Universidade de Lisboa
Faculdade de Motricidade Humana

DEVELOPMENT OF A JOB ROTATION ALGORITHM TO REDUCE OCCUPATIONAL EXPOSURE IN THE AUTOMOTIVE INDUSTRY

Ana Raquel Martins Assunção

Orientador: Professora Doutora Maria Filomena Araújo Costa Cruz Carnide

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Tese especialmente elaborada para obtenção do grau de Doutor em Motricidade Humana na especialidade de Biomecânica

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Abbreviations

%CT bent	Percentage of cycle time with the trunk bent or strongly bent
%CT shoulder	Percentage of cycle time with the arm at/above shoulder level
ASL	Arms above shoulder level
B	Trunk bent
Car	Carrying
E	Elbow
EAWS	European Assembly Worksheet
EU	European Union
f	Action forces
GA	Genetic algorithm
GA6	Elbow at 60% extension
GA8	Elbow at 80% extension
GA10	Elbow at 100% extension
GEE	Generalized estimating equations
HF	Hand and fingers
Hold	Holding
LOA	Limits of agreement
MMH	Manual material handling
MSD	Musculoskeletal disorder
MSS	Musculoskeletal symptom
NS	Neck and shoulders
OCRA	Occupational Repetitive Action
OWAS	Ovako Work Assessment System
OX	Ordered crossover
p	Posture
Pu	Push and Pull
Rep	Repositioning
SB	Trunk strongly bent
SL	Arms at shoulder level
SWSQ	Shift working sequence quality

T	Trunk
WB	Whole body
WRMSD	Work-related musculoskeletal disorder

Abstract

Musculoskeletal disorders remain the most reported occupational health workplace problem, affecting workers in all sectors of economic activity. The automotive industry is one of the industries with the highest prevalence of musculoskeletal symptoms, mainly due to the biomechanical risk factors that workers are exposed to during their workday. As this industry is one of the largest industrial forces that has contributed significantly to the growth of the global economy, it is crucial to develop efficient solutions that can be implemented in workplaces to improve working conditions by eliminating or reducing workers' exposure to the main biomechanical risk factors. The present dissertation attempts to understand the short-term relationships between biomechanical risk factors and musculoskeletal symptoms in the automotive assembly line, in addition to providing an organizational strategy that uses a mathematical approach to mitigate exposure to the same risk factors and reduce the prevalence/incidence of musculoskeletal disorders. Therefore, this dissertation presents three main investigations. The first study with a cohort design determines the short-term associations between biomechanical risk factors and musculoskeletal symptoms in the upper limbs and low back in an automotive plant. The workers were divided into low and high-risk groups for various risk factors. The results suggested that workers who were in the high-risk group had a higher likelihood to report adverse effects on their musculoskeletal symptoms at the end of a work week, particularly when exposed to certain risk factors, such as: posture for symptoms in the neck, right wrist, and left shoulder. The second study proposes a mathematical formulation based on a genetic algorithm that considers the assessment of biomechanical risk factors (EAWS) in the workplace, workers' qualifications, and organizational aspects inherent in the operation of the production line. The algorithm is based on three criteria: enhancing diversity, ensuring team homogeneity, and reducing exposure to biomechanical risk factors. The success of the algorithm in meeting these criteria has been verified. In addition, when comparing the results of the algorithm with the results of manual job rotation plans (created by a team leader), it was shown that the mathematical solution was more efficient, not only in relation to the three criteria, but also in terms of time spent on this task. Finally, the third study complements the second by comparing the results obtained via the genetic algorithm with the data obtained through the rotation plans made by team leaders of several teams on the assembly lines. Therefore, the aim of this study was to evaluate the effectiveness of the algorithm in creating job rotation plans compared to the manual process of team leaders in terms of diversity, homogeneity, exposure, shift working sequence quality and matrix quality. The job rotation plans of 7 teams (89 workers) from the assembly area were included in the sample. Exposure was the only criterion that did not show significant differences between the two methods, however, all variables at the individual level showed high values in the limits of agreement. The values of diversity, homogeneity, shift working sequence quality, and matrix quality of the job rotation plan generated by the genetic algorithm were on average higher than the values of the team leaders' job rotation plan. These results show that implementing the genetic algorithm has a promising potential to create job rotation plans that reduce musculoskeletal disorders in the automotive industry and as well as to reduce the time associated with the team leader completing this task.

