	Y	N	Y
I3	Y	Y	N	Y
I4	Y	N	Y	N
I5	N	N	Y	Y
I6	Y	Y	Y	Y
I7	N	N	Y	N
I8	N	Y	Y	Y
I9	Y	N	N	Y

TABLE 5.3 – Workers' Capability

As an example, worker number six ($I6$) is a multi-skilled worker who is able to work in all workstations whereas worker number seven ($I7$) is a mono-skilled worker who can work only in workstation three ($WS3$). In this research, we present a novel worker assignment and job rotation problem that incorporate various considerations simultaneously. The heterogeneous workers, capability and the efficiency of the workers, together with the ergonomic criteria and the dissimilarity of the workload of the jobs are the main considerations of this problem. A multi-objective mathematical model is proposed for the problem which is presented in the next section.

5.2/ MULTI-OBJECTIVE PROGRAMMING FOR JOB ROTATION SCHEDULING

The studied problem is modeled mathematically by employing a multi-objective mixed-integer programming approach. Firstly, the elements of the mathematical model as the parameters, variables and indices are presented. The formulation of the problem which is composed of three objective functions and various constraints is introduced afterwards.

5.2.1/ INDICES, PARAMETERS, AND VARIABLES

A mathematical model has one or multiple dimensions and each one is presented by an index. The proposed model contains five dimensions as worker (i), job (j), workstation (k), period (p) and day (d). The parameters and the variables of the model are introduced by employing these indices.

The parameters of the model are the constant exogenous variables which are imposed to the model as the data. The parameters of the proposed model are as follows.

m : Number of available workers to be assigned to the jobs.

n : Number of considered jobs in the production system.

r : Number of working periods per day.

t : Number of working days in the planning horizon.

A_{ij} : Binary parameters for presenting the capability of the workers, where $A_{ij} = 1$, if worker i is able to work in the job j and $A_{ij} = 0$, otherwise.

U_j, V_j, W_j : Binary parameters for presenting the workload level of the jobs, and signify respectively the low, medium and high workload level. As an example, $U_j = 1$, if the workload level of the job j is low and $U_j = 0$, otherwise.

L_j : Integer parameters that present the quantitative workload amount (from 1 to 10) of job j. It signifies that if a worker is assigned to job j for a period of a day, he is exposed to a physical workload amount of L_j.

OP_{ij} : Operation time of job j if it is done by worker i.

ε : Maximum authorized difference between total workloads that different operators are exposed.

The variables of the model are obtained by solving the model and they determine the state of the system. For solving a model, the decision variables are computed such that the objective of the model is optimized. The other variables (state variables) are computed from the decision variables and parameters of the model. The variables of the proposed job rotation model are as follows.

$X_{ijpd}(Decision\ variables)$: Binary variables where, $X_{ijpd} = 1$ if worker i is assigned to job j in the period p of day d, and $X_{ijpd} = 0$ otherwise.

DL_{id} : Daily workload that the worker i is exposed during the day d.

TL_i : Total workload that the worker i is exposed during the planning horizon.

PT_{kpd} : Production time of workstation k in period p of day d .

CT_{pd} : Production cycle time in the period p of day d .

5.2.2/ Objective functions

Three mini-max objectives are considered in the formulation of the problem which are presented as follows.

Objective 1 (Daily Workload) :

$$Minimize\ Z_1 = MAX_{i \in I,\, d \in D}\ \{DL_{id}\} \tag{5.1}$$

Objective 2 (Cycle Time) :

$$Minimize\ Z_2 = MAX_{p \in P,\, d \in D}\ \left\{CT_{pd}\right\} \tag{5.2}$$

Objective 3 (Total Workload) :

$$Minimize\ Z_3 = MAX_{i \in I}\ \{TL_i\} \tag{5.3}$$

The first one (Z_1) signifies the minimization of the maximum workload that the workers are exposed during a day. This objective results in the balancing of the daily workload among the workers. In the second objective (Z_2), the production cycle time is targeted to be minimized. In fact, by employing job rotation approach, the production time varies from one period to another because of the efficiency of the workers. In a period (p) of a day (d), the production cycle time (CT_{pd}) is equal to maximum operating time of the workers. Hence, a mini-max formulation is proposed to minimize the maximum cycle time of the different periods of the planning horizon. The third objective (Z_3) is aimed at levelling the total workload to which each worker is exposed during the planning horizon. This objective is also formulated by a mini-max equation that is to minimize the maximum total workload on a worker.

5.2.3/ Constraints and required calculations

This study concerns a combinatorial optimization problem that is composed of various constraints of diverse domains. These constraints are separately presented as follows.

5.2.3.1/ Assignment constraints

$$\sum_{i=1}^{m} x_{ijpd} = 1 \quad \forall\ j \in J,\ p \in P,\ d \in D \tag{5.4}$$

$$\sum_{j=1}^{n} x_{ijpd} = 1 \quad \forall\ i \in I,\ p \in P,\ d \in D \tag{5.5}$$

$$\sum_{j=1}^{n} x_{ijpd} = \sum_{j=1}^{n} x_{ij(p+1)d} \quad \forall\ i \in I,\ p \in P^{-},\ d \in D \tag{5.6}$$

$$\sum_{d=1}^{t} \sum_{p=1}^{r} \sum_{j=1}^{n} x_{ijpd} = t \times r \quad \forall\ i \in I \tag{5.7}$$

The first and second sets of the constraints (5.4, 5.5) are the classical constraints of the assignment problem. They guarantee respectively that a job in each period of a day is done by one and only one operator and a worker during a period is assigned to one and only one job. The third set of constraints (5.6) signifies that if a worker works in a period of a day he must also work on other periods of this day. It means that the workers have to work whole the day not only one or two periods. The constraints (5.7) signify the total number of periods in which one worker has to work and ensure that they are assigned to the jobs all of the periods every day.

5.2.3.2/ JOB ROTATION AND WORKER'S CAPABILITY CONSTRAINTS

$$\sum_{j \in WS_k} x_{ijpd} = \sum_{j \in WS_k} x_{ij(p+1)d} \quad \forall\, k \in K,\ i \in I,\ p \in P^-,\ d \in D \tag{5.8}$$

$$\sum_{j \in WS_k} \sum_{p=1}^{r} x_{ijpd} = \sum_{j \in WS_k} \sum_{p=1}^{r} x_{ijp(d+1)} \quad \forall\, k \in K,\ i \in I,\ p \in P,\ d \in D^- \tag{5.9}$$

$$x_{ijpd} \leq A_{ij} \quad \forall\, i \in I,\ j \in J,\ p \in P,\ d \in D \tag{5.10}$$

Two sets of the constraints (5.8 and 5.9) are about the special conditions of the job rotation in the considered problem. As mentioned in the problem description part, the job rotation in the studied system is just inside of the workstations. It means that the workers can be assigned to only the jobs which are in the same workstation. According to these equations, if a worker is assigned to the workstation k in the period p, in the next periods and next days he has to work in this workstation. The constraints (5.10) guarantee that a worker can be assigned to only the jobs in which he is skilled. It is assumed that if a worker is able to work in a workstation, he is capable to do all of the jobs in this workstation.

5.2.3.3/ ERGONOMIC CONSTRAINTS

$$\sum_{j=1}^{n} x_{ijpd} \times W_j \leq \sum_{j=1}^{n} x_{ij(p+1)d} \times (U_j + V_j) \quad \forall\, i \in I,\ p \in P^-,\ d \in D \tag{5.11}$$

$$\sum_{j=1}^{n} (x_{ijpd} + x_{ij(p+1)d}) \times (W_j + V_j) \leq \sum_{j=1}^{n} x_{ij(p+2)d} \times 2 \times U_j \quad \forall\, i \in I,\ p \in P - \{r,\ r-1\},\ d \in D \tag{5.12}$$

$$DL_{id} = \sum_{p=1}^{r} \sum_{j=1}^{n} x_{ijpd} \times L_j \quad \forall\, i \in I,\ d \in D \tag{5.13}$$

$$TL_i = \sum_{d=1}^{t} DL_{id} \quad \forall\, i \in I \tag{5.14}$$

$$TL_i - TL_f \leq \varepsilon \quad \forall\, i, f \in I \tag{5.15}$$

The equations (5.11, 5.12) present the ergonomic constraints that are considered in the proposed job rotation implementation. The first set (5.11) ensures that if a worker has a high workload job in a period, he must be assigned to a medium or low workload job in the next period. This constraint prevents two successive high workload jobs for a worker during a day. The constraints (5.12) are similar to the previous ones and signify that if a worker is assigned to a high and medium workload job in two successive periods, in the next period he must be assigned to a low workload job. In the studied system this constraint is a optional (soft) one and it can be employed where it is feasible. The

equation (5.13) is to calculate the daily workload to which each worker is exposed. The daily workload is determined by the sum of the workloads related to each period during the day. The total workload that the workers are exposed during the planning horizon is obtained by the sum of the daily workloads as presented in equation (5.14). Another ergonomic constraint is imposed to the model by the equation (5.15) and it guarantees balancing of total workload on the workers. Note that, the third objective function Z_3(5.3) can be replaced with this constraint by employing "epsilon method" to solve our multi-objective mathematical model. This method is applied for the studied system as explained in the next section.

5.2.3.4/ MAKESPAN CALCULATIONS

$$PT_{kpd} = MAX_{i \in I,\, j \in WS_k} \left\{ OP_{ij} \times x_{ijpd} \right\} \quad \forall\, k \in K,\ p \in P,\ d \in D \tag{5.16}$$

$$CT_{pd} = MAX_{k \in K} \left\{ PT_{kpd} \right\} \quad \forall\, p \in P,\ d \in D \tag{5.17}$$

As mentioned before, the production time of a workstation is calculated by maximum operation times of the jobs which are carried out in the workstation. The operating time of a job is depended on the efficiency of the operator (OP_{ij}). Because of the job rotation, the processing times of the workstations vary from a period to another. Hence, each workstation has a particular processing time every period. The processing times of the workstations in different periods are calculated by equation 5.16. In this study, a production cycle time is determined for each working period. It is obtained from the maximum workstation's processing times during the period as formulated mathematically in equation 5.17. The presented mathematical model is employed to optimize a part of a production system which is explained in the next section.

5.3/ NUMERICAL APPLICATION AND COMPUTATIONAL RESULTS

The multi-objective model which was presented in the previous section is used for the implementation of job rotation in a truck assembly line. In fact, the mathematical model helps us to obtain an optimal job rotation in the workstation of this manufacturing system. As mentioned in the problem description part, the considered system composed of four workstations of production line. The workstations contain one or multiple jobs and each job needs a permanent operator. Hence, a workstation needs one or multiple operators. In the studied system, four considered workstations are composed respectively of four, five, five and four jobs. The multi-objective model which is proposed to this system is aimed at assigning the heterogeneous workers to the jobs such that the production time is reduced and the workload is balanced on the workers. Because of the ergonomic constraints, we have considered the possibility of the job rotation among the workers. For that, the capability of the workers is determined by a table that indicates all of the jobs that each worker is able to do. In the studied company, the daily working time is eight hours and the workers have a pause between each two hours. Therefore, there are four working periods per day and there is a possibility of job rotation during the breaks between working periods.

To obtain the optimum worker assignment and job rotation, the mathematical model is solved by following three different scenarios. At first, only the first objective (Smoothing the daily workload) is considered and model is solved as a mono-objective. The results of this scenario for the nine first operators ($I1 - I9$) during the first day ($D1$) are shown in table 5.4.

Worker Assignment and Job Rotation based on the Workload Levels										
Day	*Period*	*I1*	*I2*	*I3*	*I4*	*I5*	*I6*	*I7*	*I8*	*I9*
D1	P1	J5	J16	J15	J11	J17	J12	J10	J9	J3
	P2	J7	J15	J17	J13	J18	J12	J14	J6	J2
	P3	J5	J16	J18	J13	J17	J12	J10	J9	J3
	P4	J6	J15	J16	J12	J18	J10	J11	J7	J4
MAX Operating Time		4.5	5	4.8	4.8	4.9	4.7	4.8	4.8	4.1
Cycle Time		CT(I2,J15) = 5								
Daily Workload		21	26	27	12	28	5	13	29	30
MAX Daily Workload		DL(I9) = 30								

TABLE 5.4 – Worker Assignment and Job Rotation based on the Workload Levels of the jobs

As shown in this table, as an example, the operator number one ($I1$) in the first period ($P1$) is assigned to the job number five ($J5$), after the first break he is assigned to job number seven ($J7$), then he works in job number five in the third period and finally he is assigned to job number six in the last working period ($P4$) of the first day ($D1$). The daily workload for each worker is calculated by the sum of the workloads of the jobs which is done by the worker in different periods. For the first operator ($I1$), the daily workload (DL) is calculated by $DL(I1) = L_5 + L_7 + L_5 + L_6 = 2 + 9 + 2 + 8 = 21$ (According to the table 5.1 in the section 5.1.2. The objective of this scenario is only to minimize the maximum "daily workload" on the operators without considering the worker's efficiency and production time. As a result, the operator number nine ($I9$) is exposed to the maximum workload amount of 30. It can be seen that the operating time and production cycle time are not considered and they are not optimized. The production cycle time by using this strategy is 5 minutes which is not a agreeable solution.

In the second scenario, the model is solved by only the second objective (Minimization of the production cycle time). The results of applying this strategy for two workstations containing nine jobs, during the first day are shown in table 5.5.

Assignment and Job Rotation based on the Operating Times										
Day	*Period*	*J1*	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*
D1	P1	I18	I9	I3	I1	I13	I11	I8	I2	I14
	P2	I18	I1	I3	I9	I8	I2	I13	I11	I14
	P3	I18	I9	I3	I1	I13	I11	I8	I2	I14
	P4	I18	I1	I3	I9	I14	I13	I2	I11	I8
MAX Processing Time		3.5	4.2	3.8	4.1	4	4.3	4.2	4.3	4.1
Workstation		WS1				WS2				
WS Processing Time		4.2				4.3				
Cycle Time		4.3								
MAX Daily Workload		DL(I1) : J4→J2→J4→J2 = 10+6+10+6 = 32								

TABLE 5.5 – Worker Assignment and Job Rotation based on the Operating Times of the workers

This table shows the sequence of the workers which are assigned to each job in different periods of the day. The assignment of the jobs to the workers is based on the efficiency of the workers by regarding to the operating time table which was presented in the section 2 (table 5.2). There are the jobs that the best operator repeats that every period by respecting the ergonomic restrictions. For instance, job number one ($J1$) is done by operator number eighteen ($I18$) in all of the periods of the day. But most of the time, because of the ergonomic constraints in the model, the best operator of each job can not repeat that every period. According to the table, for each one of the jobs the processing time is obtained from the maximum operating time of the operators who work in the job in different periods. The workstation processing time is calculated by the maximum processing time of the jobs which are done in the workstation. Finally, the cycle time is obtained from the maximum processing time of the workstations. The optimum cycle time obtained by solving the job rotation model is 4.3 minutes which is the best possible solution from the point of view of productivity. This approach does not consider the smoothing of the workloads among the operators. The maximum daily workload is on the operator number one ($I1$) with an amount of 32 which is higher than the first strategy.

In the third scenario, we consider all of the three objectives which are presented in the model formulation section. Two approaches, as Epsilon-Constraint and Linear Aggregation, are employed simultaneously to solve the proposed multi-objective model. In this way, the first and second objectives (Daily workload and Cmax) are normalized and then a weighted sum method is used to transfer to a mono-objective model. The third objective function is convert to a constraint by using the Epsilon-Constraint method as presented in the equation 5.15. The results of applying this strategy are shown in table 5.6.

Multi-Objective Analysis (Linear aggregation)						
	Objective	*Values*	*Normalized*	*Values*	*Weighted*	
Weights	*Z1 (WL)*	*Z2 (Cmax)*	*z1*	*z2*	*Sum*	*Solution State*
0–1	32	4.3	0.78	0.53	0.53	Not Dominated(1)
0.1–0.9	32	4.3	0.78	0.53	0.56	Not Dominated(1)
0.2–0.8	32	4.3	0.78	0.53	0.58	Not Dominated(1)
0.3–0.7	32	4.3	0.78	0.53	0.61	Not Dominated(1)
0.4–0.6	30	4.4	0.72	0.60	0.65	Not Dominated(2)
0.5–0.5	30	4.5	0.72	0.57	0.69	Dominated(3)
0.6–0.4	30	4.4	0.72	0.60	0.67	Not Dominated(2)
0.7–0.3	30	4.5	0.72	0.67	0.71	Dominated(3)
0.8–0.2	30	4.4	0.72	0.60	0.70	Not Dominated(2)
0.9–0.1	30	4.5	0.72	0.67	0.72	Dominated(3)
1–0	30	5	0.72	1	0.72	Dominated(4)

TABLE 5.6 – Multi-Objective Analysis (Linear aggregation)

The adapted mono-objective model is solved by employing different weights for the objectives. As shown in the column of “solution state”, four different solutions are obtained. Among these solutions, two of them are non-dominated (number 1 and number 2) and two others (number 3 and number 4) are dominated by solution 2.

One of the non-dominated solutions is the same as we have obtained by using strategy 2 (table 5.5). It can be seen that the solution obtained by strategy 1 (table 5.4) is dominated by the solution 2. With regard to the objective values of the solution 2, it can be concluded that the proposed multi-objective approach optimize the “daily workload ($Z1$)” and results in an agreeable value for the “production time ($Z2$)”.

Note that, the proposed mathematical model has been programmed by employing GMLP mathematical programming language and has been solved applying branch and bound algorithm using GUROBI solver.

5.4/ CONCLUSION

In this chapter, a job rotation platform for a manufacturing system has been implemented. The integration of the worker assignment and the job rotation problems by considering the heterogeneous workers, different task execution times for the workers, capability of the workers and different workload levels of the jobs consist a novel combinatorial optimization problem in the production domain. the production cycle time as the productivity and the daily workload as the ergonomic criteria have been targeted in the presented problem. By solving the mathematical model of the job rotation, the optimum worker sequence for the jobs is obtained. Different scenario, according to the decision maker or user point of view, can be defined for this problem and for each scenario one or more optimum solution is calculated. The numerical application illustrated the adequacy of the proposed mathematical model. For the future, proposing a heuristic or meta-heuristic algorithm for this problem can be a interesting way as the future research.

II

Workforce scheduling based on the SGAP

6

SGAP FORMULATION FOR WORKFORCE SCHEDULING

6.1/ INTRODUCTION

Human resource planning in a production system could be considered as a specific version of the Assignment Problem (AP). This part of our research deals with the weekly worker assignment to the workstations/jobs in an assembly system which is modeled as a sequencing assignment problem. The term sequencing assignment problem in the present study could be interpreted to mean a number of the classical assignments that occur sequentially. Each assignment belongs to a period of time and depends on the previous ones. Hence, the parameters of the problem must be synchronized after determining an assignment.

The study aims at obtaining the optimal assignment of the appropriate operators to the workstations. The considered assembly line consists of the workstations which are in series (flowshop system) and each workstation is composed of several jobs. In a workstation, as there are no precedence relationships between jobs, they can be processed in parallel. Consequently, several workers are assigned to the same workstation. Therefore, the studied problem can be regarded as a special type of the generalized assignment problem (GAP) which is a combinatorial optimization problem.

The problem contains the heterogeneous workers with different capacities and a planning period of one week. The restriction of working-days and off-days on the workers is also considered in this research. The production system works everyday and the workers have five working-days and two off-days per week. Therefore, seven worker assignments (one per day) are needed for this system and the objective is to minimize the production time by assigning the efficient workers to the jobs such that the number of working-days is respected for every workers. In the studied assembly line, the workers are able to do all of the jobs but their skills are different. The objective is to select the most efficient worker for each job. The daily assignments are correlated because of working-day/off-day restriction. Hence, a sequencing generalized assignment formulation is applied to model this problem mathematically by using mixed-integer programming (MIP).

The term Sequencing Generalized Assignment Problem (SGAP) was presented for the first time by Moussavi et al. (2017) as multiple generalized assignments which must be carried out one after the other. This problem is explained in detail in next sections.

6.1.1/ Generalized Assignment Problem (GAP)

The production system which was presented in the previous section, can be considered as a GAP because each workstation is composed of one or more workplaces in which one and only one worker must be assigned to a workplace in each day. To adapt this problem to GAP, the workers can be viewed as the agents and the workstations can be viewed as the jobs. Note that the maximum number of working-day for each worker is viewed as the capacity of the agents.

The classical GAP concerns the assignment of n jobs to m agents such that each job is assigned to exactly one agent by respecting the capacity of the agents (Ross et al., 1975). The decision variables x_{ij} represent the assignment of agent i to job j, with c_{ij} the cost of assigning job j to agent i, a_{ij} the resource used by job j assigned to agent i and b_i the capacity of agent i.

$$Minimize \qquad Z(x) = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{6.1}$$

$Subject\ to$:

$$\sum_{j=1}^{n} a_{ij} x_{ij} \leq b_i; \qquad \forall\ i = 1, ..., m; \tag{6.2}$$

$$\sum_{i=1}^{m} x_{ij} = 1; \qquad \forall\ j = 1, ..., n; \tag{6.3}$$

$$x_{ij} = 0\ or\ 1; \qquad \forall\ i = 1, ..., m;\ \ j = 1, ..., n; \tag{6.4}$$

Many researchers have proposed different exact and approximated methods to solve the generalized assignment problems in different scales.

On the other hand, in the literature, there exist various extensions for the GAP with divers solution methods. In this part, at first, the solution methods which existed in the earlier works for the classical GAP are presented. Afterwards, different extensions of the GAP and their related solving methods are announced.

6.1.2/ Definition of the Sequencing Generalized assignment problem (SGAP)

In this study, the worker assignment is modeled by using GAP formulation. The objective is to maximize the productivity by scheduling the workforce and with the consideration of the availability of the workers and the possibility of job rotation. To take into account the planning horizon and availability of the workers, we present an extended variant of the GAP in which there exists an additional dimension as the periods other than the classical GAP dimensions (agents and jobs). In fact, the term Sequencing Generalized Assignment Problem (SGAP), is introduced in this thesis as follows :

Definition 1 : Sequencing Generalized Assignment Problem (SGAP)

An extended variant of the assignment problem consisting of multiple GAPs that occur consecutively, whilst ensuring the number of working-days and off-days for each agent are respected.

Figure 6.1 shows an simple example for SGAP containing three workers, and six jobs. The capacity of the agents is three jobs per day (Generalized aspect), for a planning horizon of three days involving two working-days and one off-day for each worker (Sequencing aspect).

Sequencing Generalized Assignment for a planning horizon of 3 periods with a capacity of 3 jobs per period and 6 jobs per planning - considering one off-day and 2 working-days for each workers.

Period 1: (Off-Day for Worker C)

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
A	5	9	2	6	8	5
B	8	7	5	4	3	7
C	6	5	7	9	8	4

Period 2: (Off-Day for Worker B)

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
A	5	9	2	6	8	5
B	8	7	5	4	3	7
C	6	5	7	9	8	4

Period 3: (Off-Day for Worker A)

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
A	5	9	2	6	8	5
B	8	7	5	4	3	7
C	6	5	7	9	8	4

FIGURE 6.1 – Sequencing Generalized Assignment Problem

The SGAP is modeled by using an integer linear programming as follows :

$$Minimize \qquad Z(x) = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{p=1}^{l} c_{ij} x_{ijp} \tag{6.5}$$

$Subject\ to$:

$$\sum_{p=1}^{l}\sum_{i=1}^{m} x_{ijp} \leq d_j; \qquad \forall\ j = 1, ..., n; \tag{6.6}$$

$$\sum_{j=1}^{n} a_{ij}x_{ijp} \leq b_i; \qquad \forall\ i = 1, ..., m;\ p = 1, ..., l; \tag{6.7}$$

$$\sum_{i=1}^{m} x_{ijp} = 1; \qquad \forall\ j = 1, ..., n;\ \ p = 1, ..., l \tag{6.8}$$

$$x_{ijp} = 0\ or\ 1; \qquad \forall\ i = 1, ..., m;\ \ j = 1, ..., n;\ \ p = 1, ..., l \tag{6.9}$$

Where d_j represents the maximum number of authorized working-days during the planning horizon for each worker, and x_{ijp} the binary decision variable represents whether worker j is assigned to workstation i in the period (day) p or not.