Keywords: *Musculoskeletal disorders, biomechanical risk factors, genetic algorithm, preventive measures, automotive industry*

Resumo

As lesões músculo-esqueléticas continuam a ser o principal problema de saúde reportado no local de trabalho, afetando trabalhadores em todos os setores de atividades. A indústria automóvel é um dos setores com maior prevalência de sintomatologia músculo-esquelética, principalmente devido aos fatores de risco biomecânicos a que os trabalhadores estão expostos durante o seu dia de trabalho. Sendo esta indústria uma das maiores forças industriais, que contribuí de forma significativa para o crescimento da economia global e nacional, é fulcral desenvolver soluções eficientes para implementar nos postos de trabalho por forma a melhorar as suas condições, eliminando ou reduzindo a exposição dos trabalhadores aos principais fatores de risco biomecânicos. A presente dissertação procura compreender os efeitos a curto prazo dos fatores de risco biomecânicos sobre a sintomatologia músculo-esquelética na linha de montagem de uma indústria automóvel, e providencia uma estratégia organizacional, recorrendo a uma abordagem matemática, para mitigar a exposição a condições de trabalho adversas e reduzir a incidência de lesões e sintomatologia músculo-esqueléticas. Para a concretização desta dissertação, foram desenvolvidos três estudos. O primeiro estudo, com um desenho prospetivo e uma amostra de 228 trabalhadores, determinou as associações a curto prazo entre os fatores de risco biomecânicos e a sintomatologia músculo-esquelética nos membros superiores e na região lombar numa fábrica da indústria automóvel. Os trabalhadores foram divididos em grupos de baixo e elevado risco para os diferentes fatores de risco. Os resultados sugerem que ao final de uma semana de trabalho, os trabalhadores que pertencem ao grupo de alto risco têm uma predisposição superior para reportarem efeitos desfavoráveis na sua sintomatologia músculo-esquelética, principalmente quando sujeitos a determinados fatores de risco, como é o caso da postura para a sintomatologia no pescoço, punho direito e ombro esquerdo. O segundo estudo propõe uma formulação matemática com base num algoritmo genético, que tem em conta a avaliação dos fatores biomecânicos presentes nos postos de trabalho (EAWS), a qualificação dos trabalhadores e aspetos organizacionais inerentes ao funcionamento da linha de produção. O algoritmo baseia-se em três critérios: melhorar a diversidade da exposição aos fatores de risco, garantir a homogeneidade da equipa e reduzir a exposição aos fatores de risco biomecânicos. O sucesso do algoritmo no cumprimento destes critérios foi verificado. Adicionalmente, quando se compararam os resultados do algoritmo com os resultados dos planos de rotação criados manualmente por um *team leader,* verificou-se que a solução matemática despendia menos tempo na concretização da tarefa. Por fim, o terceiro estudo complementa o segundo comparando os resultados obtidos pelo algoritmo genético e os dados obtidos pelos planos de rotação gerados pelos *team leaders* de várias equipas da linha de montagem. Assim, o objetivo deste estudo é avaliar a eficácia do algoritmo em gerar planos de rotação, quando comparado com o processo manual realizado pelos *team leaders* quanto à diversidade, homogeneidade, exposição, sequência de estações de trabalho e qualidade da matriz. Os planos de rotação de 7 equipas (89 trabalhadores) da área da montagem foram incluídos na amostra. A análise de grupo demonstrou que a exposição é o único critério que não apresenta diferenças significativas entres os dois métodos, no entanto, a nível individual todas as variáveis apresentaram valores elevados nos limites de concordância. Os valores de diversidade, homogeneidade, sequência de postos de trabalho e qualidade da matriz do plano de rotação gerado pelo algoritmo genético são, em média, superiores quando comparados com os valores do plano de rotação do *team leader*. Estes resultados revelam um potencial promissor na implementação do algoritmo genético para a criação de planos de rotação para diminuir o tempo associado à realização desta tarefa pelo team leader, mas também no seu papel ativo na redução das lesões músculo-esqueléticas na indústria automóvel.

Palavras-chave: *lesões músculo-esqueléticas, fatores de risco biomecânicos, algoritmo genético, medidas preventivas, indústria automóvel*

CHAPTER 1

Dissertation Introduction

1.1. Dissertation structure

Musculoskeletal disorders (MSDs) and symptoms (MSSs) are currently the most common causes of disabilities and limitations related to daily life and gainful employment (Briggs et al., 2018; De Kok et al., 2019) and have been recognized as a problem since the 17th century (Ramazzini, 2001). A recent World Health Organization report highlighted how MSDs can affect workers and employers in all economic sectors and occupations (Briggs et al., 2018). Understanding what solutions can be implemented in a work environment and what impact they can have, is paramount in alleviating both the economic and social burden of MSDs. The present dissertation, entitled “Development of a job rotation algorithm to reduce occupational exposure in the automotive industry”, aims to understand the short-term relationships of biomechanical risk factors and MSSs in the assembly line of an automotive industry, while also providing an organizational strategy, taking the advantage of digitalization and mathematical approaches, to mitigate the exposure to these known risk factors and reduce the overall prevalence of MSDs.

The core of this dissertation is a collection of three research articles that have been published or submitted for publication in peer-reviewed journals. In order to clarify the framework of these studies, this dissertation is structured as follows:

Chapter 2 contains a background introduction in which we present an overview of the current state of the art of the epidemiology of MSDs and at the same time describe a possible conceptual model that could be used to explain the outbreak that leads to these conditions, with a particular focus on the automotive industry. We also highlight the predominant biomechanical risk factors and briefly describe how they are related to MSSs in the most affected areas of the body. Following this background, the possible solutions to reduce the incidence and prevalence of MSDs are addressed, focusing on the job rotation plans and in particular those created through a genetic algorithm approach. Finally, the second chapter concludes with the aims and overview of the dissertation, which present the different studies that integrate the current dissertation and how they are related with each other.

Chapters 3 to 5 correspond to the three research articles conducted during this dissertation to tackle the research goals described in chapter 2.

Chapter 6 provides a general discussion integrating the key insights gained with the three investigations of this dissertation as well as the general methodological issues concerning those studies. Recommendations for future research are provided alongside with practical implications for the field.

CHAPTER 2

General Introduction

2.1 Background

Epidemiology of MSDs

Nowadays, industrial organizations and companies face new demanding challenges, mainly created by the pressure of intense competition to improve productivity. Forced to survive and thrive in such volatile environments, workplaces have no choice but to develop and maintain many competitive advantages, which poses a significant threat to the health and well-being of their workers (Hochdörffer et al., 2018). According to the World Health Organization, approximately 1.71 billion people have musculoskeletal conditions worldwide, with a significant amount occurring in a working environment (Cieza et al., 2020). In this regard, the issue of work-related musculoskeletal disorders (WRMSD) was also addressed by the European Risk Observatory Report from the European Agency for Safety and Health at Work where three out of every five workers in the European Union (EU)-28 reported WRMSDs complaints. Data driven by the EU report can also be used to assess this issue in Portugal, where 54% of workers reported suffering from one or more WRMSD in the past 12 months (De Kok et al., 2019).

All of these challenges concerning WRMSDs have been recognized and addressed at a European level, where a consensus statement was made with clear future directions identifying the need for extra efforts to be taken in terms of prevention. Since WRMSDs represent a major public health issue, not only through their impact on worker's health, social well-being and performance, but also by their high economic burden, affecting companies, businesses and national health care systems (Bevan, 2015). Not surprisingly, the financial costs of WRMSDs in Europe are estimated at 240 billion euros, accounting for 2% of the gross domestic product of EU-15 (Bevan, 2015). These values are due not only to their high prevalence, but also to the costs associated with work absenteeism resulting from these disorders. In fact, a high proportion of working days lost in the EU Member States are due to WRMSDs, with workers suffering from WRMSDs being absent from work for a longer period of time compared to workers with other health problems (De Kok et al., 2019).