6.2/ Problem description

This study concerns the workers' assignment to manufacturing stations in an assembly line in order to minimize the production time. The considered assembly line consists of the serial workstations. A workstation in this system contains diverse workplaces which must be performed simultaneously. The workers are assigned to the workplaces.

The problem concerns the heterogeneous workers with different skill level. The task executing time in the workplaces depend on the workers' skill level. It means one individual may be very efficient in a workplace whereas he is not able to complete another workplace in a given period. It is assumed that all the operators are able to work in all the workplaces, only the efficiency level is different. The problem is assigning workers to the workplaces in order to minimize the production time where the task execution time must not exceed the production cycle time. The production time is the sum of the processing time of the serial workstations. The workstation processing time is calculated by maximum operating time of the operators who works in different workplaces of the workstation concurrently. For minimizing the workstation time, we must reduce the maximum workplaces execution time. Hence, the worker allocation model should consider not only the best operator for each workplace but also balancing the operating times in a workstation. Figure (6.2) shows the considered problem consisting of the tasks in parallel and the workstations in series.

In this study the term "task" implies the workplace which is placed in a workstation. Note that the task execution times are not the fixed values and they vary as a function of the workers' efficiency. According to the figure, a_j and b_j signify respectively the best and worst execution time of task j.

The generalized assignment problem can be adapted to the studied problem in which a worker is assigned to one and only one workstation in each period such that all the workplaces of the workstations should be fulfilled. This problem must be solved over a planning horizon composed of the several periods thus, the SGAP structure is adapted to

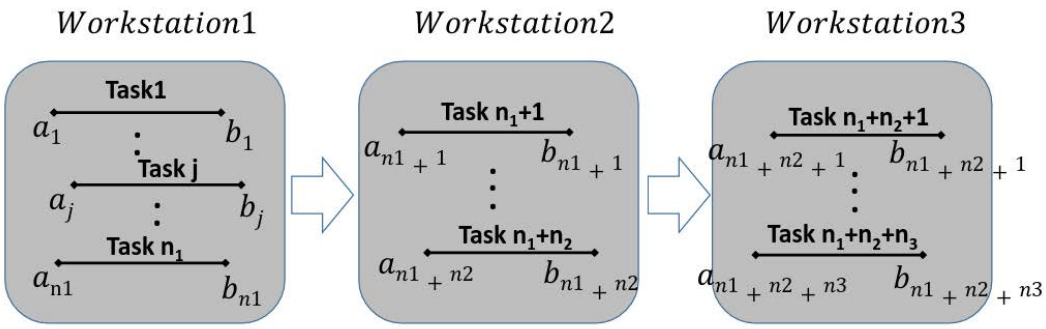


FIGURE 6.2 – Generalized assignment for the assembly line

model and optimize the studied system. The SGAP comes from the difference between the length of planning horizon and the maximum number of working-days for each worker. Therefore it is not possible to repeat the best assignment for all of the periods because of the availability of the workers.

The studied assignment problem as the daily allocation of human resources is performed by aiming to reduce the production time. On the other side, the considered production system works seven days a week whereas the operators work five days. Thus the number of available operators is more than the tasks because in each day certain operators are in working-day and others are in off-day. As a result, the employment of the best daily allocation for the following days is not possible. Note that, the manpower planning horizon is one week. In fact, we deal with the sequencing assignments in which each assignment is a generalized one and we need to connect the individual assignments. As regards the objective of the studied problem which is minimizing the maximum task executing time, we deal with a sequences of the Bottleneck Generalized Assignment Problem (BGAP) (Cattrysse et al., 1992)

On the other hand, the input of the presented optimization problem, as the assignment matrix, is the efficiency (task executing time) of the workers in different workplaces. In fact, the worker allocation is performed based on the assignment matrix. The elements of the assignment matrix in this study are the operating time of the workers in different tasks. The operating times are depended on the efficiency of the worker on the task. Note that, the efficiency of the workers in different tasks are not identical. Thus, to obtain the assignment matrix we have to calculate the efficiency of the operators. Note that, in this research we use the procedure of the efficiency calculation presented by Moussavi et al. (2016) . After that, by employing the assignment matrix, optimization problem can be solved. For solving this problem by the aim of obtaining the optimum workforce schedule, a mixed integer mathematical model is presented. With reference to the structure and the objective of the problem, this model is based on the Sequencing Bottleneck Generalized Assignment Problem (SBGAP). The objective of the allocation model is to minimize the production time in order to improve the productivity (number of product per day). The model is presented in detailed in next sections.

6.3/ PRIMAL MATHEMATICAL MODELALIZATION BASED ON THE SGAP

The mathematical model consists of the objective function which must be optimized and the constraints which should be respected. The equations of these two parts composed of the parameters which are unchangeable along the problem and the variables which must be calculated by solving the model in order to optimize the objective. The model and its relevant elements are presented as follows.

6.3.1/ PARAMETERS

The parameters are the predefined data which must be specified for solving the model. The parameters of the presented model are as the following :

N_{ws} : Number of workstations considered for the worker assignment ;

N_p : Number of periods in the planning horizon ;

n : Number of available workers during the planning ;

m : Total number of tasks in all of the workstations ;

WS_k : The tasks which are developed in workstation number k ;

M_k : Number of tasks which are developed in workstation k ;

E_{ij} : Efficiency of worker i for executing task j.

T_j^{max} : Execution time of task j by the worst worker ;

T_j^{min} : Execution time of task j by the best worker ;

t_{ij} : Execution time of task j if it is performed by worker i ;

PCT : Production cycle time ;

WD_I : Number of working days of the operators during the planning horizon ;

WD_S : Number of working days of the production system during the planning horizon ;

6.3.2/ VARIABLES

The variables are the fundamental elements of a mathematical model and they are determined by solving the model so that the objective function become optimized. The variables of the presented model are as follows.

X_{ij}^p : Binary variable where $X_{ij}^p = 1$ if worker i is assigned to task j in period p ; and $X_{ij}^p = 0$ otherwise.

S_k^p, F_k^p : Staring and ending time of workstation k in period p ;

PT^p : Production time in period p ;

6.3.3/ Model formulation

Objective function

The objective of the model is what we aim to optimize. In the studied problem the objective is a minimax one over a sequence of periods thus, the problem concerns a Sequencing Bottleneck Assignment which is defined as :

$$Minimize\ Z = \sum_{p=1}^{N_p} \sum_{k=1}^{N_{ws}} MAX_{j \in WS_k,\, i \in I}\{X_{ij}^p \times t_{ij}\} \tag{6.10}$$

The objective formula signifies the sum of the production times of all of the planning periods where $MAX_{j \in WS_k,\, i \in I}\ X_{ij}^p * t_{ij}$ implies the processing time of the workstation k, in period p (maximum executing time of all of the operators who work in this workstation in the considered period). The sum of the processing times of the workstations is the production time for the considered period. Accordingly $\sum_{k=1}^{N_{ws}} MAX_{j \in WS_k,\, i \in I}\ X_{ij}^p * t_{ij}$ signifies the production time in period p. Finally, the sum of the production times of all periods is the objective of the studied problem by aiming to minimize that.

Constraints

The sequencing assignment problem, which is studied in this research, consists of two types of the constraints. The first set of the constraints implies the assignment restrictions and the second set defines the scheduling and process constraints. The assignment constraints of the proposed model demonstrate two extensions of the classical assignment problem as the generalized and the sequencing (multiple) which has been considered in the modelization of the studied problem. In fact, these constraints determine the structure of the assignment problem and are defined as follows.

$$\sum_{p=1}^{N_p} \sum_{j=1}^{m} X_{ijp} = WD_I \qquad \forall\, i \in I \tag{6.11}$$

$$\sum_{j=1}^{m} X_{ijp} \leq 1 \qquad \forall\, i \in I,\ p \in P \tag{6.12}$$

$$\sum_{i=1}^{n} X_{ijp} = 1 \qquad \forall\, j \in J,\ p \in P \tag{6.13}$$

$$\sum_{i=1}^{n} \sum_{j \in WS_k} X_{ijp} = M_k \qquad \forall\, k \in K,\ p \in P \tag{6.14}$$

The fist set of the constraints (6.11) ensure the predefined number of working days during the planning horizon for each worker. These constraints imply the sequencing structure of the considered assignment problem.

The second and third sets (6.12,6.13) are the classical constraints of the assignment problem and signify respectively that a worker is not assigned to more than one task in a period, and each task in each period is performed by one and only one worker. The forth set of the constraints (6.14) adapts a special version of the generalized assignment for the studied problem. Note that, This set of constraints in the classical assignment problem are as the inequalities (lower or equal) whereas the considered problem which are as the equalities that is why we announced a special version of the GAP. In the presented model, these constraints

guarantee the assigning of a certain number of workers to each workstation. As explained in the previous parts, a workstation is composed of a certain number of tasks. By assigning one worker to each task, in fact, multiple workers are assigned to a workstation. The number of tasks (workers requirement) in each workstation is defined by the problem (M_k).

Apart from the assignment constraints, the studied problem concerns the production and scheduling constraints which are related to the researched system. This disaggregation of the constraints enable us to easily apply the presented assignment model to divers systems. In the studied production system,

the workstations take place in series. As a result the problem concerns the priority and scheduling considerations and their related constraints which are presented below.

$$S_1^p = 0 \ \ and \ \ F_{k-1}^p \leq S_k^p \qquad \forall\, k \in K,\ k \geq 2,\ p \in P \tag{6.15}$$

$$F_k^p = S_k^p + MAX_{j \in WS_k}\{t_{ij} X_{ijp}\} \qquad \forall\, k \in K,\ p \in P \tag{6.16}$$

$$t_{ij} = E_{ij} * (T_j^{max} - T_j^{min}) \qquad \forall\, i \in I,\ j \in J \tag{6.17}$$

$$PT^p = F_{k=N_{ws}} \qquad \forall\, p \in P \tag{6.18}$$

The first set of the process constraints (6.15) ensures the priority of the workstations, because they are in series and the execution of each workstation can be started once the previous workstation is completed. The second set (6.16) defines the relationship between starting, ending and processing times in each workstations. The constraints (6.17) calculated the executing time of the workers in different tasks as a function of the efficiency of the worker in the task. The processing time of the workstation is defined as the maximum task execution time of all of the workers who work in considered workstation concurrently $(MAX_{j \in WS_k}\{t_{ij} X_{ijp}\})$. Finally, the last set of the constraints (6.18) determines the production time for each period.

The mathematical model above, presents an extended version of the assignment problem in a production system. The structure of the system persuades us to adapt our model to the generalized assignment problem. The planning period of the considered assignment, which is one week, pushed us to present an extension of the GAP by considering a sequence of the GAPs which occur one after another. As mentioned before, this extension has been named Sequencing Generalized Assignment Problem (SGAP). The studied

SGAP is solved by three solving approaches which are attentively explained in the next sections.

As indicated in various earlier works, GAP is a well-known NP-hard combinatorial optimization problem. Consequently, the SGAP which is an extension of the GAP with one more dimension and additional constraints, will be an NP-hard. Therefore, solving the medium and large sized SGAP by any exact solver needs a huge computational efforts. In this part, as the first solving method, the presented SGAP model is solved by an exact algorithm employing Gurobi as a mixed integer solver. The computational efforts needed to solve SGAP persuade us to apply the approximation approaches. Hence, two matheuristic approaches and a hybrid heuristic approach are presented to solve such problems. The proposed algorithms reduce significantly the computational time and the obtained solutions have very slight deviations from the optimal solutions.

6.4/ IMPROVED MATHEMATICAL MODEL

The proposed mathematical model in the previous section, is improved by more organizational issues and more considerations. For instance, an upper bound and a lower bound are defined as the parameters for the number of working-days for each operator. Furthermore, the decision making in the previous model was based on the efficiency of the workers, whereas in the improved model is based on an assignment matrix (Y_{ij}) that presents the operating time of each worker on each job. The model is presented as follows.

6.4.1/ PARAMETERS

UD : Upper bound on the number of working-days during the planning.

LD : Lower bound on the number of working-days.

m : Total number of workers for the assignment. $I = \{1, ..., m\}$

n : Total number of jobs. $J = \{1, ..., n\}$

s : Number of workstations. $K = \{1, ..., s\}$

N_k : Number of jobs in workstation $k \in K$. ($N_1 = 4$: There are 4 parallel jobs in workstation 1)

t : Number of periods in the planning horizon. $P = \{1, ..., t\}$

Y_{ij} : Operating time of worker i in job j. (Decision matrix)

WS_k : The jobs which are carried out in workstation k.

$(WS_k = \{j \in J \mid \sum_{l=0}^{k-1} N_l < j \leq \sum_{l=0}^{k} N_l : \ where\ N_0 = 0\})$.

6.4.2/ VARIABLES

In the model, there is a set of decision variables named X_{ijp} and some other variables as :

X_{ijp} : Binary, where $X_{ijp} = 1$ if operator i is assigned to job j in period p, and $X_{ijp} = 0$ otherwise.

S_{kp}, PT_{kp}, F_{kp} : They present respectively the starting, processing and ending time of workstation k in period p.

W_{ikp} : Working time of worker i in workstation k in period p. Where $W_{ikp} = Y_{ij}$ if worker i is assigned to job j in the period p and job j is in workstation k ; $W_{ikp} = 0$ otherwise.

$CMAX_p$: Production time (for producing one product) in period p.

Z : Average of the production times.

The mixed-integer mathematical model which is presented in this study, contains a minimization objective function together with two different kinds of constraints as the assignment and the scheduling constraints.

6.4.3/ OBJECTIVE FUNCTION

The model is aimed to minimize the average of the production time on the planning periods and defined as the following :

$$Minimize\ Z = \sum_{p=1}^{t} CMAX_p/t; \tag{6.19}$$

6.4.4/ ASSIGNMENT CONSTRAINTS

The first set of constraints is the classical assignment constraint and implies that each job in each period is fulfilled by one and only one operator.

$$\sum_{i=1}^{m} X_{ijp} = 1 \qquad \forall\ j \in J,\ p \in P; \tag{6.20}$$

The second set of constraints implies that each worker during a day can not be assigned to more than one job. Thus the worker has whether one job (if he is in his working-day) or without the job (if he is in his off-day). This condition is defined as follows :

$$\sum_{j=1}^{n} X_{ijp} \leq 1 \qquad \forall\ i \in I,\ p \in P; \tag{6.21}$$

The maximum and minimum number of working-days (for each operator during the planning horizon) which are considered in this study as the predefined conditions in the work-

force scheduling. These assumptions are imposed on the model by the following sets of the constraints :

$$\sum_{p=1}^{l}\sum_{j=1}^{n} X_{ijp} \leq UD \qquad \forall\, i \in I; \tag{6.22}$$

$$\sum_{p=1}^{l}\sum_{j=1}^{n} X_{ijp} \geq LD \qquad \forall\, i \in I; \tag{6.23}$$

6.4.5/ SCHEDULING CONSTRAINTS

The scheduling constraints of the model contain the precedence of the production operations and the procedure of the production time calculation. The first set of the scheduling constraints presents the working time of the operators during a production cycle.

$$W_{ikp} = \sum_{j \in WS_k} X_{ijp} * Y_{ij} \qquad \forall\, i \in I,\ k \in K,\ p \in P; \tag{6.24}$$

These constraints imply the working time of worker i if he is assigned to workstation k in period p; Note that the W_{ikp} will be zero if worker i is not assigned to the jobs of workstation k in period p. The second set of the scheduling constraints signify the processing time of each workstation in each day. While there is more than one operator working in a workstation, the processing time of the workstation is the maximum working time of the operators. This assumption is modeled as the following :

$$PT_{kp} = MAX_{i \in I, j \in k}\, W_{ikd} \qquad \forall\, k \in K,\ p \in P; \tag{6.25}$$

The constraint is linearized as : $PT_{kp} \geq W_{ikd} \quad \forall\, i \in I,\ k \in K,\ p \in P$

The next set of the constraints is the classical formula for the precedence of the operations in a serial system like a production line. In this study, the workstations are in series and each one can be started once the last one would be finished and the first workstation is started at $T = 0$.

$$S_k = F_{k-1} \quad \forall\, k \geq 2 \quad where \quad S_1 = 0; \tag{6.26}$$

Finally, the last constraint of this model presents the makespan or total production time for producing one product that is the ending time of the last workstation. The makespan varies from a period to another because the assignments are not the same for all the periods.

$$CMAX_p = PT_{kp} \quad \forall\, p \in P \quad where \quad k = s; \tag{6.27}$$

The above constraints were formulated mathematically based on the generalized assignment problem. Moreover, some production and scheduling restrictions were imposed to the problem formulation as the additional constraints.

6.5/ CONCLUSION

In this chapter, the human resource planning in an assembly line system was formulated as a specific variant of the assignment problem. In this way, the sequencing generalized assignment problem was defined and the workforce scheduling in the studied system was modelized mathematically based on the formulation of this new problem. Hence, two mathematical models based on the mixed-integer programming were proposed. The model which was presented in the first step, was improved and well organized in the second step as a contribution of the GAP model.

The objective of the models were to minimize the average of the production times (makespans) on the planning horizon. These models are applicable on various types of the production systems as the parallel, serial and combinatorial systems. Considering the lots of the constraints, the presented problem is NP-hard and the exact methods are not able to solve its related MIP model for the large scales. In the next chapter, we propose an hybrid heuristic algorithm which is able to solve the considered assignment problem in a few seconds with a very slight deviation from the optimum solution. Moreover, two matheuristic approaches are proposed for the studied problem.

7

SOLUTION METHODS FOR SGAP

The proposed model in the previous section is a mixed-integer mathematical model. At first, this model is solved by employing an exact approach using Gurobi solver. This approach is evaluated by considering instances of different size. However, Gurobi is only able to solve small size instances. The considered problem is a generalization of the generalized assignment problem (GAP) which is known to be NP-hard. Therefore, the sequencing generalized assignment problem is also NP-hard. For solving medium and large size instances of the mentioned problem, three other solving methods are presented in the next sections : a two-phase matheuristic, a matheuristic based on the sequencing assignment approach, and a hybrid heuristic algorithm, which are explained in detail in the next sections.

7.1/ TWO-PHASES MATHEURISTIC APPROACH

In this part, a solving method for SGAP is proposed which is composed of two steps. The aim of the first step is the assignment of the workers to the tasks for the whole planning horizon using a linear transportation model. The first phase produces only the number of periods in which worker i is assigned to task j. However, the exact periods of assignment are not determined. These results and the data feed the second phase during which the exact periods of assignment of workers to tasks are determined in order to optimize the objective function (see Figure 7.1).

The details of this method are presented in the next parts.

7.1.1/ FIRST STEP BASED ON THE TRANSPORTATION MODEL

A linear transportation model is used to solve an essential part of the main problem : the number of periods of assignment for each worker to each task. In this transportation model, workers are regarded as resources and tasks as clients. As mentioned before, the production system works during all days of the horizon, whereas the workers do not : they have working days and off-days. Thus, in the transportation model, the supply of resources (workers) signifies the number of the working days ; and the demand of the clients (tasks) corresponds to the number of planning days. Hence, a classical linear model is presented as follows.

— Parameters :

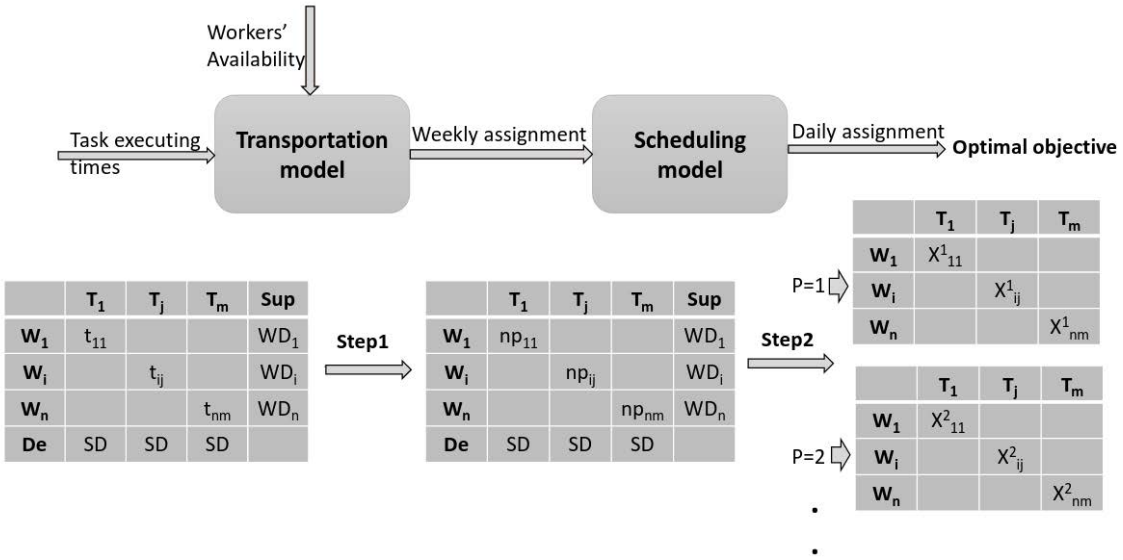


FIGURE 7.1 – Two phases matheuristic approach

- SD : The number of days that production system (the tasks) must work ;
- WD_i : The number of days that worker i is authorized to work in the planning horizon ;

— Variable :

- np_{ij} : The number of periods that worker i works in task j ;

$$Minimize\ U = \sum_{i=1}^{n} \sum_{j=1}^{m} t_{ij} \times np_{ij} \tag{7.1}$$

$$\sum_{i=1}^{n} np_{ij} = SD \qquad \forall j \in J \tag{7.2}$$

$$\sum_{j=1}^{m} np_{ij} = WD_i \qquad \forall i \in I \tag{7.3}$$

This is a classical linear transportation model, which can be easily solved by any linear programming software like Gurobi. The output of this model is the number of periods in which each worker works on different tasks. This output will be the input for the next step to determine that in which days they are assigned to different tasks by considering the objective of the main problem.

7.1.2/ SECOND STEP BASED ON THE SCHEDULING MODEL

After solving the first step, we can remove some constraints of the main problem that are complex to consider, and replace them by a parameter np_{ij}. The main model (as explained in section 6.3) is thus simplified and can be easily solved. According to the primal main model, two constraints 6.11 and 6.12 are replaced by :

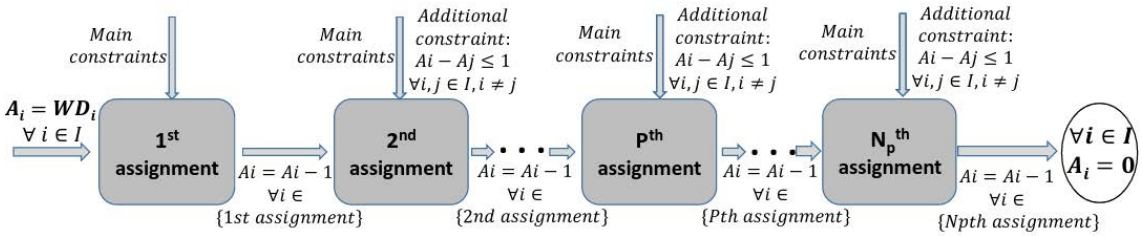


FIGURE 7.2 – Sequencing assignment for multi-period generalized assignment problem

$$\sum_{p=1}^{N_p} X_{ij}^p = np_{ij} \qquad \forall i \in I,\ j \in J \tag{7.4}$$

In fact, the mathematical model of the second step (objective function and constraints) is the same as the main problem with the only modification as explained above. By these changes, the computational time for solving the problem is extremely reduced. In the numerical application part, the computational time and the objective function of this method is compared with the exact method and also an other methods which is explained in the next section.