Within the several economic sectors affected by WRMSDs, the automotive industry is significantly impacted mainly by the occupational exposure which workers face on a daily basis at their working stations (De Kok et al., 2019). The automotive industry encompasses a wide range of companies and consortia involved in the several stages of development, manufacturing and selling motor vehicles, comprehending a large force of human resources and represents one of the world's largest industries by revenue (Grassano et al., 2021). In fact, automotive industry is a long contributor to Portugal's economy and a major employer (International Labour Organization, 2022). A significant body of literature, both cross-sectional and longitudinal, have identified a dose-response relationship between the exposure to biomechanical risk factors and the prevalence/incidence of WRMSDs reported in the automotive industry, mainly on the assembly lines (Punnett, 1998). In fact, when questioned about the pain during the previous 12-months, 47% of the plant and machine operators and assemblers reported MSSs in their shoulders, neck, and/or upper limbs, whereas 55% reported back pain (De Kok et al., 2019). Thus, this is one of the occupations with the highest prevalence of reported MS complaints (De Kok et al., 2019).

MSD definition and conceptual model

The term MSD includes a wide range of inflammatory and degenerative conditions that affect several tissues and structures such as muscles, tendons, ligaments, joints, and peripheral nerves (National Institute of Occupational Safety and Health, 2000). When impaired, these tissues and structures can lead to clinical syndromes such as tendon inflammations and related conditions (tenosynovitis, epicondylitis, bursitis), nerve compression disorders (carpal tunnel syndrome, sciatica), osteoarthrosis, myalgia, low back pain and pain in other body regions that cannot be related to a known pathology (National Institute of Occupational Safety and Health, 2000). Out of the different body segments affected by such conditions, those with higher incidence and prevalence are the low back, neck, shoulder, forearm, hand, and the lower extremity (National Institute of Occupational Safety and Health, 2000; Punnett & Wegman, 2004).

Occupational exposures, such as biomechanical risk factors (external loads), organizational factors and psychosocial context variables, are strong determinants of MSDs (Neupane et al., 2013). This issue is elegantly explained in detail in the original model of Macdonald and Oakman (Macdonald & Oakman, 2015), where a mismatch between the workplace factors mentioned above and the individual factors, such as the worker's related abilities and skills, his personality, and genetic vulnerabilities, may trigger a stress response where high internal biomechanical loads can lead to discomfort, pain, or tissue damage in the short-term and/or long-term (Figure 2.1). This stress response can result in WRMSDs through several physiological pathways, for example those affecting "the function of the fibroblasts and myofibroblasts that reside throughout the body and more specifically in the fascia", where a pro-inflammatory response and a dysfunctional regulation of the stress response hormones (e.g., cortisol and catecholamines) are also involved (Macdonald & Oakman, 2022).