7.2/ SEQUENCING MATHEURISTIC APPROACH : PRESENTATION OF THE SEQUENCING ASSIGNMENT

In this section, the second matheuristic approach for the sequencing generalized assignment problem is presented This approach is based on the decomposition of the formulation into several classical GAPs. Actually, there are three essential factors that complicate the main model of the problem : the “worker”, the “task” and the “period”. To simplify the main model of the SGAP, an approach is proposed in which the period’s dimension p is removed. As a result, an assignment for the first period is obtained for all workers. After this step, the parameters are modified and the number of working days for the assigned workers is reduced by one. In fact, the number of working days in this approach is regarded as the availability of the workers. The output of the first assignment together with the modified availability of the workers (which is reduced by one for the assigned worker) are the input for the second assignment. This assignment is the workers’ allocation for the second period. Once again the availability of the workers is updated and the third assignment is performed according to the new data. This procedure is repeated until the worker allocation is performed for all periods. Actually, the main model is replaced by N_p number of simplified models where N_p is the number of periods in the planning horizon. Note that, from the second assignment, a constraint must be imposed to the next models that guarantees that the difference between availability of the different workers does not exceed one : $A_i - A_j \leq 1 \quad \forall i, j \in I,\ i \neq j$. The procedure of this algorithm is shown in figure (7.2).

In the beginning of the algorithm, the availability of all of the workers (A_i) is equal to the number of days that each worker is authorized to work (WD_i). After each assignment, the

availability of the workers who have been assigned, is reduced by one. To avoid infeasibility, an additional constraint must be added to the main (primal) constraints. According to this procedure, the availability of the workers must be zero after the assignments of the last period, which means all of the operators have worked all authorized number of days. Because of discarding the factor of "period" in this method, the complexity of the problem and, consequently, the computational time are greatly reduced.

7.3/ HYBRID HEURISTIC ALGORITHM

The third solving method, presented in this thesis, is a hybrid heuristic algorithm for the sequencing generalized assignments. The algorithm is a greedy heuristic combined with a local search. Its starts from the best possible solution and moves to the feasibility. Four principal steps of the algorithm are as follows : 1. Choosing the best possible solution (without caring about feasibility), 2. Going towards the feasibility, 3. Applying two-exchange neighbourhood for improving the solution and finally, 4. Developing the algorithm for the sequential assignment. Figure 7.3 shows the principal steps of the algorithm in summary. It is explained in more detail in the next sections.

7.3.1/ SELECTING THE BEST SOLUTION

In the assignment matrix, the columns represent the jobs and the rows represent the workers. The elements of the matrix present the decision parameters. In this study, the operating times of the operators at different jobs are considered as the decision parameters. For the classical assignment problem, the first step of the algorithm is to select the best score in each column. This score presents the minimum operating time for the corresponding job, and the row number of the selected score presents the most appropriate worker for the job. In this way, a primal solution is found which is the best possible solution. Most of the time, the obtained solution is infeasible because of the overlapping, where a worker is selected for more than one job or a job is assigned to more than one worker. For the generalized assignment problem where more than one worker is needed in a workstation, obtaining the primal solution is more complicated. As an example, if a workstation is composed of three jobs (operators), three best scores must be selected from its related column. Note that, in this case the columns of the assignment matrix represent the workstations. Figure 7.4 shows a simple example for this step of the algorithm.

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	3	6	3
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

FIGURE 7.4 – Selecting the best solution of the assignment matrix

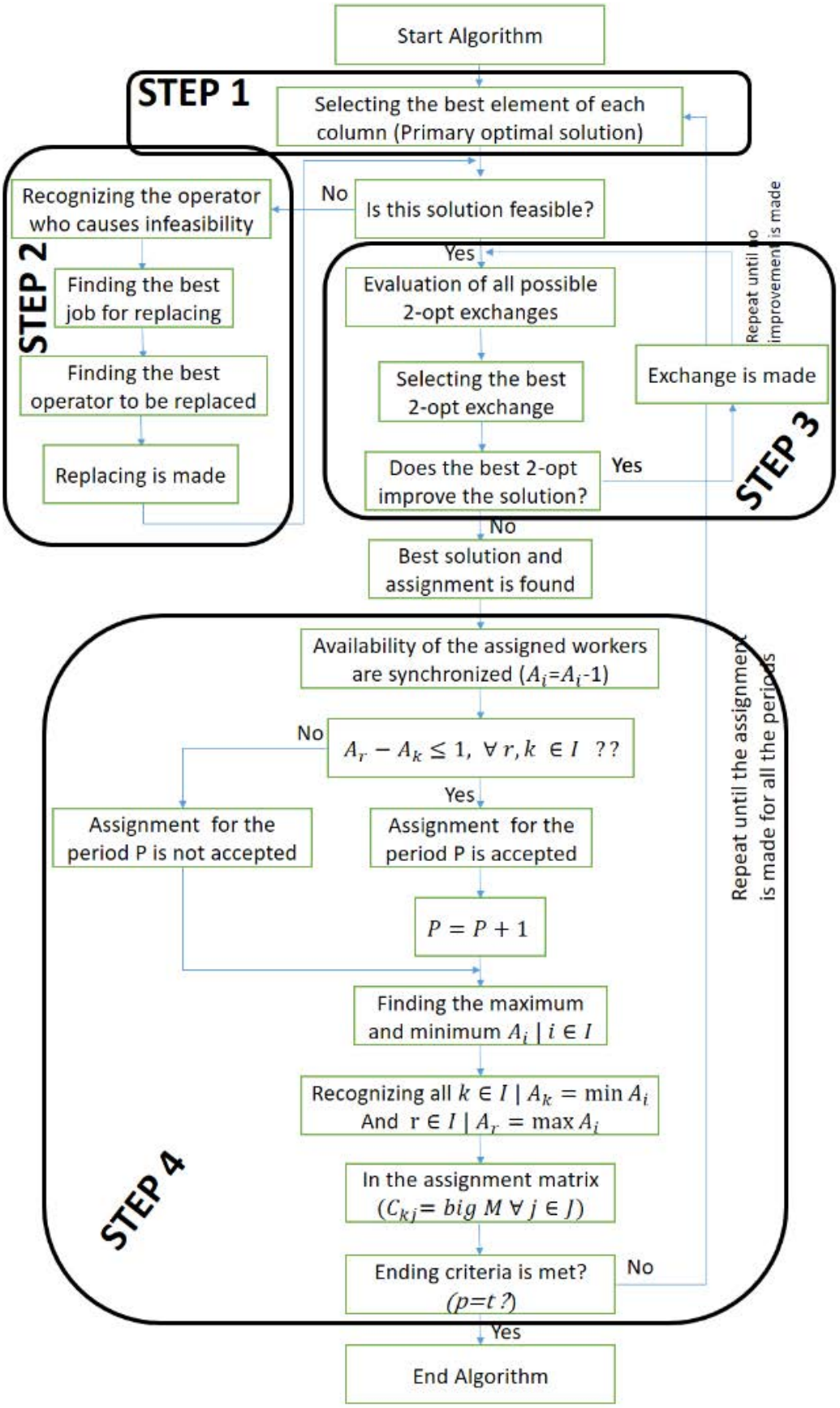


FIGURE 7.3 – The procedure of the heuristic algorithm

Once the best possible solution is obtained, its feasibility must be examined. For the feasibility evaluation, the classical assignment constraints are applied. In this way, two set of constraints must be respected ; 1. Each operator must be assigned to one and only one job, 2. Each job must be fulfilled by one and only one operator. If the primal solution is feasible, the algorithm is finished and the obtained solution is the optimum solution for the assignment problem. But if there are the operators assigned to the more than one job, in at least one job, he must be replaced by another available operator.

7.3.2/ MOVING TOWARDS FEASIBILITY

Once the primal solution does not respect all the constraints, the operators who cause the violation must be replaced by others. As an example, if an operator is assigned to the two jobs at the same time, he must be replaced in one of them by another available operator. At first, we have to choose a job for the operator reassignment. Then, for the chosen job, an available operator must be selected to take place the previously assigned operator. For this purpose, there are various possibilities which are compared and the best one is selected.

In this way, a penalty matrix with two rows is created. The number of columns of the matrix is equal to the number of available operators. A simple example of the penalty matrix is presented in figure 7.5. According to the figure 7.4, worker number 1 is assigned to two tasks (task 1 and task 3). In one of these tasks, he has to be replaced by an available worker. The workers number 2, 3 and 5 are the available workers in this example, because they are not assigned to any task in the first step.

	Worker 2	Worker 3	Worker 5
Task 1	4	1	2
Task 3	1	2	1

FIGURE 7.5 – Penalty matrix for replacing a multi-job worker by the vailable workers

Each element of this matrix indicates the replacing penalty. For instance, the element in the first row and second column implies the penalty of replacing the violating operator (worker 1) at his first job (task 1) by the second available operator (Worker 3). The element with the minimum penalty is selected and the replacement is made. After this replacement, the assignment is re-evaluated in terms of its feasibility. If the assignment is now feasible, hence, it is considered as the output of this step and the input of the step three as is explained in the next section. If there are still the operators to which two or more jobs are assigned, another replacing penalty matrix is created and the above procedure is repeated until a feasible solution is obtained.

7.3.3/ TWO-EXCHANGE NEIGHBOURHOOD TO IMPROVE THE SOLUTION

The solution obtained through two previous steps, is a feasible solution such that each operator is assigned to one and only one job and each job is carried out by one and only one operator. In this step, a local search is developed by aiming to improve the obtained

feasible solution. For this purpose, all the two-exchange possibilities are examined. the two-exchange neighbourhood in this algorithm represents another solution where two workers change their jobs or two jobs change their assigned workers. Figure 7.6 presents a 2-opt exchange to improve the solution of the assignment problem.

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	3	6	5
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

2-opt exchange

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	3	6	5
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

FIGURE 7.6 – Two-Exchange neighbourhoud for the assignment problem

In this example, for the task number 3, the assigned worker (worker 2) is replaced by an available worker (worker 5). The best exchange is selected and the objective function (production time) is evaluated. If the best two-exchange improves the solution, then the mentioned exchange is applied and this procedure will be repeated until no improvement is made. The output of this step is the best solution found by the algorithm for the classical assignment problem.

7.3.4/ DEVELOPING THE ALGORITHM FOR THE MULTIPLE (SEQUENCING) ASSIGNMENTS

The above three steps of the proposed algorithm generate the best operator assignment for one period of time. The studied problem in this research considers a series of assignments where each assignment is related to a period (day) and the assignment is developed for several periods. As mentioned before, the best assignment can not be repeated for all of the periods because of the limitations which are defined by the number of the working-days for the operators. Therefore, the availability of the operators must be considered in the algorithm. For this purpose, after each assignment, the availability variable (the number of working-days which remains) for each worker is synchronized. This synchronization is shown in figure 7.7 by a simple example.

Assignment of period "1"

	Availability
Worker1	5
Worker2	5
Worker3	5
Worker4	5
Worker5	5

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	3	6	5
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

	Availability
Worker1	4
Worker2	4
Worker3	5
Worker4	4
Worker5	5

FIGURE 7.7 – Synchronization of the availability of the workers after each assignment

Hence, if an operator has worked two days during the three first days and the maximum number of working-days for him is predefined to be five days, the availability variable for him at the beginning of the fourth day is three.

According to the proposed algorithm, the difference between the availability of different workers must not exceed one score ($A_i - A_q \leq 1 \quad \forall i, q \in I and i \neq q$). In this way, after each assignment (period), for the operators with the minimum availability, their related score in the assignment matrix are replaced by a big score to avoid the same assignment for the next period. This step of the algorithm is shown in figure 7.8.

Assignment of period "p"

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	3	6	5
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

	Avail
Worker1	2
Worker2	4
Worker3	3
Worker4	4
Worker5	4

Modified Assignment of "p"

	WS 1		WS 2
	Task1	Task2	Task3
Worker1	100	100	100
Worker2	7	5	4
Worker3	4	4	5
Worker4	5	3	6
Worker5	5	6	4

FIGURE 7.8 – Synchronization of the assignment matrix according to the availability

As can be seen in this figure, the availability of the worker 1 after the assignment of period p is 2 days whereas the availability of the worker 2, 4 and 5 is equal to 4. Therefore, this assignment is not permitted and the assignment matrix is modified so that the worker 1 is not assigned in this period. In this way, the assignment of the period p is obtained. This procedure is followed until the assignment is made for all the periods.

7.4/ DISCUSSION

As mentioned before, the generalized assignment problem is NP-hard and solving such problems by mathematical modelization and exact algorithms could be very complicated for the large scales instances. To reduce the computational times needed to solve such problems, in this chapter, three approximate approaches were proposed. These methods

are not only for solving the GAP but they can be also applied to solve the sequencing generalized assignment problem (SGAP).

The first and second proposed methods are the matheuristic approaches based on the decomposition of the formulation to simplify the main mathematical model. This strategy aims at simplifying the main mathematical model and breaking that into two or more models which are more simple. The third solving method is a hybrid heuristic composed of a greedy algorithm combined with a local search. In the next chapter, these three methods are evaluated by various instances of different sizes. The efficiency, accuracy and the computational time of the proposed methods in comparison with the exact algorithm will be discussed in the following section.

8

NUMERICAL APPLICATION FOR SGAP'S SOLUTION METHODS

8.1/ CASE STUDY OF TWO MATHEURISTIC APPROACHES

The two matheuristic methods, which have been presented in the previous chapter, are evaluated in this section by a real setting case study. Actually, the studied manpower planning problem, which is presented in the format of the sequencing generalized assignment problem, is applied in a part of a truck assembly line consisting of three workstations and fourteen tasks. The layout of the tasks is 4-5-5. It means four tasks are placed in the workstation number one, and five tasks in two other workstations. The production cycle time of this assembly line is eight minutes thus the task executing time of the workers must not exceed eight minutes. The workstations are placed in series and the production time for one article is calculated by the sum of the processing time of all of the workstations. The manpower planning is performed for a duration of one week (seven days). The operators are authorized to work five days, thus they have two off-days per week whereas the production system that works all seven days of the week. Twenty workers are available for executing fourteen daily tasks during a week. All of the workers are able to perform all of the tasks but their capacities are different, and the execution time of a task depends on the capacity of the worker. The objective of the problem is the assignment of the best worker to each task so that the production time of an article (sum of the workstations' processing time) is minimized.

This problem is modeled as an SGAP using mixed integer programming approach (as explained in the previous section) and solved by the exact algorithm using Gurobi solver. To obtain the optimal solution through this approach, a computational time of four hours ($1.7 * 10^4$) is needed. On the other hand, the presented SGAP, which is an extension of the generalized assignment problem, is an NP-hard combinatorial optimization problem. Hence, in this thesis, two matheuristic approaches (as explained in chapter 7) are presented for solving the sequencing generalized assignment problem. These methods are able to solve the studied problem in a few seconds instead of $1.7 * 10^4$ seconds where the deviation from the optimal solution is less than 1%.

The SGAP is a novel extension of the GAP which is presented in this research, thus, there is no benchmark instances in the literature. Therefore, in order to generalize and validate the proposed matheuristic approaches, a total of 27 test problems are simulated by generating random numbers for the different factors. In fact, there are four fundamental

factors in such problems as the number of periods, the total number of tasks, the number of workstations and the number of tasks in a workstation. Table 8.1 shows the description and the variation domain of the factors to which the computational experiments is done.

Most important factors of the sequencing generalized assignment		
Factor	*Description*	*Variation domain*
tasks	number of tasks for worker assignment	12-100
workstations	number of workstations in the planning	3-20
task/workstation	average number of tasks in each workstation	3-30
period	duration of the planning	1-7

TABLE 8.1 – Most important factors of the sequencing generalized assignment

8.1.1/ COMPUTATIONAL RESULTS

The efficiency of the solving approaches is evaluated by using an experimental design on the problem parameters. The generated instances are solved for different values of the presented parameters (table 8.1) by employing three different solving approaches. This analysis is performed for 3, 4, 10 and 20 workstations with 12, 14, 20, 40, 50, 90 and 100 tasks, on the 1, 2..,7 periods. The computational results of the experimentations are shown in the table (8.2). Note that the objective value of the model (PT) presents the production time needed for producing one article. The production time for one period is calculated by the sum of the processing time of the workstations and PT in the case of the multiple periods is calculated by the sum of the PT of the individual periods. In the table (8.2), the computational time needed for solving the problem is indicated by CT (the unit is second) ; and E_{max} presents the maximum error of the approximated approaches in comparison with the exact optimal solution obtained by Gurobi.

As shown in the table of the computational results, the computing time (CT) is significantly decreased by using two approximated algorithms so that for the studied assembly line (3 workstations with 14 tasks) both of algorithms, solved the manpower planning model in less than one second whereas the computing time of the Gurobi algorithm for 7 periods is more than 4 hours. The approximated solutions have a very slight deviation from the optimal ones. The errors of both of the algorithms are less than 1%. For the studied problem (on 7 periods) the error of the Sequential method is less than two-phase method (0.13% vs 0.24%) but the two-phase is much more simple to be used. The Sequential method is limited for the users because for each period an assignment must be performed and after each assignment, the parameters of the model must be modified. Thus, for the long planning horizons, the employing this method for solving SGAPs is very complicated.

As shown in results' table, deviations of the matheuristic approaches (E_{max}) never exceed 1% over all the instances. The computational times of the Sequential approach highly grow by increasing the number of tasks, and the number of workstations and the difficulty of this approach grows by increasing the number of periods. The advantage of the Sequential method is the quality of its solutions which are very near to the optimal solutions. For most of the instances, the quality of the solution obtained by Sequential is better than two-phase whereas the computational time of two-phase is significantly less than the Sequential mainly in the instances with a large number of tasks. Thus we can observe that Gurobi is only efficient for solving the small size of the SGAP. Sequential

Computational results												
Comparison of the three solution methods												
WS	Task	Structure	Period	solving method								
				Gurobi			2 phases			Sequential		
				PT	CT	Gap	PT	CT	E_{MAX}	PT	CT	E_{MAX}
3	14	4-5-5	2	42.69	<1s		42.82	<1s	0.30%	42.73	<1s	0.09%
			4	85.57	36s		85.7	<1s	0.15%	85.73	<1s	0.19%
			7	149.98	17000s		150.34	<1s	0.24%	150.18	<1s	0.13%
3	20	6-7-7	2	42.75	<3s		42.77	<1s	0.05%	42.75	<2s	0.00%
			4	85.61	161s		85.91	<1s	0.35%	85.74	<1s	0.15%
			7	150.02	10018s		150.68	<1s	0.44%	150.22	<2s	0.13%
3	90	30-30-30	2	42.25	107s		42.28	<1s	0.07%	42.25	26s	0.00%
			4	84.5	1086s		84.62	<3s	0.14%	84.56	41s	0.07%
			7	147.93	19146s		148.16	<5	0.16%	148.04	88s	0.07%
4	12	3-3-3-3	2	57.18	<3s		57.27	<0.1s	0.16%	57.18	<0.1s	0.00%
			4	114.53	77s		114.89	<0.1s	0.31%	114.64	<0.1s	0.10%
			7	200.69	6538s		201.21	<0.1s	0.26%	200.85	<0.1s	0.08%
4	20	5-5-5-5	2	56.9	<4s		56.99	<1s	0.16%	56.94	<1	0.07%
			4	114.03	865s		114.29	<1s	0.23%	114.19	<3	0.14%
			7	199.84> 199.23<	>20000	0.30%	200.32	<1s	0.55%	200.13	<11	0.45%
4	100	25-...-25	2	56.28	156s		56.35	<1s	0.12%	56.28	57s	0.00%
			4	112.58	1011s		112.64	<4s	0.05%	112.58	89s	0.00%
			7	197.05	15472s		197.22	<9s	0.09%	197.07	134s	0.01%
10	20	2-2-...-2	2	141.58	37s		141.63	<1s	0.04%	141.62	<4s	0.03%
			4	283.58	3431s		283.78	<1s	0.07%	283.82	<8s	0.08%
			7	496.74	6181s		497.04	<1s	0.06%	497.19	14s	0.09%
10	50	5-5-...-5	2	141.05	980s		141.2	<1s	0.11%	141.08	59s	0.02%
			4	282.43> 280.52<	>20000	0.67%	282.6	<3s	0.74%	282.52	95s	0.71%
			7	494.53> 491<	>20000	0.71%	494.9	<4s	0.79%	494.61	1191s	0.74%
20	40	2-2-...-2	2	281.9> 281.37<	>20000	0.19%	281.86	<1s	0.17%	281.8	106s	0.15%
			4	564.36> 561.08<	>20000	0.58%	564.47	<2s	0.60%	564.38	699s	0.59%
			7	988.49> 981.84<	>20000	0.67%	988.31	<4s	0.66%	988.18	474s	0.75%

TABLE 8.2 – Computational results : Application of matheuristic methods to solve SGAP

algorithm seems to be very efficient for medium sized instances and the two-phase algorithm performs very well on the tested large sized instances. Further experiments should be undertaken to confirm these conclusions. As an example, for an SGAP problem with the planning horizon of 100 periods, the Sequential approach is extremely complicated with 100 steps and it needs 99 times of manipulation whereas two-phase algorithm is easily able to solve this problem with 2 steps in a few seconds.

8.1.2/ PRODUCTION RESULTS

The results in the previous section validate our solving approaches for various sizes of instances. In this section, the production results are compared with the current status of the real-life case. In the studied assembly line the cycle time is defined as :

Production cycle time = Maximum tasks execution time + idle time

In this production system, the idle time is considered as 10% of the task execution time and the manpower planning horizon is one week or seven periods. In fact, the worker assignment is repeated every week. Table (8.3) shows the results of the proposed worker assignment for each period (day) and in each workstation.

Production results							
Day	*Max task duration*			*Max WS duration*	*Prod Time*	*Idle time =0.1*TD*	*Cycle Time*
	WS1	*WS2*	*WS3*				
Day1	7.24	7.06	7.07	7.24	21.37	0.72	7.96
Day2	7.19	7.15	7.07	7.19	21.41	0.71	7.90
Day3	7.25	7.14	7.06	7.25	21.45	0.72	7.97
Day4	7.23	7.08	7.12	7.23	21.43	0.72	7.95
Day5	7.34	7.17	7.12	7.34	21.63	0.73	8.07
Day6	7.15	7.06	7.08	7.15	21.29	0.71	7.86
Day7	7.25	7.05	7.10	7.25	21.40	0.72	7.97

TABLE 8.3 – Production results

The operation time of workstation equals the maximum duration of the tasks which are performed in the workstation. The production time (PT) in each day is calculated by the sum of the workstations operation times. The table (8.3) shows that the maximum task duration by the proposed assignment occurs in workstation 1 on the fifth day and is equal to 7,34 minutes. It is the objective of the proposed worker assignment model (equation 6.10) to minimize maximum task duration (as explained in section 6.3).

Actually, the current production cycle time in the studied system is fixed at 9,00 minutes because of the maximum task execution time of 8,17 (The current worker assignment leads to a maximum task duration of 8,17). Hence, the workers have a minimum idle time of 0,83 in each cycle.

As could be observed in figure (8.1), the proposed worker assignment leads to a maximum task execution time of 7,34 which is 11% less than the current status. Now the production cycle time could be modified to 8,07 instead of 9 minutes. This reduction in the tasks duration and cycle time brings on a better productivity which is earned by assignment of more efficient workers to the tasks.

In this study, the approximated (matheuristic) approaches are proposed because the times needed for solving the SGAP by the exact algorithms is highly increased by growing the size of the instances. In this way, the impact of the fundamental parameters of the SGAP (table 8.1) on the computational time of the exact solving method is analyzed. This evaluation is shown is figure (8.2). Note that all computing times in this figure correspond to the exact algorithm by employing Gurobi solver.

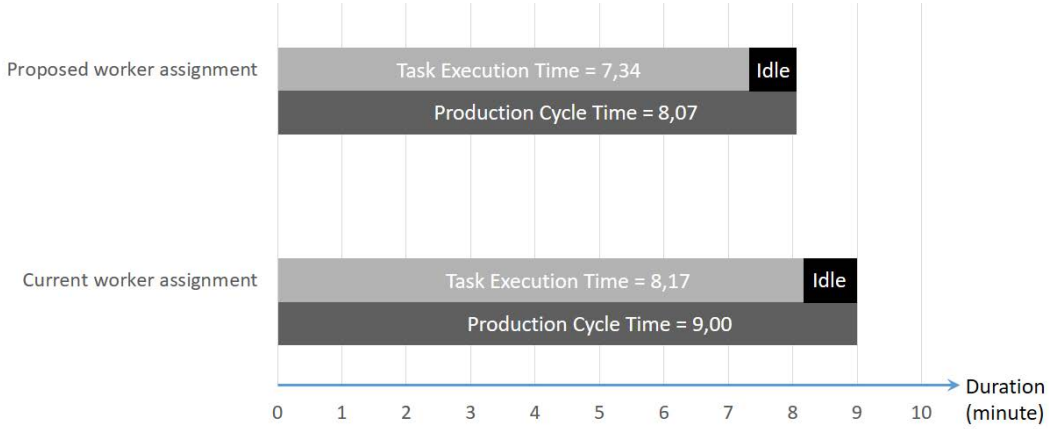
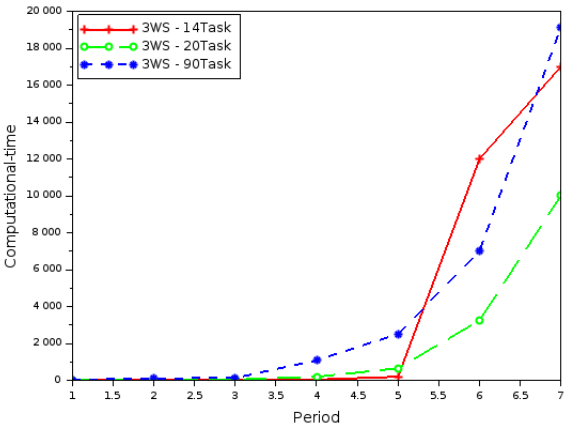
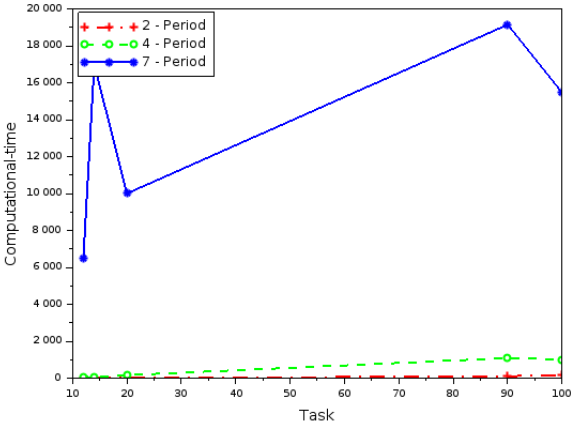


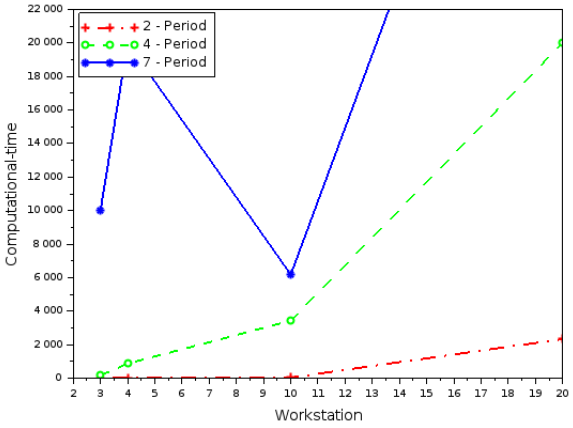
FIGURE 8.1 – Production cycle time



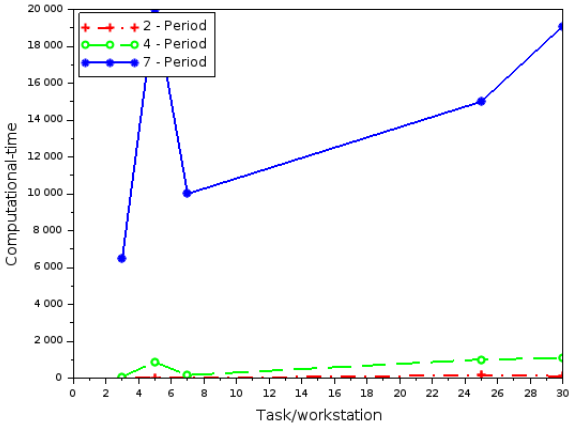
(a) Computational time vs number of periods



(b) Computational time vs number of tasks



(c) Computational time vs number of workstations



(d) Computational time vs number of tasks in each workstation

FIGURE 8.2 – Evaluation of the Gurobi computational times as a function of the different parameters of the problem.

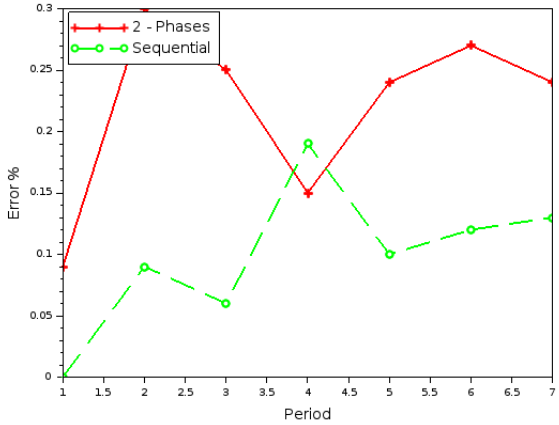
8.1.3/ Analysis of the parameters and solving approaches

As seen in the figure (8.2-a), the solving time by the exact algorithm is exponentially increased by growing the planning horizon. Thus, for a long planning horizon even if the size of the instance on other parameters is small, the computing time is extremely large. As a result, the exact algorithm is not an efficient approach for solving SGAPs with the long planning duration. Figure (8.2-b) shows the variation of the computing time as a function of the number of tasks. These results correspond to the small number of workstations (3 and 4) and different number of tasks (from 12 to 100). As shown in this figure, increasing the computing time as a function of the number of tasks is not very extensive but it can be estimated by a linear function with a small slope. Hence, the impact of the duration of the planning on the computational time is much more important than the number of tasks. In figure (8.2-c) the computational time is evaluated by different number of workstations. It can be concluded that the computational time varies linearly but the slope is bigger than figure (8.2-b). It means the impact of the number of workstations is more important than the number of tasks and less important than the planning duration. The last analysis about the computational times is done by considering the ratio of the number of tasks to the number of workstation. This ratio presents the average number of the tasks which are placed in each workstation. The variation of the computing time as a function of this ratio is also linear with a small slope like the number of tasks. As a result, the problem is much more complicated to solve by the exact algorithm, where the duration of the planning increases.

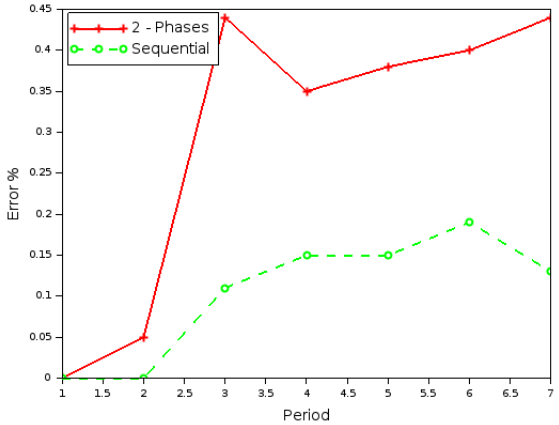
Generally, the approximated methods are analyzed by deviation of their solutions from the optimal and the computational time needed to solve the problem. As shown in table 8.2, the computational time of two-phase method is always less than 5 seconds even for the large size instances. About the Sequential method, the computational time varies as a function of the size of the instances. As an example, for an instance with 50 tasks and a planning horizon of 7 periods, the computing time of the sequential is 1191 seconds whereas the two-phase algorithm that solve this instance in less than 4 seconds. Therefore, two-phase algorithm is more efficient than the Sequential from a point of view of computing time. On the other hand, the errors of both methods are quite slight and vary from an instance to another. Hence, a precise analysis on the errors of two matheuristic approach has been performed as shown in figure (8.3). In this figure, the deviations of two proposed solving approach for the SGAP are analyzed over several instances of different sizes.

In this figure, the deviations of the solving methods for the SGAP are shown as a function of the planning duration. In most cases, the deviation stays the same or slightly increases by growing the length of the planning horizon. This feature guarantees the efficiency of our methods for the large size instances. The accuracy of both methods on all of instances is reasonable (more than 99%). In addition, the error of the Sequential method is mostly less than the two-phase method. Hence, it can be concluded that the Sequential is generally more efficient than two-phase from the point of view of accuracy. By analyzing the figures (8.3-e), it can be seen that the error of the sequential method is quite near to zero when the number of tasks increases. Finally, figure (8.3-f) shows that when the number of tasks in each workstation increases the deviation of two-phase algorithm is less than Sequential.

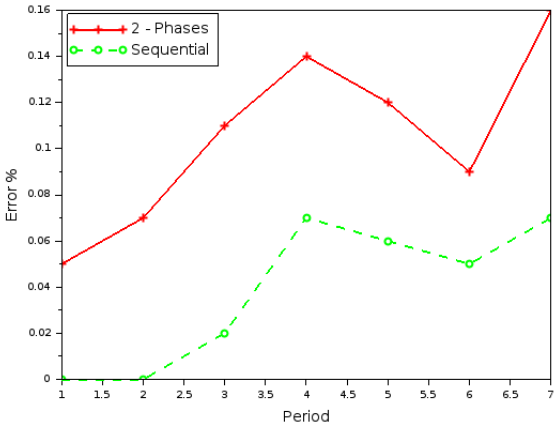
The numerical application results show the efficiency of the proposed methods. Each



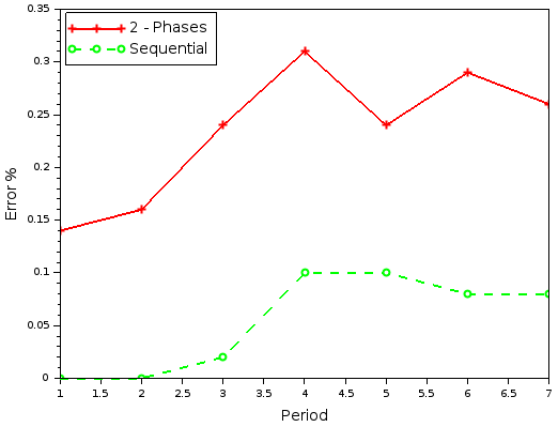
(a) 3 workstations with 14 tasks



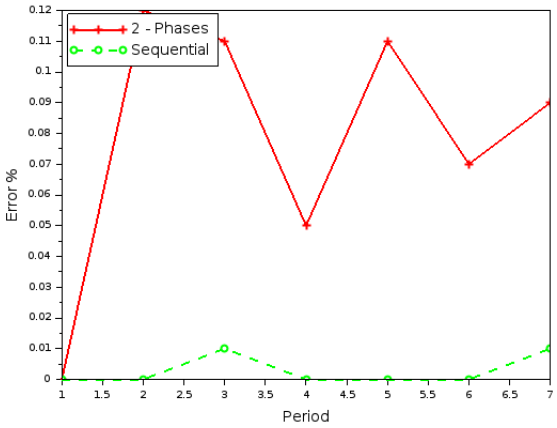
(b) 3 workstations with 20 tasks



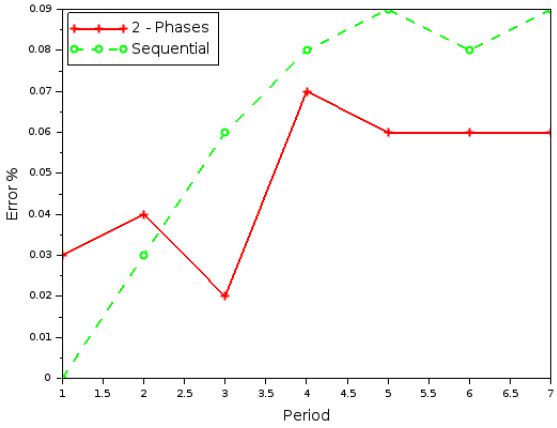
(c) 3 workstations with 90 tasks



(d) 4 workstations with 12 tasks



(e) 4 workstations with 100 tasks



(f) 10 workstations with 20 tasks

FIGURE 8.3 – Evaluation of the deviations of "two phases" and "sequential" solving approaches in comparison with the optimal solutions obtained by Gurobi.

method has the advantages and the restrictions and no one can dominate over another one. As a consequence, the best solving approach for an SGAP is related to the sizes of different factors of the problem, the accuracy which is needed, and the limitation level on the computing time.

8.2/ CASE STUDY OF HYBRID HEURISTIC APPROACH

After evaluation of the matheuristic methods in the previous section, in this section the proposed hybrid heuristic approach, which was presented in section 7.3 to solve SGAP, is analysed by another case study. As mentioned in the previous section, a production system has been considered to evaluate the proposed solution methods for the SGAP. For this system, a sequential daily assignment is needed to manage the operators during a week. The studied production system is a truck assembly line consisting of the workstations, machines, operators, ... The considered part of this assembly line contains three workstations in which there are respectively four, five and five jobs in parallel. The system works seven days per week whereas the operators have five working-days and two off-days per week. Therefore, for these three workstations, fourteen $(4 + 5 + 5)$ operators are needed per day where the system needs twenty $(14 * 7/5 = 19,6 \sim 20)$ available operators for the weekly manpower planning. The production cycle time in the system is eight minutes and each operator, depending on his capacities, has different operating times at different jobs which are between seven and eight minutes. It means the more efficient operators in each job, have the operating times near to seven minutes.

According to the structure and the restrictions of the studied production system, all four operators in the first workstation have to carry out their jobs in less than eight minutes. The processing time of the mentioned workstation is equal to the maximum operating time of the four operators working in this workstation in parallel. Thus in each workstation, there is a critical operator who determines the processing time of the workstation. The objective is to find the best job assignment to reduce total production time (the sum of the processing time of the three studied workstations) for one product.

For solving the mentioned generalized assignment problem, we have proposed a mixed-integer mathematical model as explained in section 2. This model is solved for a planning horizon of one week by employing an exact solving software named Gurobi. As a result, the optimum assignment (workforce schedule) and its related objective value (production time) are obtained. The assignment of the operators during the first period is presented in table 8.4.

Manpower planning and production time for the first period									
	WS1		WS2			WS3			Production time
Job	Operator	Time	Job	Operator	Time	Job	Operator	Time	
J1	**O9**	**7.17**	J5	O18	7.05	**J10**	**O2**	**7.07**	
J2	O16	7.06	J6	O11	7.01	J11	O10	7.01	
J3	O13	7.09	J7	O6	7.01	J12	O17	7.06	
J4	O14	7.08	J8	O1	7.04	J13	O19	7.01	
			J9	**O5**	**7.06**	J14	O7	7.00	
WS time : 7.17			WS time : 7.06			WS time : 7.07			**PT : 21.30**

TABLE 8.4 – Manpower planning and production time for the first period

This table shows the structure of the studied production system and the problem considered in this research. As shown, the best operator is assigned to each of the jobs so that the processing time of the corresponding workstation is minimized. Among four operators which are assigned to the workstation number one ($WS1$), the operator number nine ($O9$) or the job number one ($J1$) correspond to the maximum operating time. The operating time of this operator/job determines the processing time of the workstation. There are three workstations in series, thus the total production time is equal to the sum of the processing times of the workstations.

The generalized assignment is an NP-hard problem and hence the computational time to solve such problems is highly increased by raising the size of the assignment matrix. Therefore, a heuristic algorithm for the GAP is presented that is able to solve the large size sequential and generalized assignments in a few seconds. Both of two solving methods have been employed to solve the considered problem on the studied assembly line. The results of the solving methods for the different numbers of periods are compared in table 8.5.

Gurobi vs Heuristic for solving generalized assignment problem					
No of periods	*Gurobi*		*Heuristic*		*GAP*
	Prod Time	*Comput Time*	*Prod Time*	*Comput Time*	
$P = 1$	21.30	$< 1s$	21.32	$< 1s$	0.09%
$P = 2$	42.69	$< 1s$	42.87	$< 1s$	0.42%
$P = 3$	64.28	$40s$	64.87	$< 1s$	0.76%
$P = 4$	85.57	$36s$	86.15	$< 1s$	0.67%
$P = 5$	107.00	$196s$	107.67	$< 3s$	0.62%
$P = 6$	128.55	$12 * 10^3 s$	129.55	$< 5s$	0.77%
$P = 7$	149.98	$17 * 10^3 s$	151.25	$< 10s$	0.84%

TABLE 8.5 – Gurobi vs Heuristic for solving generalized assignment problem

As shown in the table, by increasing the length of the planning horizon, the computational time for solving the problem by the exact method is exponentially grown. For the considered instances, the proposed heuristic algorithm is able to solve this sequential assignment with a very small deviation from the optimal solution, less than 1%, where the computational time is highly decreased. Note that the planning horizon for the job assignment in the considered case study in real-time is one week (seven periods or days). The last column of table 8.5, where $P = 7$, shows that the exact method solves this instance in about five hours (17000 seconds) whereas the heuristic approach spends just ten seconds to attain a solution quite near to the optimal solution. From the CT columns of the table, it can be concluded that the heuristic algorithm seems to be very efficient in the computational time even when the number of planning period is raised.

8.3/ CONCLUSION

In this chapter, a manufacturing system has been considered as the case study to evaluate the proposed solving approaches for the assignment problems. As the studied production system consists of the tasks in parallel and in series hence, we have adapted our problem with the generalized assignment problem. Because of the length of the planning

horizon, which consists of multiple periods, the time dimension also imposed to the assignment problem and the term sequencing generalized assignment problem (SGAP) is proposed for such problems.

The considered worker scheduling problem has been modeled using mixed-integer programming by employing GAP structure. The mathematical model is solved for the case study by an exact approach using Gurobi solver. The results illustrated the disability of the exact approach for this problem. Thus two approximate methods based on the matheuristic approach and also a hybrid heuristic algorithm are proposed for the SGAP. A total of 27 instances of different sizes are solved by three mentioned methods. Two matheuristic approaches have been completely analyzed by different factors and size of the instances. The computational results showed the efficiency of the proposed approximate approaches for the considered instances. These methods were able to solve the SGAPs with the large sizes in a few seconds with a very slight deviation from the optimal solution.

III

Integration of worker assignment and vehicle routing problems : Application to home healthcare scheduling

9

Home healthcare routing and scheduling problem

9.1/ Introduction

In this part of thesis, the human resource planning in the home healthcare system is studied. This problem can be considered as an integration of the worker assignment and vehicle routing problems. The home healthcare system, as a particular type of the home delivery service systems, is a growing scope of application in the manpower planning and operations research domain. Typically, a home healthcare system is composed of the staff members, patients, and the needed services by the patients. The planning of such systems consists of assigning the patients' services to the staffs and constructing the routes for each staff member. Accordingly, both vehicle routing and assignment problems (AP and VRP), which are the well-known operational research problems, have the key roles in Home Healthcare Planning Problem (HHPP). As each one of the staff members is allocated to the multiple services during a day, the assignment part of the problem must be formulated by considering the Generalized Assignment Problem (GAP) characteristics. Since the needed services have the starting and ending times and the staff members must arrive before the starting time, the vehicle routing part of the studied problem can be viewed as a VRP with the time windows. Hence, for developing an optimal planning in a home healthcare system, we deal with a hybrid combinatorial optimization problem.

The objective of this research is to obtain the optimal services schedules for each one of the staff members so that the total and individual distance travelled by the staffs would be minimized. A distinguishing characteristic of the studied problem is that the planning is developed on a horizon of multiple periods (e.g. one week or one month) by considering the number of working-days and off-days for the staffs. The maximum and minimum number of working hours per day for each staff are also counted in the studied problem. In the modelization phase of the research, both aspects of the problem (assignment and routing) are formulated together in a same model by employing mixed-integer programming approach. As the mathematical model is highly complicated to be solved by the exact algorithm, we develop a novel matheuristic approach based on decomposition of the formulation to simplify the model and reduce the computational time needed to solve the problem.

9.2/ Objectives and Problem description

The planning of the staff of a home healthcare company is considered to be optimized by applying mathematical programming. The table 9.1 shows a part of the data given by the company that presents the services needed by the patients. The company has a number of staffs (employees) available to cover these services. This study concerns the determination of the optimum planning for the staffs. The services last one or two hours, and the staffs work six to eight hours per day. It means each staff is allocated to a number of services during a day. The services assigned to an employee, are not necessarily for the same patient. Hence, they travel between patients during the day. The objective is to minimize the travel distances for each one or all the staffs.

Required services by the patients			
Patient	*Service1*	*Service2*	*Service3*
J1	7 :00-8 :00	12 :00-13 :00	-
J2		No need	
J3	12 :00-14 :00	-	-
J4	18 :00-19 :00	-	-
J5		No need	
J6	7 :00-8 :00	20 :00-21 :00	
J7	8 :00-9 :00	12 :00-13 :00	20 :00-21 :00
J8	10 :00-12 :00	15 :00-17 :00	-
J9	16 :00-18 :00	-	-
J10		No need	

TABLE 9.1 – Raw data for the required services by the patients during a specified day

Table 9.1 shows the services needed by ten patients ($J1$..., $J10$) during a given day. As it can be observed, some patients do not need any service in this day and others need one, two or three services. The problem contains sequence of plannings over several days, a planning for each day. Therefore, the problem can be formulated as a Sequencing Generalized Assignment Problem (SGAP) presented by Moussavi et al. (2017). To solve this combinatorial optimization problem, a mixed-integer mathematical model is proposed. The model involves various dimensions including the patients, staffs, services, number of days considered for the planning, number of periods during a day. Many various constraints are considered in the modelization of the problem such as the number of authorized working-days for each staff during the planning, number of services which are assigned to a staff during a day, number of authorized working-hours per day,...

A mathematical model is composed of the parameters which must be given to the model as the data, and the variables which are determined by solving the model. To model the problem by integer linear programming (ILP) approach, the parameters and the variables must be defined as integer or binary values. The most important parameters of the studied model are the required services which are neither integer nor binary. They are provided by the company in the format shown in table 9.1. This raw data must be converted to the numerical parameters to be applicable in our optimization model. Hence, a binary approach is used for this transformation by fixing the periods of a day. The results are shown in table 9.2 that presents the needed services by a set of binary parameters. This structured data is used in our proposed optimization approach in this study and can be

used in any other mixed-integer models.

Structured daily services required by the patients											
Day	*Period*	*Patients*									
		J1	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*	*J10*
D1	P1	1	0	1	0	0	1	0	0	0	0
	P2	0	0	0	0	0	0	1	0	0	0
	P3	0	0	0	1	0	0	0	0	0	0
	P4	0	0	0	0	0	0	0	1	0	0
	P5	0	0	0	0	0	0	0	1	0	0
	P6	1	0	1	0	0	0	1	0	0	0
	P7	0	0	1	0	0	0	0	0	0	0
	P8	0	0	0	0	0	0	0	0	0	0
	P9	0	0	0	0	0	0	1	1	0	0
	P10	0	0	0	0	0	0	1	1	1	0
	P11	0	0	0	0	0	0	0	0	1	0
	P12	0	0	0	1	0	0	0	0	0	0
	P13	0	0	0	0	0	0	0	0	0	0
	P14	0	0	0	0	0	1	1	0	0	0

TABLE 9.2 – Structured daily services required by the patients

In this table, $P1$ presents the first working-hour (period) of the day, i.e., "from $7:00$ to $8:00$" and $P14$ represents the last working-hour (period) which is "from $20:00$ to $21:00$". In this research, the parameters of the needed services named INT_{jpd} (as explained in the next section) are presented as the binary numbers. Table 9.2 is an instance of the INT matrix. The other parameters, such as the duration of the planning, the number of working hours, ... are integer. Our optimization approach determines which staffs are allocated to the services needed by patients on different periods during the days. Therefore, the studied problem composed of two different aspects : 1. the assignment of the staffs to the services (Assignment Problem), 2. the distance travelled by the staffs to move from one patient to another (Routing Problem). In next sections, the problem is formulated mathematically to be solved by a mixed-integer solver. In this way, two approaches are proposed. The first is a united MIP model and the second is a matheuristic approach which are explained in the next sections.

9.3/ UNITED MIP MODEL TO INTEGRATE AP AND VRP

For the mentioned problem, an integrated MIP approach is proposed that contains both assignment and routing aspects. The objective function of the model is the travel distance which is a routing objective. The constraints involve the assignment and routing constraints. In this formulation approach, a change of variable is made to draw a correlation between the assignment and routing constraints. Considering two aspects in the same mathematical model results in a combinatorial optimization model which is presented in this section by it's related induces, parameters, variables, and model formulation consisting of objective function and constraints.

9.3.1/ INDICES, PARAMETERS, AND SETS

INDICES :

The indices of the model are as follows :

i :Employee ;

j *and* k :Patient ;

p :Period ;

d :Day ;

s :Service ;

PARAMETERS :

The parameters of the studied problem which must be given to the model as the constant values or matrices are presented as :

m :Number of employees ;

n :Number of patients ;

h :Number of working-periods per day ;

t :Number of days in the planning horizon ;

r : Maximum number of services which can be assigned to an employee during a day ;

NP :The maximum number of periods on which one employee is authorized to work during a working-day.

INT_{jpd} : Matrix of the services needed by the patients ; e.g. if patient j needs a service in period p of day d, the corresponding INT is equal to 1; Otherwise is equal to 0.

DIS_{jk} : The distance between patient j and patient k.

SETS

A variation range must be defined for each index (dimension) of the model. This range is predetermined by the sets as follows :

$I = \{1, 2, ..., m\}$: Set of employees ;

$J = \{1, 2, ..., n\}$: Set of patients ;

$P = \{1, 2, ..., h\}$: Set of periods during a day ;

$D = \{1, 2, ..., t\}$: Set of days during the planning horizon ;

$S = \{1, 2, ..., r\}$: Set of services needed by the patients.

9.3.2/ Decision variables

The variables are the elements of the model which must be optimally determined by solving the model. The objective of the model depends on the values of the variables. The variables of the proposed model are as follows :

x_{ijpd} : Binary ; equals to 1 if employee i is assigned to patient j in period p of day d ; otherwise 0.

w_{ijpd} : Binary ; equals to 1 if period p of day d is the first period of a service needed by patient j and this service is assigned to employee i ; otherwise 0.

y_{ijpd} : Integer ; if period p of day d is the first period of a service needed by patient j which is done by employee i, it presents the ordinal number of services which employee i carries out during day d. For example, if a service is the 3rd service of employee i during day d and this service is for patient j and it starts in period p, in consequence, $y_{ijpd} = 3$;

u_{ijds} : Binary, equals to 1 if s^{th}service of employee i in day d is on patient j ; Otherwise 0.

T_{ijkds} : Binary, equals to 1 if employee i has a travel from patient j to patient k after his s^{th}service ; (He is assigned to patient j as the s^{th}service and he is assigned to patient k as the $(s+1)^{th}$service).

TI_{id} : The distance travelled by employee i during day d.

TD_i : The distances travelled by employee i during the planning horizon. (Sum of the daily travel distances for each employee)

TI^{max} : Maximum distance travelled by an employee during one day.

TD^{max} : Maximum distance travelled by an employee during the planning horizon.

TT : Total distance travelled by all of the employees during the planning horizon. (Total planning distance)

9.3.3/ Objective functions

The objective functions of the model are the intended purpose of the problem which is modelled mathematically. Three objectives are considered in the studied problem as follows :

$$Objective\ 1 :\ Minimize\ Z^1 = TT \tag{9.1}$$

$$Objective\ 2 :\ Minimize\ Z^2 = TI^{max} \tag{9.2}$$

$$Objective\ 3 :\ Minimize\ Z^3 = TD^{max} \tag{9.3}$$

The first objective function (Z^1) aims at minimizing the total planning distance ; e.g. the sum of the daily distances travelled by all of the employees for all of the planning days. The second objective function (Z^2) aims at minimizing the maximum distance travelled by one employee during a day. The aim of the third objective function (Z^3) is to minimize

the maximum distance travelled by one employee during the planning horizon. The characteristics of the three objectives and their related advantages and inconveniences are explained as follows :

— First objective : Various proposal assignments (plannings) can be easily compared by using the value of this objective. It does not consider the balancing of the travel distance among the employees.
— Second objective : It results in a balanced travel distance among the employees every day ; But it does not consider the total or daily travel distance of the planning.
— Third objective : Employing this objective leads to the balanced total distances travelled by each employee on the planning horizon. It does not care about the daily distance of the employees and the total travel distance of the planning.

9.3.4/ CONSTRAINTS

The restrictions of the problem are mathematically formulated as the following constraints :

$$\sum_{i=1}^{m} x_{ijpd} = INT_{jpd} \quad \forall\, p \in P,\ j \in J,\ d \in D \tag{9.4}$$

$$\sum_{j=1}^{n} x_{ijpd} \leq 1 \quad \forall\, j \in J,\ p \in P,\ d \in D \tag{9.5}$$

$$\sum_{j=1}^{n} \sum_{p=1}^{h} x_{ijpd} \leq NP \quad \forall\, i \in I,\ d \in D \tag{9.6}$$

$$x_{ijpd} + \sum_{k \in J-j} x_{ik(p+1)d} \leq 1 \quad \forall\, i \in I,\ j \in J,\ p \in P^{-},\ d \in D \tag{9.7}$$

$$x_{ijpd} + \sum_{l \in I-i} x_{lj(p+1)d} \leq 1 \quad \forall\, i \in I,\ j \in J,\ p \in P^{-},\ d \in D \tag{9.8}$$

$$w_{ijpd} = x_{ijpd} \times (1 - x_{ij(p-1)d}) \quad \forall\, i \in I,\ j \in J,\ p \in \{P \mid P \geq 2\},\ d \in D \tag{9.9}$$

$$w_{ij1d} = x_{ij1d} \quad \forall\, i \in I,\ j \in J,\ d \in D \tag{9.10}$$

$$y_{ijpd} = w_{ijpd} \times \sum_{k \in J} \sum_{q=1}^{p} w_{ikqd} \quad \forall\, i \in I,\ j \in J,\ p \in P,\ d \in D \tag{9.11}$$

$$\sum_{p=1}^{h} y_{ijpd} = \sum_{s=1}^{r} s \times u_{ijds} \quad \forall\, i \in I,\ j \in J,\ d \in D \tag{9.12}$$

$$\sum_{j=1}^{n} u_{ijds} \leq 1 \quad \forall\, i \in I,\ d \in D\ s \in S \tag{9.13}$$

$$\sum_{j=1}^{n} u_{ijd(s+1)} \leq \sum_{j=1}^{n} u_{ijds} \quad \forall\, i \in I,\ d \in D\ s \in S^{-} \tag{9.14}$$

$$T_{ijkds} = u_{ijds} \times u_{ikd(s+1)} \quad \forall\, i \in I,\ j \in J,\ k \in J,\ d \in D\ s \in S^{-} \tag{9.15}$$

$$TI_{id} = \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{s=1}^{r} DIS_{jk} \times T_{ijkds} \quad \forall\, i \in I,\ d \in D \tag{9.16}$$

$$TD_i = \sum_{d=1}^{t} TI_{id} \quad \forall\, i \in I \tag{9.17}$$

$$TD^{max} = Max_{i \in I}\{TD_i\} \tag{9.18}$$

$$TI^{max} = Max_{i \in I,\, d \in D}\{TI_{id}\} \tag{9.19}$$

$$TT = \sum_{d=1}^{t} \sum_{i=1}^{m} TI_{id} \tag{9.20}$$

The first set of constraints (equation 9.4) ensures that if a patient needs a service, one and only one employee is assigned to this service. Equation 9.5 guarantees that an employee can not be assigned to more that one patient in a period. The next set of constraints (equation 9.6) prevents the employees to work more than authorized working-hours during a day. The set of constraints presented in equation 9.7 ensures that if an employee works on a patient in a period, he can not work on another patient in the next period, because the model considers a travelling time of one period for the movement between two patient's homes. Hence, an employee can not start a service just after ending the previous service. The constraints 9.8 are about the services which last more than one period. These constraints ensure that if an employee is assigned to a period of a service, he will be assigned to other periods of this service. It means one and only one employee is assigned to a service even if the service lasts multiple periods. The equations 9.9 and 9.10 are the non-linear constraints that imply a change in the decision variables and introduce a set of novel variables for the next steps. These binary variables (w_{ijpd}) represent only the first period of the assigned services. The constraints 9.11 produce another set of integer variables (y_{ijpd}) that shows the ordinal number of the services which are done by an employee during a day. For example, $y_{1274} = 3$ signifies that employee 1 is assigned to

patient 2 in the 7th period of day 4 as his 3rd daily task. The index of period in these variables signifies only the starting period of a service. It means, in the mentioned example, if a service last three periods as 7, 8 and 9 ; then $y_{1274} = 3$ but $y_{1284} = 0$ and $y_{1294} = 0$. The constraints 9.12 and 9.13 carry out a change of variable from y_{ijpd} (assignment of the employees to the periods of day) to u_{ijds}(assignment of employees to the services) which are the binary variables. As an example, "$u_{1234} = 1$" implies that the 4^{th}service assigned to employee 1 during day 3 is on the patient 2. The constraints 9.14 ensure the ordinal nature of the variables u_{ijds} on index s. It means for an employee in each day, second service can not be on while his first service in this day is off.

Note that all changes in the variables from the x_{ijpd} to the u_{ijds} are carried out to integrate the vehicle routing problem in the assignment model. Now, by using the variables u_{ijds}, the sequence of the patients which are visited by an employee can be obtained. Thus, the distance travelled by every employees in each day and during the whole of the planning horizon is calculated. The equation 9.15 formulates a set of variables that represent the travels between two services for each employee. In this model, the variables T_{ijkds} perform the transferring phase from the assignment problem to the vehicle routing problem. Hence, these constraints imply that an employee's movement occurs once two consecutive services are on two different patients. Thus, the employee must travel from the first patient to the second one. By equation 9.16, the daily distance travelled by each employee is calculated. The total distance travelled by each employee during the planning horizon is calculated by equation 9.17. The constraints 9.18 and 9.19 respectively represent the maximum of the total distance and the daily distance traveled by one employee. Finally, constraints 9.20 indicate the total planning distance which is obtained by the sum of the employees' travelling distances.

The mathematical model presented above aims to minimize the travel distances by considering the routing and assignment constraints together with additional constrains of the studied problem.

9.4/ Discussion

This chapter concerned the human resource planning in a home healthcare system. This planning problem has been considered as a combination of the generalized assignment and vehicle routing problems. In the assignment phase, the staff members are assigned to the patients (needed services by the patients), and in the vehicle routing phase, the sequence of patients is determined for each staff. At first, the description of the problem was presented in detail. Then, a mixed-integer mathematical model composed of both aspects of the problem was proposed in a united form. The elements of the model, as the parameters, variables, objective functions and constraints were explained in the last section of this chapter. Three objective functions were considered in the problem formulation as follows : The total distance travelled by all of the staff members (Planning distance) ; The distance travelled by a staff member during a working-day ; The distance travelled by a staff member during the planning.

The united model presented in this chapter is an optimization approach that takes into account all aspects of the problem simultaneously in the same model. The high complexity of the model persuades us to apply an approximate approach to solve the studied problem, because the presented model is not able to solve large scale instances. To simplify

this model which is strongly NP-Hard, in the next chapter, a matheuristic optimization approach is presented for this problem that considers both aspects but in the different models as the steps of the approach.

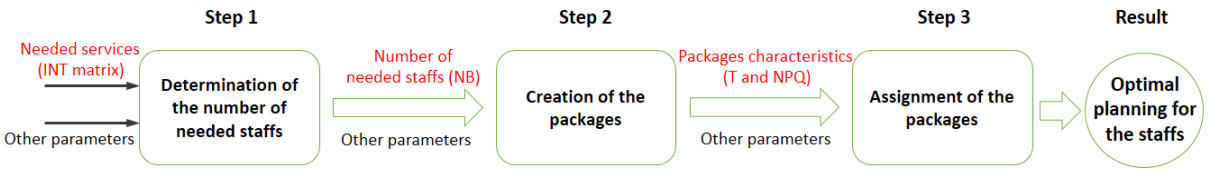
10

MATHEURISTIC APPROACH TO INTEGRATE AP AND VRP : DECOMPOSITION OF THE FORMULATION

10.1/ INTRODUCTION

In this study a matheuristic optimization approach containing three steps is proposed to optimize the home healthcare routing and scheduling problem. As mentioned before, the needed services is given to the optimization approach as a data. Other various parameters, as presented in section 9.3.1, must be defined by the users and given to the model. The first step of the algorithm aims to determine the number of staffs needed to cover all the required services. It takes the matrix of services (INT) and other parameters as the inputs, and the output of this step is the optimal number of required staffs (NB). The second step takes into consideration the number of staffs as the input and aims to create the daily packages (sets) of services by considering daily restrictions of the staffs. In this study, a daily package of services implies a set of services which should be assigned to an employee during a day. Hence, the results of this step are the packages of services and their characteristics. Two most important characteristics of the packages are the travel distance T_{qd} and the number of working-periods (working-hour) NPQ_{qd} attributed to each package. These results are used by the third steps as the input. The third and last step of the algorithm is to assign each daily package to a staff. As an example, if a staff is assigned to the first package in the first day and the travel distance of this package is $50km$, and in the second day he is assigned to the package number three with the travel distance of $25km$, the travel distance on the planning horizon of two day for this staff is $75km$. Figure 10.1 shows the steps of the proposed matheuristic algorithm.

FIGURE 10.1 – Matheuristic approach for the home healthcare planning



INT :

Period	Patient		
	J1	J2	J3
P1	1	0	0
P2	1	1	0
P3	0	1	0
P4	0	1	1
P5	1	0	1
P6	1	0	1

$\Longrightarrow SI$:

Period	Patient		
	J1	J2	J3
P1	1	0	0
P2	0	1	0
P3	0	0	0
P4	0	0	1
P5	1	0	0
P6	0	0	0

TABLE 10.1 – Matrix INT vs matrix SI

In the next sections, the presented steps of the algorithm is modeled mathematically by using MIP approach to be solved by the MIP solver.

10.2/ STEP 1 : DETERMINATION OF THE NUMBER OF NEEDED STAFFS

A Mixed-integer programming approach is employed to model this step. The elements of the model together with the model formulation is presented as follows.

10.2.1/ ADDITIONAL PARAMETERS

In addition to the parameters which were defined for the united model, another set of parameters is needed for the modelization of this step of the algorithm which is presented as follows.

SI : A matrix derived from the matrix of INT that shows only the first period of each service. The difference between matrix of services (INT) and matrix of SI is shown by a small example presented in table 10.1.

10.2.2/ VARIABLES

For this step of the algorithm, a number of variables that are different from those of the united model are defined as follows. C_{pd} : Number of employees needed in period p of day d to cover all of the services in this period. (Number of patients who need the service in period p of day d)

EP_d : Number of employees needed for covering the services in day d by considering the number of parallel services during the day.

ET_d : Number of employees needed for covering the services in day d by considering the authorized daily working-hours for the staffs.

NB : Number of staffs needed to cover all of the services during the planning horizon.

10.2.3/ Model Formulation

The objective of this step is to minimize the number of staffs needed for covering all services which is defined as follows :

$$Minimize\ NB = Max\{Max_d\{EP_d\},\ Max_d\{ET_d\}\}; \tag{10.1}$$

$Subject\ to$:

$$C_{pd} = \sum_{j \in J} INT_{jpd} + \sum_{j \in J} SI_{jp+1d} \quad \forall p \in P - \{h\},\ d \in D; \tag{10.2}$$

$$C_{pd} = \sum_{j \in J} INT_{jpd} \quad \forall p = h; \tag{10.3}$$

$$EP_d = Max_p\{C_{pd}\} \quad \forall d \in D; \tag{10.4}$$

$$ET_d = \sum_{p \in P} \sum_{j \in J} INT_{jpd}/NP \quad \forall d \in D; \tag{10.5}$$

The objective function of the presented model (equation 10.1) determines the minimum number of staffs by which the needed services during the whole planning horizon can be covered. The first and second sets of the constraints (10.2 and 10.3) determine the number of patients who need the service in each period. Hence, the periodic needed staffs is obtained. As mentioned before, the employees can not be assigned to another service just after ending a service because of the travelling time consideration. It means they need to travel from a patient to another and it takes one period. Therefore, for the calculation of the needed staffs in each period, the services which are started in the subsequent period (SI_{jP+1d}) must be considered as well. The constraints 10.4 signify that the daily needed staffs is obtained from the maximum periodic staffs during the day. As an example, for a day containing three periods, where 10, 12 and 9 staffs are needed for the first, second and third periods respectively ; the needed staffs for this day is equal to 12. The number of authorized working-hours for the employees is imposed to the model by constraints 10.5. According to this equation, the number of daily staffs is obtained by “total hours of the services which must be covered during the day” divided by “maximum number of authorized working-hours per day for each staff”. Hence, there are two variables that determine the minimum number of staffs needed for each day (EP_d, ET_d). The real number of daily staffs is the maximum of these variables for the relevant day. Similarly, the number of needed staffs to cover all the planning horizon is the maximum of the daily needs (as presented in the objective function).

After determination of the number of staffs, the packages of the services must be constructed. Each package is to be assigned to a staff. A package contains a number of services which are in the same day. Note that, the number of working-hours of a package must not exceed the maximum authorized working-hours of a staff. Furthermore, the number of packages in each day must not exceed the number of staffs. A mathematical model is presented to construct the daily packages of services as presented in following.

SI_{jpd} :

Period	Patient		
	J1	J2	J3
P1	1	0	0
P2	0	1	0
P3	0	0	0
P4	0	0	1
P5	1	0	0
P6	0	0	0

$\Longrightarrow$

SIN_{jpd1} :

Period	Patient		
	J1	J2	J3
P1	1	0	0
P2	0	1	0
P3	0	0	0
P4	0	0	1
P5	0	0	0
P6	0	0	0

SIN_{jpd2} :

Period	Patient		
	J1	J2	J3
P1	0	0	0
P2	0	0	0
P3	0	0	0
P4	0	0	0
P5	1	0	0
P6	0	0	0

TABLE 10.2 – Matrix SI vs matrix SIN

10.3/ STEP 2 : CREATION OF THE PACKAGES OF SERVICES

This step is mathematically modelled by applying the mixed-integer programming as follows. Note that, the number of staffs which was obtained in the previous step is used as the input (parameter) and is equivalent to the number of daily packages.

10.3.1/ ADDITIONAL PARAMETERS

NB : Number of staffs assigned to develop the planning. (This parameter is obtained in the first step)

SIN_{jpds} : A set of binary parameters which are derived from parameters SI_{jpd}; They present starting periods of the services in the order of the number of services for each patient. As an example, SIN_{jpd1}presents the first period of the first service of patient j in day d. It means if the service number s of patient j in day d is started at period p, therefore, $SIN_{jpds} = 1$; otherwise, $SIN_{jpds} = 0$. The transformation from parameters SI to parameters SIN is shown in table 10.2, by employing the example presented above.

DIS_{jk} : The distance between patients j and k.

PS_{jsd} : The length of the s^{th}service of patient j in day d. (In terms of number of periods)

NS : Maximum number of services which one employee is authorized to do during a working-day.

10.3.2/ ADDITIONAL SETS

$Q = \{1, 2, ..., NB\}$; Set of the packages of services ;

$L = \{1, 2, ..., NS\}$; Set of the services in one package ;

10.3.3/ ADDITIONAL VARIABLES

B_{qljsd} : Binary variables for representing the packages of services ; Where $B_{qljsd} = 1$, if the sth service of patient j in day d is considered as the lth service of package q ; and $B_{qljsd} = 0$ otherwise.

NPQ_{qd} : The number of working-periods for package q in day d. These variables present the working duration of the packages. For a package, the working duration is calculated by sum of the duration of the services which are placed in the package.

F_{qljkd} : Binary variables to represent the movements in every packages ; Where $F_{qljkd} = 1$, if the l^{th}service of package q in day d is on patient j and the $(l+1)^{th}$ service of this package is on patient k. It means, there is a movement from patient j to patient k after l^{th} service.

T_{qd} : The travel distance related to the package q during day d. It indicates the distance travelled by an employee during day d if he is assigned to package q in this day.

T^{max} : Maximum distance travelled of a package during a working-day. It presents the travel distance of the package with maximum movements.

10.3.4/ MODEL FORMULATION

$$Minimize\ T^{max} = Max_{qd}\{T_{qd}\} \tag{10.6}$$

$Subject\ to$:

$$\sum_{q\in Q}\sum_{l\in L} B_{qljsd} = \sum_{p\in P} SIN_{jpds} \quad \forall\ j \in J,\ n \in N,\ d \in D; \tag{10.7}$$

$$\sum_{j\in J}\sum_{s\in S} B_{qljsd} \leq 1 \quad \forall\ q \in Q,\ l \in L\ d \in D; \tag{10.8}$$

$$\sum_{l\in L}\sum_{j\in J}\sum_{s\in S} B_{qljsd} \geq 1 \quad \forall\ q \in Q,\ d \in D; \tag{10.9}$$

$$\sum_{l\in L}\sum_{j\in J}\sum_{s\in S} B_{qljsd} \leq NS \quad \forall\ q \in Q,\ d \in D; \tag{10.10}$$

$$\sum_{l\in L}\sum_{j\in J}\sum_{s\in S} B_{qljsd} \times PS_{jsd} \leq NP \quad \forall\ q \in Q,\ d \in D; \tag{10.11}$$

$$NPQ_{qd} = \sum_{l\in L}\sum_{j\in J}\sum_{s\in S} B_{qljsd} \times PS_{jsd} \quad \forall\ q \in Q,\ d \in D; \tag{10.12}$$

$$\sum_{j\in J}\sum_{s\in S} B_{q1jsd} \geq \sum_{j\in J}\sum_{s\in S} B_{(q+1)1jsd} \quad \forall\, q \in Q - \{NB\},\ d \in D; \tag{10.13}$$

$$\sum_{j\in J}\sum_{s\in S} B_{qljsd} \geq \sum_{j\in J}\sum_{s\in S} B_{q(l+1)jsd} \quad \forall\, q \in Q,\ l \in L - \{NS\},\ d \in D; \tag{10.14}$$

$$F_{qljkd} \leq \sum_{s\in S} B_{qljsd} \qquad \forall\, q \in Q,\ l \in L,\ j,k \in J,\ d \in D; \tag{10.15}$$

$$F_{qljkd} \leq \sum_{s\in S} B_{q(l+1)ksd} \qquad \forall\, q \in Q,\ l \in L - \{NS\},\ j,k \in J,\ d \in D; \tag{10.16}$$

$$F_{qljkd} \geq \sum_{s\in S} B_{qljsd} + \sum_{s\in S} B_{q(l+1)ksd} - 1 \quad \forall\, q \in Q,\ l \in L - \{NS\},\ j,k \in J,\ d \in D; \tag{10.17}$$

$$T_{qd} = \sum_{l\in L}\sum_{j\in J}\sum_{k\in J} F_{qljkd} \times DIS_{jk} \quad \forall\, q \in Q,\ d \in D; \tag{10.18}$$

The mathematical model aims to balance the travel distances of the packages. For that purpose, a mini-max equation (10.6) is proposed to formulate this target mathematically ; where T_{qd} presents the travel distance related to package q in day d. The objective function of the model minimizes the maximum travel distance of the packages. The first set of constraints (10.7) ensures that each one of the services is assigned to the packages. The second set (10.8) guarantees that each position of a package must be attributed to maximum one service. The constraints 10.9 signifies that every packages must contain at least one service per day. This assumption means that no one of the daily packages is empty. The number of services in each packages is limited by the constraints 10.10. By this equation a package in each day can not contain more than authorized number of services. For this restriction, parameter NS is employed because each daily package must be assigned to an employee. In addition to restricting the number of services, the working duration of the packages must be limited. This restriction is imposed to the model by equation 10.11, where parameter PS indicates the duration of the services and NP the maximum authorized working periods for a staff during a day. As mentioned before, a package is equivalent to a working day of a staff. Accordingly, for the package limitations, we use the same parameters as the staffs' ones such as NS and NP which were presented in the previous sections. The constraints 10.13 signify the order of precedence for allocating the packages to the services. According to this equation, the second package can not be allocated before the first package, the third one can be allocated after the second package and so on. Similarly, the constraints 10.14 guarantee the order of assignment of the positions inside a package. It means, in a package, the first position is assigned before the second position and the third one after the second and so on. The

next three sets of constraints (10.15, 10.16 and 10.17) define the variables of movement (F_{qljkd}) inside the packages. These equations signify that there is a movement between patients j and k after the lth service of package q ($F_{qljkd} = 1$) if and only if the lth position of package q is assigned to a service of patient j and the the $(l+1)^{th}$ position of this package is assigned to a service of patient k. The travel distance of the packages is calculated by equation 10.18, where any movement is multiplied by its corresponding distance. Hence, a travel distance is attributed to each package in each day.

In this step of our modelization approach, the packages of services are formed. In each day of the planning, the number of packages must be equal to the number required staff (NB) which is calculated in the first step of the algorithm. The next and the final step concerns the assignment of daily packages to the employees.

10.4/ STEP 3 : ASSIGNMENT OF THE PACKAGES TO THE STAFF MEMBERS

The third step of the proposed approach is to assign the packages of services to the employees. Two sets of variables as T_{qd} and NPQ_{qd} which are obtained in the previous section, are employed as the parameters in this step. Each employee is allocated to a package in each day. The objective is to balance the total distance travelled by each staff during the planning horizon. The mixed-integer programming approach is employed to model this step which is presented as follows.

10.4.1/ ADDITIONAL PARAMETERS

T_{qd} : Travel distance corresponding to package q in day d.

NPQ_{qd} : Number of working-periods of package q in day d.

H : Coefficient for conversion number of periods to number of hours. Here $H = 1$ implies that one period is equivalent to an hour.

10.4.2/ ADDITIONAL VARIABLES

A_{iqd} : Binary decision variables for representing the assignment of packages to the employees ; Where $A_{iqd} = 1$, if package q is assigned to employee i in day d and $A_{iqd} = 0$, otherwise.

TI_{id} : The distance travelled by employee i in day d. These variables present the daily movement of the staffs.

TD_i : The distance travelled by employee i during whole planning horizon.

TT : Total travel distance of the planning. (The sum of the distances travelled by the employees on whole the planning)

TD^{max} : Maximum total distance travelled by an employee during the planning horizon.

TI^{max} : Maximum daily distance travelled by an employee.

10.4.3/ MODEL FORMULATION

$$Objective\ 1:\ Minimize\ ZA^1 = TT \tag{10.19}$$

$$Objective\ 2:\ Minimize\ ZA^2 = TI^{max} \tag{10.20}$$

$$Objective\ 3:\ Minimize\ ZA^3 = TD^{max} \tag{10.21}$$

$Subject\ to:$

$$\sum_{i \in I} A_{iqd} = 1 \quad \forall\, q \in Q,\ d \in D; \tag{10.22}$$

$$\sum_{q \in Q} A_{iqd} \leq 1 \quad \forall\, i \in I,\ d \in D; \tag{10.23}$$

$$\sum_{d \in D} \sum_{q \in Q} A_{iqd} \leq ND \quad \forall\, i \in I; \tag{10.24}$$

$$\sum_{d \in D} \sum_{q \in Q} A_{iqd} \times NPQ_{qd} \times H \leq UH \quad \forall\, i \in I; \tag{10.25}$$

$$\sum_{d \in D} \sum_{q \in Q} A_{iqd} \times NPQ_{qd} \times H \geq LH \quad \forall\, i \in I; \tag{10.26}$$

$$TI_{id} = \sum_{q \in Q} T_{qd} \times A_{iqd} \quad \forall\, i \in I,\ d \in D; \tag{10.27}$$

$$TD_i = \sum_{d \in D} TI_{id} \quad \forall\, i \in I; \tag{10.28}$$

$$TI^{max} = Max_{i \in I,\, d \in D}\{TI_{id}\}; \tag{10.29}$$

$$TD^{max} = Max_{i \in I}\{TD_i\}; \tag{10.30}$$

$$TT = \sum_{i \in I} TD_i; \tag{10.31}$$

The third and last step of the algorithm is to assign the daily packages of services to the employees in an optimal manner. For this optimization sub-problem, a mathematical model based on the assignment problem (AP) has been proposed. The objectives of this model (equations 10.19, 10.20, 10.21) are the same as the united model presented in section 9.3, to compare our matheuristic approach with the exact algorithm. The first and

second sets of constraints (10.22, 10.23) are the classical constraints of the assignment problem. The equation 10.22 signifies that each one of the daily packages must be assigned to one and only one employee and the equation 10.23 implies that the staffs are not authorized to do more than one package of services during a working-day. It means an employee is either in his working-day and thus he is allocated to one package of services, or in his off-day hence no package is assigned to him. The third set of constraints (10.24) implies that the proposed assignment problem is an extended version named sequencing assignment problem. These constraints indicate that the problem concerns a sequence of assignments (one for each day) and each staff must work during a limited number of days. It is assumed that the employees have a number of working days and a number of off-days during the planning horizon.

The constraints 10.25 and 10.26 concern the limitation on the number of working-hours per day. Its guarantee the respect of the maximum and minimum limits on the working-hours for each staff during his working-days. The equation 10.27 is to calculate the distance travelled by each staff during a day. It is calculated by using the distance of the daily package which is assigned to the staff. Note that, the distance attributed to each package was obtained in the previous step of the algorithm. Similarly, the total distance travelled by an employee during the planning horizon is obtained by equation 10.28. It is calculated by the sum of the daily distances travelled by the employee. Finally, the equations 10.29 , 10.30 and 10.31 concern the objective functions calculations. Note that, the planning distance (TT) in this model is obtained from the sum of the operators' distances travelled on the whole of the planning.

The output of this step, as the last step of the algorithm, is the solution of the studied human resource planning problem. This solution defines the best (not necessarily optimal) planning for the staff members and presents the objective values of the planning.

10.5/ Discussion

The procedure of the presented matheuristic approach was developed in an interface by using the Gurobi solver. The interface extracts the solution of each step and converts them to the parameters to be used in the next step. The mathematical model of each step is programmed by using the GMPL language and the solution of each step is obtained by solving the GMPL model employing the Gurobi solver. The parameters of the first step of this approach are almost the same as the parameters of the united model presented in the previous chapter. They are the main parameters of the problem. The output of the first step of the algorithm together with some of the main parameters constitute the parameters of the second step. Likewise, the output of the second step constitutes a part of the parameters of the third step. The output of the third step, as the last step of the algorithm, is the solution of the problem which is obtained by this approach.

In the next chapter, the proposed algorithm is evaluated on a set of instances of different sizes and compared with the united model which was presented in the previous chapter. In fact, solving the united model by using the Gurobi solver, as the exact method, obtains the optimal solution of the problem. In this way, the proposed matheuristic, which is an approximate optimization approach, is compared with the optimal solution obtained by the exact method.

11

NUMERICAL EXPERIMENTS FOR THE HHC PLANNING PROBLEM

In this part, a set of real data is employed to be used in our optimization approach. Knowing that the results of the evaluation of an approach by one sample is not reliable, a Monte Carlo Simulation (MCS) is performed to simulate the instances of various sizes. The planning of the staffs of a home healthcare company is considered to be optimized by employing two proposed methods : the united mixed-integer model and the matheuristic approach. Table 9.1 presented in section 9.2 as a part of the data given by the company is used as the basis for simulation more instances of required services.

Based on this sample, we have generated 31 instances of different sizes. The three parameters considered for the instance generation are : 1. The number of days for the planning, 2. The number of considered patients and 3. The number of employees. The variation domain of the simulation parameters is presented in table 11.1.

Variation domain for the simulation parameters	
Parameter	*Variation domain*
Duration of the planning (per day)	2-14
Number of patients	10-30
Number of employees	4-10

TABLE 11.1 – Variation domain for the simulation parameters

In the presented study, two optimization approaches are proposed to model and optimize the planning of the home healthcare staffs during a given period. The efficiency of the both methods are analyzed and compared by the simulated instances. The comparison is carried out based on the objective function values and the computational time needed for solving the problem. The mathematical model of two approaches contain three different objective functions. All three objectives present the travel distance as introduced in section 9.3. Applying the optimization approach on the considered problem results in an optimal planning for the staffs and an organized program of the visits for the patients.

11.1/ CASE STUDY

11.1.1/ PLANNING FOR THE STAFF MEMBERS

As an example, the planning of a given day to cover ten patients by employing four employees is shown in table 11.2.

Planning of 4 home healthcare staffs to cover 10 patients during a given day															
Day	*Period*	*Patient*										*Employee*			
		J1	*J2*	*J3*	*J4*	*J5*	*J6*	*J7*	*J8*	*J9*	*J10*	*I1*	*I2*	*I3*	*I4*
D1	P1	I1		I2			I3					J1	J3	J6	
	P2							I4							J7
	P3				I1							J4			
	P4								I2				J8		
	P5								I2				J8		
	P6	I4		I1				I3				J3		J7	J1
	P7			I1								J3			
	P8														
	P9							I3	I2				J8	J7	
	P10							I3	I2	I4			J8	J7	J9
	P11									I4					J9
	P12				I1							J4			
	P13														
	P14						I2	I3					J6	J7	

TABLE 11.2 – Planning of 4 home healthcare staffs to cover 10 patients during a given day

In this small instance, according to the patients columns of the table, the first patient ($J1$) needs two services in the first and sixth periods ($P1$, $P6$). The first service of this patient is performed by the staff number one ($I1$) and his second service is done by the staff number four ($I4$). The allocated staffs to the other patients are shown in this table in the same manner. On the other hand, the results can be displayed based on the staffs. The planning of the staffs for the considered instance is shown in the employees columns of this table. As can be seen, the first employee ($I1$) is allocated to four services in this day. The first service is on the patient number one ($J1$) and lasts one hour or one period. The second service on the patient four ($J4$) lasts one period, but his third service on the patient three ($J3$) takes two periods ($P6$, $P7$). Similarly, the planning of the other employees are presented in this table.

As mentioned before, the number of employees needed to cover all of the patients' services is not a given value but must be calculated. By employing the mathematical model presented in section 10.2, the minimum staff size for a given set of services is obtained. According to this model, for the first period of the considered example, four staffs are needed. The model considers the services of the treated period plus the services which are started in the next period (because of the trip time consideration). In this case, there are three services in the first period and one service which is started in the second period. For each period, the needed staff size must be calculated and the maximum one will be

the staff size needed for the planning. In the studied instance, the maximum staff size is attributed to the first period and is equal to four.

11.1.2/ ANALYSIS OF THE SOLUTIONS

The distances between every pair of patients are given by the company as the distance table and imposed to the model as the DIS_{jk} parameters presented in section 9.3. A segment of the distance table is presented in table 11.3.

TABLE 11.3 – The distances between every pair of patients

	J1	J2	J3	J4	J5	J6	J7	J8	J9
J2	14								
J3	12	10							
J4	5	5	8						
J5	12	19	12	12					
J6	16	10	20	12	9				
J7	6	19	14	20	7	10			
J8	14	19	6	15	19	9	11		
J9	8	12	10	12	19	6	9	19	
J10	5	20	15	5	15	17	18	16	18

The values in this table are per kilometer. As shown, the longest distance is between patients 2 and 10 which is $20km$ and the shortest one is $5km$ between patients 1 and 4, between 2 and 4, between 1 and 10, also between 4 and 10. By considering these values and according to the sequence of the patients assigned to the staffs (table 11.2), the distance traveled by each staff are calculated. Consequently, the values of the three objective functions of the proposed home healthcare scheduling model are calculated. By solving the model, the results of the optimization approach contains the optimal sequence of the patients to be visited and it's related distance to be crossed by each staff. For the mentioned example, the results are shown in table 11.4.

Numerical results of the case study								
Staff	*Sequence of patients*	*Services*	*Hours*	$TI_{id}\ (TI_{i1})$	TI^{max}	TD_i	TD^{max}	TT
I1	$J1 \rightarrow J4 \rightarrow J3 \rightarrow J4$	4	5	$5+8+8=21$	21	21	21	60
I2	$J3 \rightarrow J8 \rightarrow J8 \rightarrow J6$	4	6	$6+0+9=15$		15		
I3	$J6 \rightarrow J7 \rightarrow J7 \rightarrow J7$	4	5	$10+0+0=10$		10		
I4	$J7 \rightarrow J1 \rightarrow J9$	3	4	$6+8=14$		14		

TABLE 11.4 – Numerical results of the case study

This table shows the results of the planning for a duration of one day. The objective of the planning is to minimize three different criteria as TI^{max}, TD^{max} and TT. In fact, the optimization approach determines the best sequence of patients for each staff so that all of the needed services are covered with a minimum travel distance. In addition, there are various other considerations such as the daily and weekly working-hours, working-day and off-days, trip time,... As shown in the results of the mentioned example (table 11.4), during the given day, the staff 1 $(I1)$ performs 4 services and works for 5 hours. He has 3 trips, the first is from patient one $J1$ to patient four $(J4)$, second is from patient four to

patient three ($J3$) and the third is from patient three to patient four. The total displacement for this staff during the studied day (TI_{id}) is $21km$. The trip distances during this day for other staffs are respectively, 15, 10, and $14km$. The planning horizon of the studied instance is one day, and hence the criterion TD_i, which is obtained by the sum of the daily displacement, is equal to the criterion TI_{id} ; ($TD_i = \sum_{d \in D} TI_{id}$, & $D = \{1\} \implies TD_i = TI_{id}$). The maximum trip distance is for staff number one with $21km$ and the planning distance (TT), which is the sum of the distances travelled by all of the staffs, is $60km$.

11.2/ COMPUTATIONAL RESULTS

As mentioned before, for solving such combinatorial optimization problems, which are composed of the assignment and routing problems, two solution approaches are proposed in this research. At first, a united mixed-integer programming approach is presented and then a three steps matheuristic method is proposed as well. A set of simulated instances are produced and solved by both solution methods to compare them by considering all three objective functions separately. Three parameters as the planning horizon size, the number of patients and the number of staffs vary from one instance to another. Two criteria are used to compare the methods as the objective function value and the computational time. The computational time means the time needed to solve the instance. The computational results are presented in table 11.5. Note that, the increasing patient size do not necessarily lead to the higher staff size. The staff size must be calculated and it depends on the instance and the number of services that the patients need.

In this table, the columns of “Value” present the value of the objective function and the columns of “CT” present the Computing Time needed to solve the problem. The first instance concerns the planning of four staffs to cover the services required by tens patients over two days. In this instance, the maximum distance by an employee during a day (TI^{max}) is $51km$, and the maximum total distance travelled by an employee during the planning horizon, which in this instance is two days, (TD^{max}) is also $51km$. For this example, the optimal planning distance (TT), the distance travelled by all staffs during the whole planning horizon, is $119km$. Two solving approaches are employed as the “United MIP” and “Matheuristic”. The united MIP signifies the united Mixed-Integer Programming. The MIP model is solved by Gurobi, which is an exact MIP solver, and results in the optimal solution. The matheuristic is an approximate method to solve the problem more quickly. As can be seen in the table 11.5, for the first example, the matheuristic generates the optimal solution for the TI^{max} and TD^{max} with a considerable reduction in computing time. For the objective function TT, the matheuristic obtains a solution ($121km$) very closed to the optimal ($119km$), where the gap is less than 2%, but the computing time is reduced from three seconds to less than a second. Although the matheuristics are the approximate methods, in most of the studied random instances, our matheuristic generates the optimal solution as can be seen in the results. As an example, for the objective function TI^{max}, the matheuristic obtains the optimal solution for 30 instances among 31 random samples. The only case in which the matheuristic can not reach to the optimal is for the planning on 2 days, for 30 patients. Note that the unit of the computing times (CT) in table 11.5 is the second and the time limit for the solver is set at 10000 seconds. In certain instances, the solver is not able to find the optimal solution in the time limit such as the planning for the 30 patients over 2 days with considering the objective function TD^{max}.

Numerical results of the case study														
N°of Days	N°of Patient	N°of Staff	Objective function											
			TI^{max}				TD^{max}				TT			
			United MIP		Matheuristic		United MIP		Matheuristic		United MIP		Matheuristic	
			Value	*CT*	*Value*	*CT*	*Value*	*CT*	*Value*	*CT*	*Value*	*CT*	*Value*	*CT*
2	10	4	51	3s	51	1s	51	7s	51	1s	119	3s	121	$< 1s$
2	15	8	18	19s	18	7s	18	13s	18	7s	31	775s	31	7s
2	20	6	49	752s	49	22s	49	598s	49	23s	143	4133s	143	116s
2	30	10	> 63 < 64	$> 10^4$	64	7669	–	$> 10^4$	78	7670	–	$> 10^4$	–	$> 10^4$
3	10	4	82	$< 1s$	82	$< 1s$	108	1s	108	$< 1s$	312	1s	312	$< 1s$
3	15	6	32	4s	32	1s	32	7s	32	1s	69	5s	69	14s
3	20	6	65	54s	65	6s	65	289s	68	23s	199	8s	199	23s
3	20	7	75	30s	75	225s	75	2124s	82	417s	400	2048s	400	341s
3	20	8	57	2790s	57	331s	57	3004s	72	332s	–	$> 10^4$	–	$> 10^4$
3	20	9	32	1305s	32	886s	32	1551s	46	899s	–	$> 10^4$	–	$> 10^4$
4	10	4	48	1s	48	$< 1s$	48	1s	48	$< 1s$	118	1s	118	$< 1s$
4	15	4	45	2s	45	1s	65	31s	70	1s	249	2s	249	1s
4	15	5	69	10s	69	18s	73	190s	73	47s	325	19s	325	46s
4	15	6	95	451s	95	371s	95	466s	95	378s	574	2470s	574	312s
4	20	8	29	23s	29	12s	29	164s	29	13s	114	1115s	114	151s
5	10	4	70	2s	70	2s	106	157s	106	3s	371	4s	371	2s
5	15	6	55	360s	55	129s	98	4174s	98	261s	464	1501s	464	260s
5	20	9	40	820s	40	98s	62	4932s	63	100s	–	$> 10^4$	–	$> 10^4$
6	10	5	50	2s	50	1s	50	2s	50	2s	132	4s	132	2s
6	15	5	149	276s	149	1851	149	239s	158	132s	602	62s	602	143s
6	15	9	22	196s	22	45s	22	144s	22	46s	56	52s	56	31s
6	20	8	54	5613s	54	600s	–	$> 10^4$	–	$> 10^4$	517	10^4	517	5294s
7	10	5	41	5s	41	4s	41	8s	41	6s	122	7s	122	6s
7	15	6	43	71s	43	14s	–	$> 10^4$	76	62s	339	93s	339	61s
7	20	6	93	142s	93	96s	–	$> 10^4$	110	490s	617	56s	617	498s
10	10	5	31	3s	31	1s	31	4s	31	2s	40	4s	40	1s
10	15	7	48	615s	48	146s	–	$> 10^4$	–	$> 10^4$	445	7192s	445	854s
10	20	8	59	496s	59	365s	–	$> 10^4$	–	$> 10^4$	–	$> 10^4$	–	$> 10^4$
14	10	5	40	6s	40	4s	40	15s	40	5s	146	9s	146	4s
14	15	7	25	212s	25	72s	25	912s	25	74s	67	42s	67	55s
14	20	9	27	328s	27	151s	27	1383s	27	97s	149	629s	149	95s

TABLE 11.5 – Computational results

11.3/ STATISTICAL ANALYSIS

To evaluate the proposed matheuristic, a comprehensive analysis on the “proportion of optimal solutions which are obtained” and “the computational time needed to solve the problem”, is carried out. The results of this analysis is presented in tables 11.6 and 11.7.

Proportion of optimal solutions obtained				
Solution method	*Objective function*			*Total*
	TI^{max}	TD^{max}	TT	
United MIP	$30/31 = 96\%$	$25/31 = 80\%$	$26/31 = 83\%$	$81/93 = 87\%$
Matheuristic	$31/31 = 100\%$	$21/31 = 67\%$	$25/31 = 80\%$	$77/93 = 82\%$

TABLE 11.6 – Proportion of optimal solutions obtained

Percentage of best computational time obtained over all instances				
Solution method	*Objective function*			*Total*
	TI^{max}	TD^{max}	TT	
United MIP	$3/31 = 9\%$	$0/28 = 0\%$	$6/26 = 23\%$	$9/85 = 10\%$
Matheuristic	$28/31 = 91\%$	$28/28 = 100\%$	$20/26 = 77\%$	$76/85 = 90\%$

TABLE 11.7 – Percentage of best computational time obtained over all instances

Table 11.6 shows the number of instances for which each solution method obtains the optimal solution. Generally, for the studied instances, the united model is slightly more efficient than the matheuristic in this aspect, because it solved 81 instances to optimality (87%) whereas the matheuristic obtained the optimal solution for 77 instances (82%). The number of optimal solutions for different objective functions is presented separately. This table shows that for the considered instances, the matheuristic is very efficient for the objective function TI^{max}, because it solved all of the instances to optimality in the time limit defined for the solver and is less efficient for the objective function TD^{max}, because only 21 instances (67%) are optimally solved. On the other hand, another statistical analysis is performed on the computational times which is shown in table 11.7. According to this table, for the studied instances, the matheuristic approach is much more efficient than the united mixed-integer programming (MIP) approach because for 76 instances (90%), the matheuristic obtains the optimal solution more quickly than the united model. The analysis is made on the only instances that the optimal solutions are obtained in the time limit. As can be seen, for the objective function TI^{max}, all instances are solved to optimality, but for the TD^{max}, the number of considered instances is 28 and for the TT only 26 instances are solved in the time limit. The table 11.7 shows that for all 28 considered instances with the objective function TD^{max}, the matheuristic is more quickly than united model. For the objective function TI^{max}, only for 3 instances (9%) the united model obtains the optimal solution before the matheuristic.

Furthermore, as can be seen in table 11.5, the computational time needed to solve the problem varies depending on the duration of the planning, the number of patients and the number of staffs. Hence, an statistical analysis is made on the variation of the computational time considering each one of the mentioned parameters separately. At first, the assessment is performed based on the duration of the planning. Eight different lengths of duration are studied for the problem as shown in the results table : $2, 3, 4, 5, 6, 7, 10$, and 14. The variation of the computational times depending on the duration of the planning for both solving approaches is presented in figure 11.1. The analysis is made on the three objective functions (TI^{max}, TD^{max}, TT) separately. Note that, the computational time for each duration is calculated by the average of the CTs of the instances with considered duration. For example, the CT for the objective function TI^{max} corresponding to the duration 2 is obtained by : $(3+19+752)/3 = 258s$ for the united model, and $(1+7+22)/3 = 10s$.

In this example, the forth instance (30 patients) is not considered because the solver does not obtain the optimal solution in the time limit.

11.4/ COMPARISON OF SOLUTION METHODS

Figure 11.1a shows that for the objective function TI^{max}, the matheuristic method is always faster than the united model. Likewise, for two other objectives (figures11.1c and 11.1b), the matheuristic mostly obtains the optimal solution more quickly than united model. According to these figures, the variation of the computational time does not follow a specific model as a function of planning duration, but it can be concluded that the objective function TI^{max} is less time consuming for the solver than other objectives.

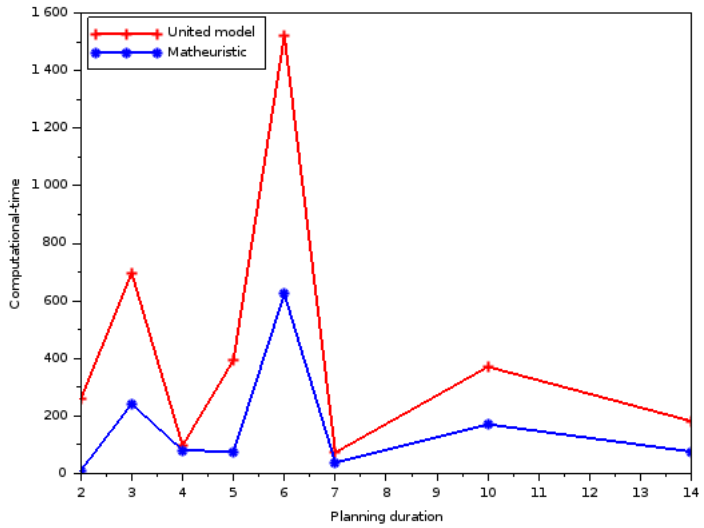
The second analysis on the computational time is made based on the number of patients. Because for each number of patients there are several instances, similar to the last analysis, the average values are considered for each number of patients. The instances with 10, 15, 20, and 30 patients are assessed and shown in figure 11.2.

After analysis of three different objectives, it can be concluded that the computational time needed to solve the problem highly increases with the number of patients. As three figures (11.2a,11.2b,11.2c) show, the computational times of the matheuristic are always lower than the united model for different numbers on patients. The difference between the CTs of two solution methods is significant mainly for the objective function TD^{max} (figure 11.2b). Another result which can be clearly seen, is the ability of the proposed approaches to solve the small and medium sizes (from the point of view of the number of patients) of the considered problem in the reasonable time. Figure 11.2a shows that the solution methods, especially the metheuristic, are very efficient for solving the problem with the objective TI^{max} for less than 20 patients. Similarly, figure 11.2c shows that the matheuristic is a effective method for the problem with objective TT with less than 15 patients.

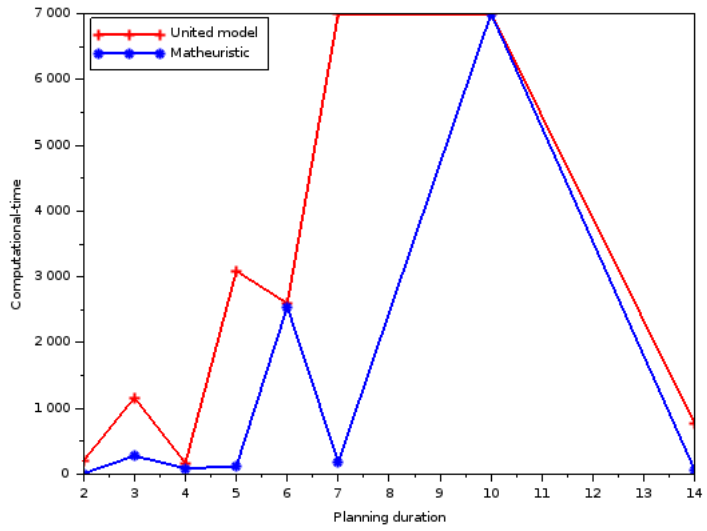
The third analysis is made on the variation of the computational time based on the number of staffs. As shown in the results table, the instances with $4, 5, 6, 7, 8, 9$ and 10 staffs are solved. The variation of CTs depending on the number of staffs by considering three different objectives are separately shown in figure 11.3.

This assessment shows that the computational times of the matheuristic with different number of staffs is mostly lower than the united model. According to the figure 11.3a, the solution approaches are highly efficient for solving the problem with the objective TI^{max}, while the number of staffs are lower than or equal to 9. The three figures 11.3a, 11.3b and 11.3c show the increase in the computational time with the increase in the number of staffs. Obtaining a function to model the variation of the CT depending on the number of staffs is overly complicated because the variations are irregular, but it can be concluded that the solution methods are not able to solve very large sizes of problem in the reasonable time. The figure 11.3c shows that the difference between matheuristic and united model, by considering the objective TT, for the medium instances is considerable but for the large instances they converge towards the same value. As a result, our proposed approaches, especially the matheuristic, are much more suitable if we consider the objective function TI^{max} for the problem.

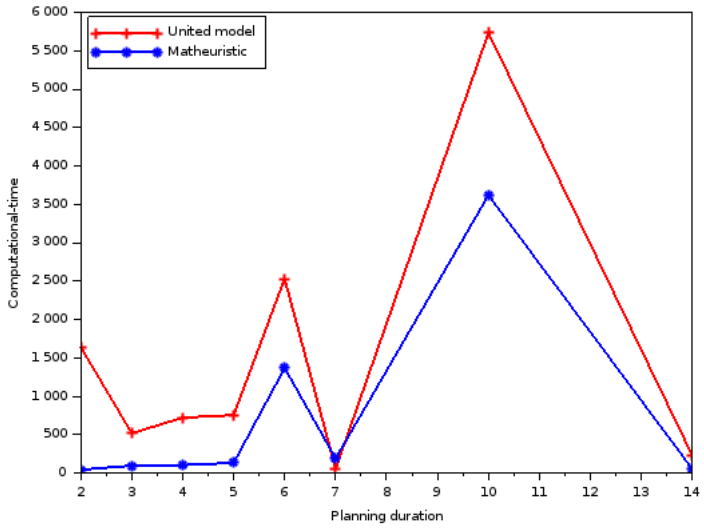
The two solution approaches proposed in this study, were evaluated by it's computational



(a) Analysis on the objective function TI^{max}]

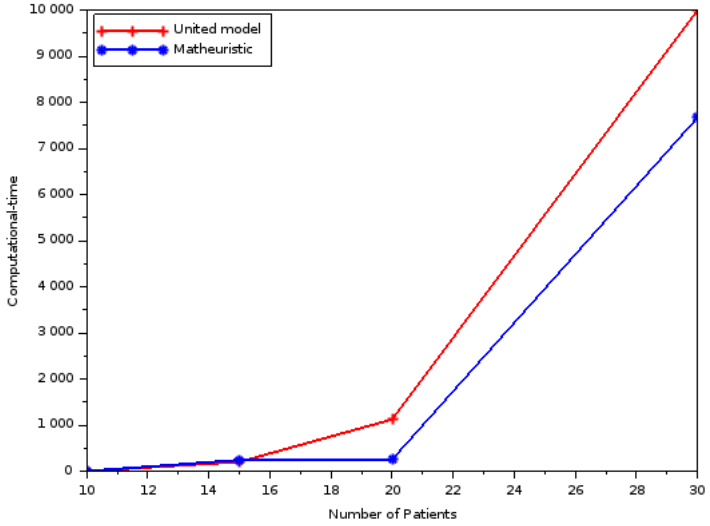


(b) Analysis on the objective function TD^{max}

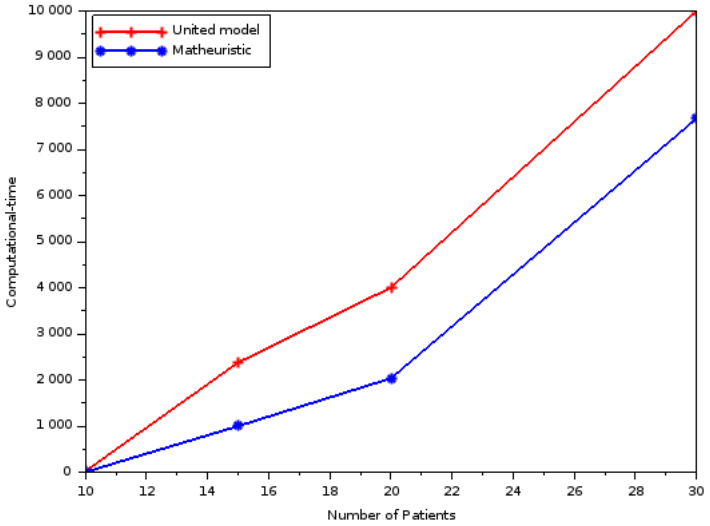


(c) Analysis on the objective function TT

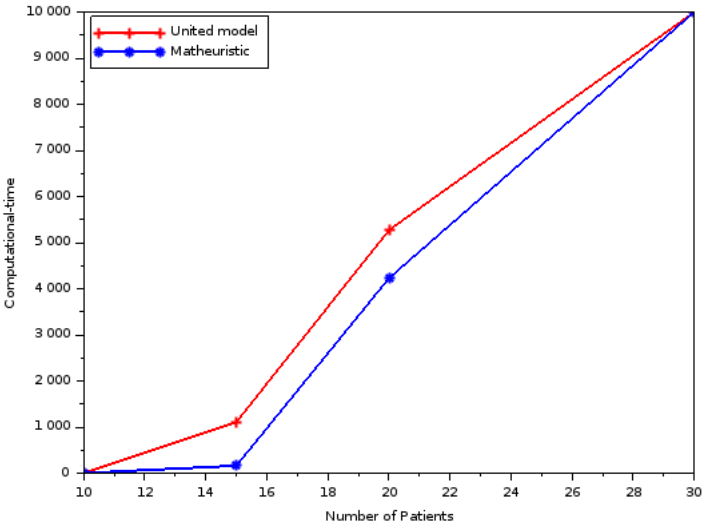
FIGURE 11.1 – Variation of the computational times depending on the planning duration



(a) Analysis on the objective function TI^{max}

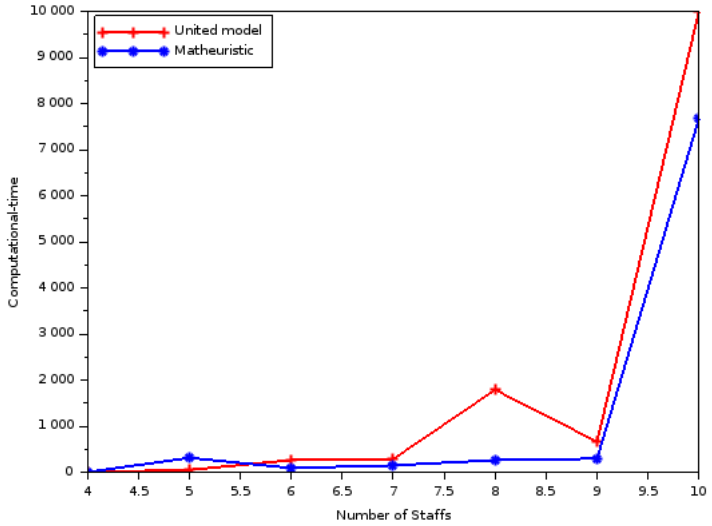


(b) Analysis on the objective function TD^{max}

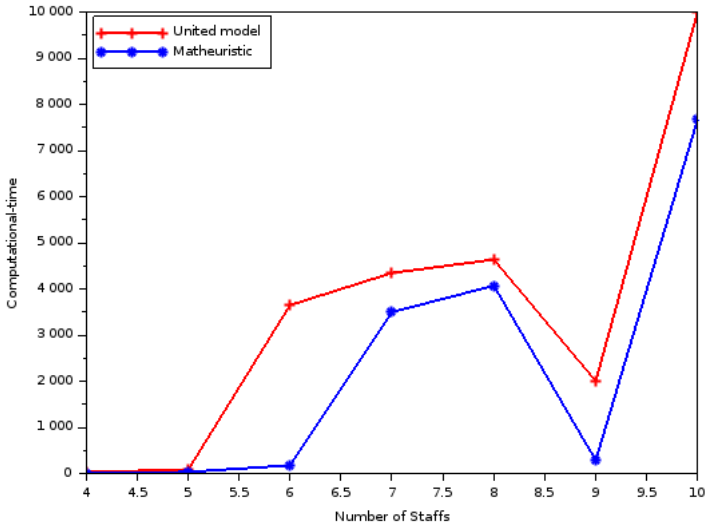


(c) Analysis on the objective function TT

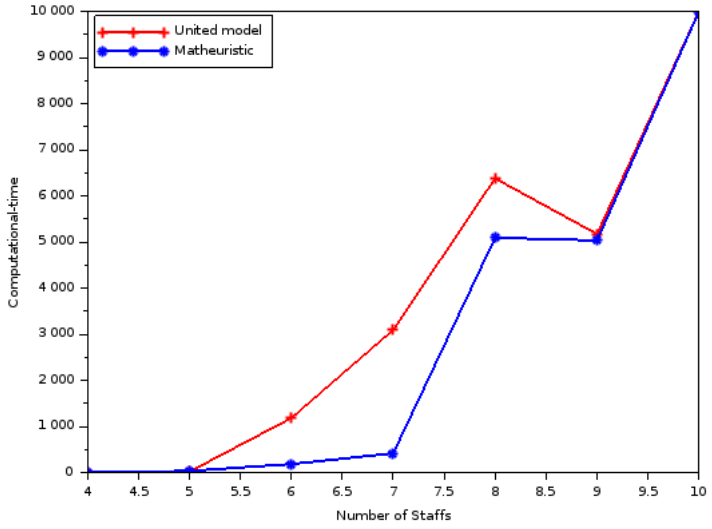
FIGURE 11.2 – Variation of the computational times depending on the number of patients



(a) Analysis on the objective function TI^{max}



(b) Analysis on the objective function TD^{max}



(c) Analysis on the objective function TT

FIGURE 11.3 – Variation of the computational times depending on the number of staffs

times on the 31 different instances. The variations of the computational time were analyzed as well in terms of the number of staffs, number of patients and the planning duration. The results show the efficiency of our matheuristic for the medium-size instances.

11.5/ CONCLUSION

The human resource planning in a home health care system was studied in this research. The targeted planning concerns the assignment of the staff members to the patients services for a duration of multiple days in which the patients services and consequently the staff assignment vary from a day to another. This problem was formulated by using the properties of the sequencing generalized assignment problem which is a novel variant of the assignment problem. Hence, a mixed-integer mathematical model was presented for the studied problem. This model contains two different aspects of the home health care planning problem : Assignment and Routing. In the assignment phase, the staff members must be assigned to the patients services. The sequence of patients, which must be visited by each staff, is determined in the routing phase. The consideration of the time in the assignment part of the model and also for determining the routes for the staffs is another contribution of this research. By this additional dimension, the proposed combinatorial model becomes greatly complicated. This research proposed a three-phases matheuristic approach based on the decomposition of formulation to simplify the studied optimization problem. The two programming approaches (combinatorial MIP model and matheuristic approach) were implemented by applying the GMPL programming language. The accuracy and the computational time of both methods were evaluated by 31 instances of different sizes. The Gurobi solver was applied to solve the instances. A statistical analysis were performed on the computational results. This analysis shows that both methods solve the problem to optimality for more than 80% of the studied instances. Obtaining the optimal solution for 82% of the instances by the proposed matheuristic, which is an approximate approach, proved the efficiency of this approach. Another statistical analysis on the computational times needed to solve the problem, were performed in this study. It shows that for 90% of the studied instances, the matheuristic approach is more efficient than the combinatorial MIP model in the computational time aspect.

IV

Conclusion and perspectives

This thesis contains three main parts as follows : 1. Worker assignment and job rotation considering ergonomic criteria ; 2. Workforce scheduling by using sequencing generalized assignment formulation ; 3. Integration of the worker assignment and vehicle routing problems. In the first part, a mathematical method is proposed to determine an ergonomic adequation level between jobs and workers in a manufacturing system. In this way, the personal capacities of the workers and the jobs requirements are analyzed by using the ergonomic criteria. Then, the linear utility functions are employed for determining the ergonomic appropriateness between operators and jobs. A regression analysis showed that this appropriateness has an impact on the efficiency of the workers. According to this analysis, the operating times of the workers in each job depend on their ergonomic compatibility with the job. To minimize the production time of the studied system, the most efficient worker must be assigned to each job. For this assignment problem, a mixed-integer mathematical model is presented in which the objective is to improve the productivity by considering the impact of the ergonomic factors on the efficiency of the workers. The model generates the optimal daily worker assignments for a given planning period (multiple days) by respecting the operator restrictions as well as the workstation and production constraints. It determines which worker performs which job in which working-day in an optimum manner. The numerical application illustrates that the ergonomic considerations in the job assignment has an important impact on the production cycle time.

In the second step of the first part, the objective of the worker assignment is changed. In this step, the assignment of the jobs to the workers is not based on their efficiency or their operating times, but it is based on the workload of the jobs. Actually, the workers are exposed to different workload levels by working in different jobs, because the studied manufacturing system is composed of the heterogeneous jobs from the ergonomic point of view. In comparison with the first step in which the productivity was targeted, second step aims at developing a job rotation planning to balance the daily physical workloads on the workers. Hence, the chapter 4 of this thesis presented a specific type of job rotation in which the rotations occur only inside the predefined groups. This strategy needs less cost and time for learning the staffs in comparison with the classical job rotation and balances the physical workloads exposed to the operators of each group. In this way, an ergonomic analysis was carried out for the jobs and the its physical workloads were evaluated by different ergonomic criteria. The workload levels were classified into high, medium and low categories. Afterwards, a mixed integer mathematical model was developed to obtain optimal sequences for the group job rotation by aiming to balance the daily physical workloads on the workers. Furthermore, the constraints of the proposed model prevent the operators to face the successive high workloads.

The proposed approach was applied to plan the workforce scheduling for a truck assembly line. The computational results and its related statistical analysis demonstrate that the workload scores are balanced among the operators. The model is well adaptable for other production and service systems to reduce the risks of the WMSDs and occupational diseases. The proposed job rotation method in this chapter can be favourable for the systems in which the skills required by different jobs are largely different.

As a result, in the workforce scheduling of chapter 3, the workload on the operators is ignored whereas in chapter 4, the efficiency of the workers and productivity are ignored. Hence, chapter 5 of this thesis proposed a multi-objective programming approach to balance the workloads on the operators and also improve the productivity by assigning most efficient workers to the jobs. Both productivity and ergonomic aspects are considered simultaneously in the workforce scheduling model which is presented in this chapter. In

fact, a job rotation platform for the studied manufacturing system has been implemented by developing a mathematical model. The integration of the worker assignment and the job rotation problems constructs a novel combinatorial optimization problem in the production domain. In this optimization problem is expanded by considering the heterogeneous workers, different task execution times for the workers, capability of the workers and different workload levels of the jobs. The production cycle time as the productivity and the daily workload as the ergonomic criteria have been targeted in the presented problem. By solving the mathematical model of the job rotation, the optimum sequence of jobs is obtained for each worker. Different scenario, according to the decision maker or user point of view, can be defined for this problem and for each scenario one or more optimum solution is calculated. The numerical application illustrated the adequacy and efficiency of the proposed mathematical model to optimize both objectives simultaneously. However, three different mathematical models for the human resource planning in manufacturing system with specific regard to the ergonomic considerations are developed in the first part of this thesis.

In the second part, according to the structure of the studied manufacturing system, the human resource planning is modelled based on the Generalized Assignment Problem (GAP). The GAP, as an enlarged variant of the assignment problem, is a well-known problem in the operational research domain. This adaptation helped us to well organize the structure of our human resource planning model. Because of the length of the planning horizon, which consists of multiple periods, the time dimension is also imposed to the assignment problem and the term sequencing generalized assignment problem (SGAP) is proposed for such problems. Moreover, two extra considerations are added to the classical generalized assignment problem. The first one is the restriction which is imposed on the working-days and off-days of the operators. The second consideration is the dynamics of the assignment which can be changed from a period to another. Because of these additional concerns, the problem is much more complicated than the classical GAP which is an NP-complete problem. The considered worker scheduling problem has been modelled using mixed integer programming by employing GAP structure. This model is solved by employing Gurobi mixed-integer solver for the various sizes of the problem. The solver, as an exact solving approach, is only able to solve the small-scale problems. Three approximate approaches have been proposed for solving such problems in the medium and large sizes. Hence, this thesis presented a hybrid heuristic and two matheuristic algorithms to solve GAP and SGAP. Various instances of different sizes are solved by three mentioned methods. The proposed approximate approaches have been completely analyzed by different factors and size of the instances. The computational results show the efficiency of the proposed approaches. These approximate algorithms present the solutions with a very slight deviation from the optimal ones. The numerical results demonstrate the great reduction in the computational time in comparison with the Gurobi solver.

After studying the human resource planning problem in the manufacturing system in the two first parts, this optimization problem was considered for a home healthcare system in the third part of this thesis. This planning problem concerns the assignment of the staff members to the patients services so that the distance travelled by the staffs would be minimized. The duration of the planning is multiple days in which the patients services and consequently the staff assignment vary from a day to another. This problem was formulated mathematically by using the properties of the SGAP which was presented in the second part of this thesis as a novel variant of the assignment problem. Considering the characteristics of the studied system, an integration of the SGAP with the Vehicle Rou-

ting Problem (VRP) was presented in this part. Hence, the proposed model contains two different aspects of the home health care planning problem : Assignment and Routing. In the assignment phase, the staff members were assigned to the patients services. The sequence of patients, which must be visited by each staff, is determined in the routing phase. This thesis proposes a three-phases matheuristic approach based on the decomposition of formulation to simplify the studied combinatorial optimization problem. The matheuristic algorithm was developed by applying the GMPL programming language. It's accuracy and computational time was evaluated by various instances of different sizes. The Gurobi solver was applied to solve the instances. A statistical analysis were performed on the computational results. This analysis shows the proposed method solve the problem to optimality for more than 80% of the studied instances. Obtaining the optimal solution for 82% of the instances by the proposed matheuristic, which is an approximate approach, proved the efficiency of this approach. Another statistical analysis on the computational times needed to solve the problem, were performed in this study. It shows that for 90% of the studied instances, the matheuristic approach is more efficient than the exact algorithm in the computational time aspect.

For the future works, three following axes are the possible directions to expand the researches which are carried out in this thesis. The first axis is the consideration of the human resource planning problem. In the first part of this thesis, a job rotation based on the workloads of the jobs was presented. In this way, considering the productivity factors into the job rotation model combined with the ergonomic issues may be an interesting axis for the future studies. On the other hand, we can consider uncertainty concerns for the estimation of the workload scores by employing the Fuzzy logic or Statistical approaches. The analyzing of the learning-forgetting effect and learning costs can be other ways as the further researches. Moreover, considering the the idle times for the workers and correlation between processing time and workload of the jobs can be studied as the futures works.

For the sequencing generalized assignment problem which is presented in the second part, the uncertainty considerations, fuzzy or stochastic SGAP and multi-objective consideration could be the interesting future research of this novel problem. In this thesis, the classical SGAP is solved by applying two mat-heuristic approaches. For the solving method, divers exact or approximated approaches (heuristics, combinatorial heuristics, meta-heuristics and hyper-heuristics) could be developed for the SGAP. With regard to the solving methods proposed for the GAP in the literature, developing a genetic algorithm, tabu search, Bees algorithm for the SGAP or it's extensions could be the interesting prospects for the future researches. A combinatorial heuristic containing one or more of the mentioned meta-heuristics may be another future solution approach for the SGAP. Furthermore, in the second part of this thesis, a hybrid heuristic algorithm is proposed to solve the GAPs and SGAPs. Developing and generalization of this algorithm and comparing that with the meta-heuristic approaches can be the interesting subjects of the future researches.

Reference

Akyol, S. D., et Baykasoğlu, A. (2016). **Ergoalwabp : a multiple-rule based constructive randomized search algorithm for solving assembly line worker assignment and balancing problem under ergonomic risk factors**. *Journal of Intelligent Manufacturing*, pages 1–12.

Alaei, S., Hajiaghayi, M., et Liaghat, V. (2013). **The online stochastic generalized assignment problem**. Dans *Approximation, Randomization, and Combinatorial Optimization. Algorithms and Techniques*, pages 11–25. Springer.

Alfares, H. K. (2002). **Optimum workforce scheduling under the (14, 21) days-off timetable**. *Advances in Decision Sciences*, 6(3) :191–199.

Allaoua, H., Borne, S., Létocart, L., et Calvo, R. W. (2013). **A matheuristic approach for solving a home health care problem**. *Electronic Notes in Discrete Mathematics*, 41 :471–478.

Aptel, M., Cail, F., Gerling, A., et Louis, O. (2008). **Proposal of parameters to implement a workstation rotation system to protect against msds**. *International Journal of Industrial Ergonomics*, 38(11) :900–909.

Asensio-Cuesta, S., Diego-Mas, J., Cremades-Oliver, L., et González-Cruz, M. (2012). **A method to design job rotation schedules to prevent work-related musculoskeletal disorders in repetitive work**. *International journal of production research*, 50(24) :7467–7478.

Azizi, N., Zolfaghari, S., et Liang, M. (2010). **Modeling job rotation in manufacturing systems : The study of employee's boredom and skill variations**. *International Journal of Production Economics*, 123(1) :69–85.

Baker, B. M., et Sheasby, J. (1999). **Extensions to the generalised assignment heuristic for vehicle routing**. *European Journal of Operational Research*, 119(1) :147–157.

Balogh, I., Ohlsson, K., Hansson, G.-Å., Engström, T., et Skerfving, S. (2006). **Increasing the degree of automation in a production system : consequences for the physical workload**. *International Journal of Industrial Ergonomics*, 36(4) :353–365.

Battini, D., Calzavara, M., Otto, A., et Sgarbossa, F. (2016a). **The integrated assembly line balancing and parts feeding problem with ergonomics considerations**. *IFAC-PapersOnLine*, 49(12) :191–196.

Battini, D., Delorme, X., Dolgui, A., Persona, A., et Sgarbossa, F. (2016b). **Ergonomics in assembly line balancing based on energy expenditure : a multi-objective model**. *International Journal of Production Research*, 54(3) :824–845.

Berlin, C., Örtengren, R., Lämkull, D., et Hanson, L. (2009). **Corporate-internal vs. national standard–a comparison study of two ergonomics evaluation procedures**

used in automotive manufacturing. *International Journal of Industrial Ergonomics*, 39(6) :940–946.

Botti, L., Mora, C., et Calzavara, M. (2017). **Design of job rotation schedules managing the exposure to age-related risk factors**. *IFAC-PapersOnLine*, 50(1) :13993–13997.

Braekers, K., Hartl, R. F., Parragh, S. N., et Tricoire, F. (2016). **A bi-objective home care scheduling problem : Analyzing the trade-off between costs and client inconvenience**. *European Journal of Operational Research*, 248(2) :428–443.

Bredström, D., et Rönnqvist, M. (2008). **Combined vehicle routing and scheduling with temporal precedence and synchronization constraints**. *European journal of operational research*, 191(1) :19–31.

Cattrysse, D. G., et Van Wassenhove, L. N. (1992). **A survey of algorithms for the generalized assignment problem**. *European journal of operational research*, 60(3) :260–272.

Chen, X., Thomas, B. W., et Hewitt, M. (2017). **Multi-period technician scheduling with experience-based service times and stochastic customers**. *Computers & Operations Research*, 82 :1–14.

Chiang, W.-C., Urban, T. L., et Luo, C. (2016). **Balancing stochastic two-sided assembly lines**. *International Journal of Production Research*, 54(20) :6232–6250.

Chiasson, M.-È., Imbeau, D., Aubry, K., et Delisle, A. (2012). **Comparing the results of eight methods used to evaluate risk factors associated with musculoskeletal disorders**. *International Journal of Industrial Ergonomics*, 42(5) :478–488.

Chu, P. C., et Beasley, J. E. (1997). **A genetic algorithm for the generalised assignment problem**. *Computers & Operations Research*, 24(1) :17–23.

Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C., et Matta, A. (2017). **Or problems related to home health care : A review of relevant routing and scheduling problems**. *Operations Research for Health Care*, 13 :1–22.

Cohen, R., Katzir, L., et Raz, D. (2006). **An efficient approximation for the generalized assignment problem**. *Information Processing Letters*, 100(4) :162–166.

Corréa, A. I., Langevin, A., et Rousseau, L.-M. (2007). **Scheduling and routing of automated guided vehicles : A hybrid approach**. *Computers & operations research*, 34(6) :1688–1707.

Cortez, P. M., et Costa, A. M. (2015). **Sequencing mixed-model assembly lines operating with a heterogeneous workforce**. *International Journal of Production Research*, 53(11) :3419–3432.

Costa, A. M., et Miralles, C. (2009). **Job rotation in assembly lines employing disabled workers**. *International Journal of Production Economics*, 120(2) :625–632.

Côté, J. N., Ngomo, S., Stock, S., Messing, K., Vézina, N., Antle, D., Delisle, A., Bellemare, M., Laberge, M., et St-Vincent, M. (2013). **Quebec research on work-related musculoskeletal disorders : deeper understanding for better prevention**. *INDUSTRIAL RELATIONS/RELATIONS INDUSTRIELLES*, pages 643–660.

Dalmeijer, K., et Spliet, R. (2018). **A branch-and-cut algorithm for the time window assignment vehicle routing problem**. *Computers & Operations Research*, 89 :140–152.

De Maio, A., et Roveda, C. (1971). **An all zero-one algorithm for a certain class of transportation problems**. *Operations Research*, 19(6) :1406–1418.

de Oliveira Sato, T., et Coury, H. J. C. G. (2009). **Evaluation of musculoskeletal health outcomes in the context of job rotation and multifunctional jobs**. *Applied ergonomics*, 40(4) :707–712.

Dıaz, J. A., et Fernández, E. (2001). **A tabu search heuristic for the generalized assignment problem**. *European Journal of Operational Research*, 132(1) :22–38.

Diego-Mas, J., Asensio-Cuesta, S., Sanchez-Romero, M., et Artacho-Ramirez, M. (2009). **A multi-criteria genetic algorithm for the generation of job rotation schedules**. *International journal of industrial ergonomics*, 39(1) :23–33.

Ehmke, J. F., Campbell, A. M., et Urban, T. L. (2015). **Ensuring service levels in routing problems with time windows and stochastic travel times**. *European Journal of Operational Research*, 240(2) :539–550.

Elshafei, M., et Alfares, H. K. (2008). **A dynamic programming algorithm for days-off scheduling with sequence dependent labor costs**. *Journal of Scheduling*, 11(2) :85–93.

En-nahli, L., Afifi, S., Allaoui, H., et Nouaouri, I. (2016). **Local search analysis for a vehicle routing problem with synchronization and time windows constraints in home health care services**. *IFAC-PapersOnLine*, 49(12) :1210–1215.

En-nahli, L., Allaoui, H., et Nouaouri, I. (2015). **A multi-objective modelling to human resource assignment and routing problem for home health care services**. *IFAC-PapersOnLine*, 48(3) :698–703.

Enderer, F., Contardo, C., et Contreras, I. (2017). **Integrating dock-door assignment and vehicle routing with cross-docking**. *Computers & Operations Research*, 88 :30–43.

Errarhout, A., Kharraja, S., et Corbier, C. (2016). **Two-stage stochastic assignment problem in the home health care**. *IFAC-PapersOnLine*, 49(12) :1152–1157.

Falck, A.-C., Örtengren, R., et Rosenqvist, M. (2014). **Assembly failures and action cost in relation to complexity level and assembly ergonomics in manual assembly (part 2)**. *International Journal of Industrial Ergonomics*, 44(3) :455–459.

Fallentin, N., Kilbom, Å., Viikari-Juntura, E., et Wærsted, M. (2000). **Evaluation of physical workload standards/guidelines from a nordic perspective**. Dans *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 44, pages 6–429. SAGE Publications.

Fikar, C., et Hirsch, P. (2017). **Home health care routing and scheduling : A review**. *Computers & Operations Research*, 77 :86–95.

Fisher, M. L., et Jaikumar, R. (1981). **A generalized assignment heuristic for vehicle routing**. *Networks*, 11(2) :109–124.

Fisher, M. L., Jaikumar, R., et Van Wassenhove, L. N. (1986). **A multiplier adjustment method for the generalized assignment problem**. *Management Science*, 32(9) :1095–1103.

Frazer, M., Norman, R., Wells, R., et Neumann, P. (2003). **The effects of job rotation on the risk of reporting low back pain**. *Ergonomics*, 46(9) :904–919.

Frifita, S., Masmoudi, M., et Euchi, J. (2017). **General variable neighborhood search for home healthcare routing and scheduling problem with time windows and synchronized visits**. *Electronic Notes in Discrete Mathematics*, 58 :63–70.

Fuller, J. R., Lomond, K. V., Fung, J., et Côté, J. N. (2009). **Posture-movement changes following repetitive motion-induced shoulder muscle fatigue**. *Journal of Electromyography and Kinesiology*, 19(6) :1043–1052.

Ghoniem, A., Flamand, T., et Haouari, M. (2016a). **Exact solution methods for a generalized assignment problem with location/allocation considerations**. *INFORMS Journal on Computing*, 28(3) :589–602.

Ghoniem, A., Flamand, T., et Haouari, M. (2016b). **Optimization-based very large-scale neighborhood search for generalized assignment problems with location/allocation considerations**. *INFORMS Journal on Computing*, 28(3) :575–588.

Goel, A., et Meisel, F. (2013). **Workforce routing and scheduling for electricity network maintenance with downtime minimization**. *European Journal of Operational Research*, 231(1) :210–228.

Grosse, E. H., Calzavara, M., Glock, C. H., et Sgarbossa, F. (2017). **Incorporating human factors into decision support models for production and logistics : current state of research**. *IFAC-PapersOnLine*, 50(1) :6900–6905.

Hassanzadeh, A., et Rasti-Barzoki, M. (2017). **Minimizing total resource consumption and total tardiness penalty in a resource allocation supply chain scheduling and vehicle routing problem**. *Applied Soft Computing*, 58 :307–323.

Huang, S.-H., et Pan, Y.-C. (2014). **Ergonomic job rotation strategy based on an automated rgb-d anthropometric measuring system**. *Journal of Manufacturing Systems*, 33(4) :699–710.

Hussin, M. S., et Stützle, T. (2017). **Hybrid simulated annealing for the bi-objective quadratic assignment problem**. Dans *International Workshop on Multi-disciplinary Trends in Artificial Intelligence*, pages 462–472. Springer.

Jonsson, B. (1988). **Electromyographic studies of job rotation**. *Scandinavian journal of work, Environment and Health*, 14 :108–109.

Jörnsten, K., et Näsberg, M. (1986). **A new lagrangian relaxation approach to the generalized assignment problem**. *European Journal of Operational Research*, 27(3) :313–323.

Kiraz, B., et Topcuoglu, H. R. (2010). **Hyper-heuristic approaches for the dynamic generalized assignment problem**. Dans *Intelligent Systems Design and Applications (ISDA), 2010 10th International Conference on*, pages 1487–1492. IEEE.

Klingman, D., et Stutz, J. (1974). **Computational testing on an integer generalized network code**. Dans *45th Joint National Meeting of the Operations Research Society and the Institute of Management Sciences, Boston, Mass.(April 1974)*.

Kuo, Y., Wang, C.-C., et Chuang, P.-Y. (2009). **Optimizing goods assignment and the vehicle routing problem with time-dependent travel speeds**. *Computers & Industrial Engineering*, 57(4) :1385–1392.

Laguna, M., Kelly, J. P., González-Velarde, J., et Glover, F. (1995). **Tabu search for the multilevel generalized assignment problem**. *European journal of operational research*, 82(1) :176–189.

Leider, P. C., Boschman, J. S., Frings-Dresen, M. H., et van der Molen, H. F. (2015). **When is job rotation perceived useful and easy to use to prevent work-related musculoskeletal complaints ?** *Applied ergonomics*, 51 :205–210.

Lin, M., Chin, K. S., Wang, X., et Tsui, K. L. (2016). **The therapist assignment problem in home healthcare structures**. *Expert Systems with Applications*, 62 :44–62.

MAHMOUDABADI, M. Z. (2015). **Représentation partagée des facteurs de risque des troubles musculosquelettiques et comparaison des méthodes d'évaluation : une étude expérimentale dans le secteur de l'assemblage de camions**. PhD thesis, Bretagne Loire University.

Manavizadeh, N., Hosseini, N.-s., Rabbani, M., et Jolai, F. (2013). **A simulated annealing algorithm for a mixed model assembly u-line balancing type-i problem considering human efficiency and just-in-time approach**. *Computers & Industrial Engineering*, 64(2) :669–685.

Mateus, G. R., Resende, M. G., et Silva, R. M. (2011). **Grasp with path-relinking for the generalized quadratic assignment problem**. *Journal of heuristics*, 17(5) :527–565.

Mathiassen, S. E. (2006). **Diversity and variation in biomechanical exposure : what is it, and why would we like to know ?** *Applied ergonomics*, 37(4) :419–427.

McKendall, A., et Li, C. (2017). **A tabu search heuristic for a generalized quadratic assignment problem**. *Journal of Industrial and Production Engineering*, 34(3) :221–231.

Michalos, G., Makris, S., Rentzos, L., et Chryssolouris, G. (2010). **Dynamic job rotation for workload balancing in human based assembly systems**. *CIRP Journal of Manufacturing Science and Technology*, 2(3) :153–160.

Miralles, C., Garcia-Sabater, J. P., Andres, C., et Cardos, M. (2007). **Advantages of assembly lines in sheltered work centres for disabled. a case study**. *International Journal of Production Economics*, 110(1-2) :187–197.

Miranda, D. M., et Conceição, S. V. (2016). **The vehicle routing problem with hard time windows and stochastic travel and service time**. *Expert Systems with Applications*, 64 :104–116.

Moccia, L., Cordeau, J.-F., Monaco, M. F., et Sammarra, M. (2009). **A column generation heuristic for a dynamic generalized assignment problem**. *Computers & Operations Research*, 36(9) :2670–2681.

Moons, S., Ramaekers, K., Caris, A., et Arda, Y. (2017). **Integrating production scheduling and vehicle routing decisions at the operational decision level : A review and discussion**. *Computers & Industrial Engineering*, 104 :224–245.

Moreira, M. C. O., et Costa, A. M. (2013). **Hybrid heuristics for planning job rotation schedules in assembly lines with heterogeneous workers**. *International Journal of Production Economics*, 141(2) :552–560.

Moussavi, S., Mahdjoub, M., et Grunder, O. (2016). **Reducing production cycle time by ergonomic workforce scheduling**. *IFAC-PapersOnLine*, 49(12) :419–424.

Moussavi, S., Mahdjoub, M., et Grunder, O. (2018). **A hybrid heuristic algorithm for the sequencing generalized assignment problem in an assembly line**. *IFAC-PapersOnLine*, 51(2) :695–700.

Moussavi, S.-E., Mahdjoub, M., et Grunder, O. (2017). **Productivity improvement through a sequencing generalised assignment in an assembly line system**. *International Journal of Production Research*, pages 1–15.

Narasimhan, R. (1997). **An algorithm for single shift scheduling of hierarchical workforce**. *European Journal of Operational Research*, 96(1) :113–121.

Niakan, F., Baboli, A., Moyaux, T., et Botta-Genoulaz, V. (2014). **A multi-objective mathematical model considering economic and social criteria in dynamic cell formation**. Dans *IFIP International Conference on Advances in Production Management Systems*, pages 46–53. Springer.

Osman, I. H. (1995). **Heuristics for the generalised assignment problem : simulated annealing and tabu search approaches**. *Operations-Research-Spektrum*, 17(4) :211–225.

Osorio, M. A., et Laguna, M. (2003). **Logic cuts for multilevel generalized assignment problems**. *European Journal of Operational Research*, 151(1) :238–246.

Othman, M., Gouw, G. J., et Bhuiyan, N. (2012). **Workforce scheduling : A new model incorporating human factors**. *Journal of Industrial Engineering and Management*, 5(2) :259.

Otto, A., et Scholl, A. (2011). **Incorporating ergonomic risks into assembly line balancing**. *European Journal of Operational Research*, 212(2) :277–286.

Otto, A., et Scholl, A. (2013). **Reducing ergonomic risks by job rotation scheduling**. *OR spectrum*, 35(3) :711–733.

Özbakir, L., Baykasoğlu, A., et Tapkan, P. (2010). **Bees algorithm for generalized assignment problem**. *Applied Mathematics and Computation*, 215(11) :3782–3795.

Özgüven, C., et Sungur, B. (2013). **Integer programming models for hierarchical workforce scheduling problems including excess off-days and idle labour times**. *Applied Mathematical Modelling*, 37(22) :9117–9131.

Padula, R. S., Comper, M. L. C., Sparer, E. H., et Dennerlein, J. T. (2017). **Job rotation designed to prevent musculoskeletal disorders and control risk in manufacturing industries : A systematic review**. *Applied Ergonomics*, 58 :386–397.

Posta, M., Ferland, J. A., et Michelon, P. (2012). **An exact method with variable fixing for solving the generalized assignment problem**. *Computational Optimization and Applications*, 52(3) :629–644.

Rasmussen, M. S., Justesen, T., Dohn, A., et Larsen, J. (2012). **The home care crew scheduling problem : Preference-based visit clustering and temporal dependencies**. *European Journal of Operational Research*, 219(3) :598–610.

Rattanamanee, T., et Nanthavanji, S. (2013). **Multi-workday ergonomic workforce scheduling with days off**. Dans *Proceedings of the 4th International Conference on Engineering, Project, and Production Management*, pages 1117–1125.

Rivière, S., Penven, E., Cadéac-Birman, H., Roquelaure, Y., et Valenty, M. (2014). **Underreporting of musculoskeletal disorders in 10 regions in france in 2009**. *American journal of industrial medicine*, 57(10) :1174–1180.

Roquelaure, Y., Ha, C., Leclerc, A., Touranchet, A., Sauteron, M., Melchior, M., Imbernon, E., et Goldberg, M. (2006). **Epidemiologic surveillance of upper-extremity musculoskeletal disorders in the working population**. *Arthritis Care & Research*, 55(5) :765–778.

Roshani, A., et Giglio, D. (2017). **Simulated annealing algorithms for the multi-manned assembly line balancing problem : minimising cycle time**. *International Journal of Production Research*, 55(10) :2731–2751.

Ross, G. T., et Soland, R. M. (1975). **A branch and bound algorithm for the generalized assignment problem**. *Mathematical programming*, 8(1) :91–103.

Rossi, D., Bertoloni, E., Fenaroli, M., Marciano, F., et Alberti, M. (2013). **A multi-criteria ergonomic and performance methodology for evaluating alternatives in “manuable” material handling**. *International Journal of Industrial Ergonomics*, 43(4) :314–327.

Sadykov, R., Vanderbeck, F., Pessoa, A., et Uchoa, E. (2015). **Column generation based heuristic for the generalized assignment problem**. *XLVII Simpósio Brasileiro de Pesquisa Operacional, Porto de Galinhas, Brazil*.

Savelsbergh, M. (1997). **A branch-and-price algorithm for the generalized assignment problem**. *Operations research*, 45(6) :831–841.

Seçkiner, S. U., et Kurt, M. (2008). **Ant colony optimization for the job rotation scheduling problem**. *Applied Mathematics and Computation*, 201(1-2) :149–160.

Sethanan, K., et Pitakaso, R. (2016). **Improved differential evolution algorithms for solving generalized assignment problem**. *Expert Systems with Applications*, 45 :450–459.

Sgarbossa, F., Battini, D., Persona, A., et Visentin, V. (2016). **Including ergonomics aspects into mixed-model assembly line balancing problem**. Dans *Advances in physical ergonomics and human factors*, pages 991–1001. Springer.

Shmoys, D. B., et Tardos, É. (1993). **An approximation algorithm for the generalized assignment problem**. *Mathematical programming*, 62(1-3) :461–474.

Speklé, E. M., Heinrich, J., Hoozemans, M. J., Blatter, B. M., van der Beek, A. J., van Dieën, J. H., et van Tulder, M. W. (2010). **The cost-effectiveness of the rsi quickscan intervention programme for computer workers : Results of an economic evaluation alongside a randomised controlled trial**. *BMC musculoskeletal disorders*, 11(1) :259.

Spliet, R., et Desaulniers, G. (2015). **The discrete time window assignment vehicle routing problem**. *European Journal of Operational Research*, 244(2) :379–391.

Subtil, R. F., Carrano, E. G., Souza, M. J., et Takahashi, R. H. (2010). **Using an enhanced integer nsga-ii for solving the multiobjective generalized assignment problem**. Dans *Evolutionary Computation (CEC), 2010 IEEE Congress on*, pages 1–7. IEEE.

Tapkan, P., ÖZbakıR, L., et BaykasoğLu, A. (2013). **Solving fuzzy multiple objective generalized assignment problems directly via bees algorithm and fuzzy ranking**. *Expert systems with applications*, 40(3) :892–898.

Tasgetiren, M. F., Suganthan, P. N., Chua, T. J., et Al-Hajri, A. (2009). **Differential evolution algorithms for the generalized assignment problem**. Dans *Evolutionary Computation, 2009. CEC'09. IEEE Congress on*, pages 2606–2613. IEEE.

Törnström, L., Amprazis, J., Christmansson, M., et Eklund, J. (2008). **A corporate workplace model for ergonomic assessments and improvements**. *Applied ergonomics*, 39(2) :219–228.

Triggs, D. D., et King, P. M. (2000). **Job rotation**. *Professional safety*, 45(2) :32.

Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., et De Boeck, L. (2013). **Personnel scheduling : A literature review**. *European Journal of Operational Research*, 226(3) :367–385.

Vidal, T., Crainic, T. G., Gendreau, M., et Prins, C. (2014). **Implicit depot assignments and rotations in vehicle routing heuristics**. *European Journal of Operational Research*, 237(1) :15–28.

Vilà, M., et Pereira, J. (2014). **A branch-and-bound algorithm for assembly line worker assignment and balancing problems**. *Computers & Operations Research*, 44 :105–114.

Wells, R., Mathiassen, S. E., Medbo, L., et Winkel, J. (2007). **Time—a key issue for musculoskeletal health and manufacturing**. *Applied Ergonomics*, 38(6) :733–744.

Widanarko, B., Legg, S., Devereux, J., et Stevenson, M. (2015). **Interaction between physical and psychosocial risk factors on the presence of neck/shoulder symptoms and its consequences**. *Ergonomics*, 58(9) :1507–1518.

Wilson, J. (1997). **A genetic algorithm for the generalised assignment problem**. *Journal of the Operational Research Society*, 48(8) :804–809.

Woodcock, A. J., et Wilson, J. M. (2010). **A hybrid tabu search/branch & bound approach to solving the generalized assignment problem**. *European journal of operational research*, 207(2) :566–578.

Yalçındağ, S., Cappanera, P., Scutellà, M. G., Şahin, E., et Matta, A. (2016). **Pattern-based decompositions for human resource planning in home health care services**. *Computers & Operations Research*, 73 :12–26.

Yoon, S.-Y., Ko, J., et Jung, M.-C. (2016). **A model for developing job rotation schedules that eliminate sequential high workloads and minimize between-worker variability in cumulative daily workloads : Application to automotive assembly lines**. *Applied ergonomics*, 55 :8–15.

Zacharia, P. T., et Nearchou, A. C. (2016). **A population-based algorithm for the bi-objective assembly line worker assignment and balancing problem**. *Engineering Applications of Artificial Intelligence*, 49 :1–9.

ZARE, M., Malinge-Oudenot, A., Höglund, R., Sophie, B., et Roquelaure, Y. (2016). **Evaluation of ergonomic physical risk factors in a truck manufacturing plant : case study in scania production angers**. *Industrial health*, 54(2) :163–176.

Zeltzer, L., Aghezzaf, E.-H., et Limère, V. (2017). **Workload balancing and manufacturing complexity levelling in mixed-model assembly lines**. *International Journal of Production Research*, 55(10) :2829–2844.

Zhang, Z., Qin, H., Wang, K., He, H., et Liu, T. (2017). **Manpower allocation and vehicle routing problem in non-emergency ambulance transfer service**. *Transportation Research Part E : Logistics and Transportation Review*, 106 :45–59.

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