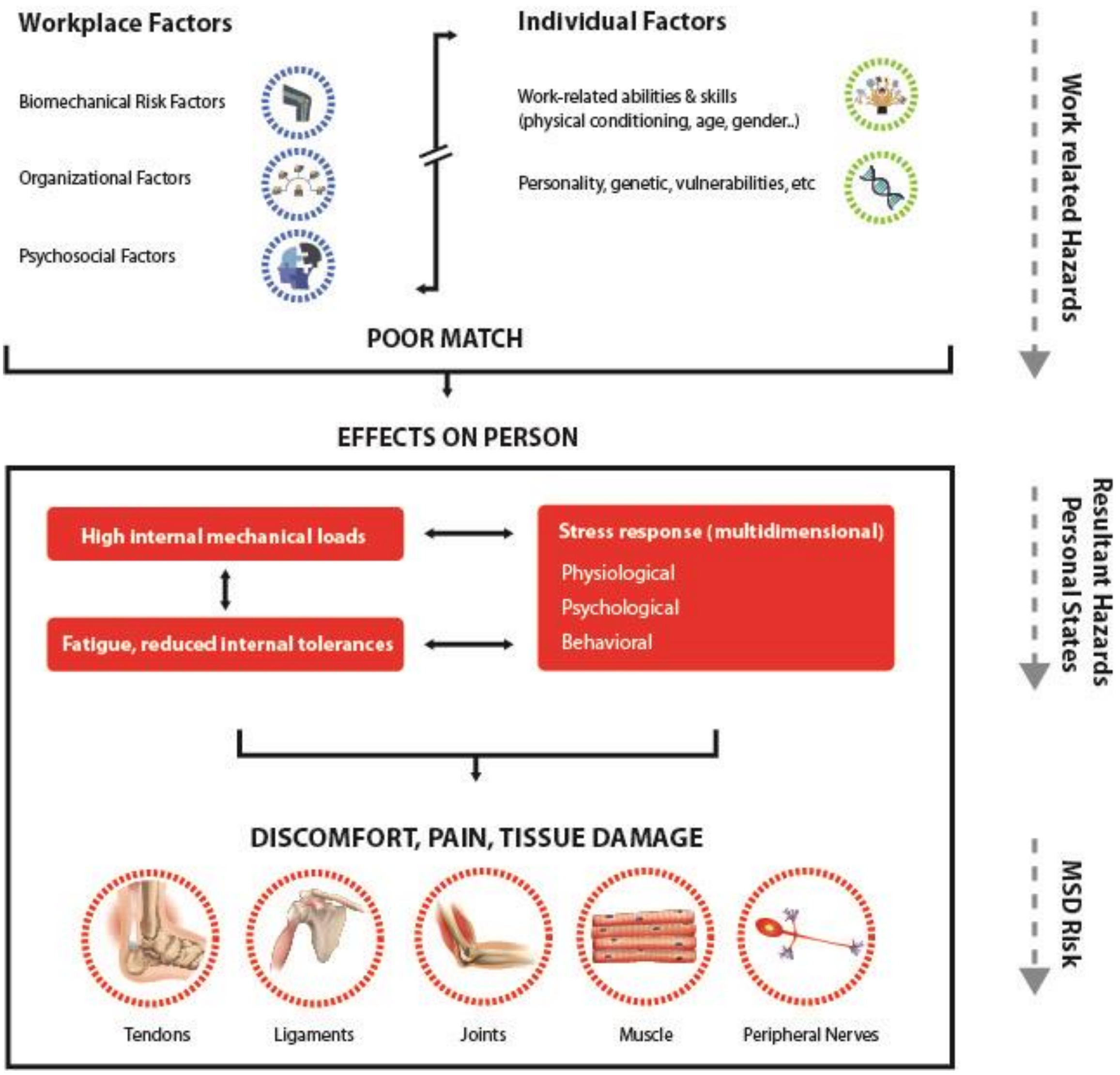

Figure 2.1 – Model of causation for MSD risk (adapted from Macdonald & Oakman, 2015)

Biomechanical Risk Factors and MSDs

Within the scientific areas of study involved in WRMSDs, the science of Ergonomics plays an important role as it is a scientific discipline specializing in MSDs risk assessment and control. In the automotive industry and throughout the development and manufacturing processes, simple tasks such as tightening, picking up, gripping with variable intensity and material handling are performed in the production lines – all of which involve the exposure to biomechanical risk factors. From an ergonomist point of view, awareness must be made of the various biomechanical risk factors associated with a particular occupation, which, in the automotive industry, includes rapid work pace and repetitive motion patterns; insufficient recovery time; manual material handling of heavy loads and forceful manual exertions; non-neutral body postures (either dynamic or static); mechanical pressure concentrations; segmental or whole-body vibration; local or whole-body exposure to cold; or a combination of these different risk factors, in addition potentially associated with the organizational and psychosocial factors (Macdonald & Oakman, 2022; Punnett & Wegman, 2004). Looking at the current literature, several observational, cross-sectional and prospective studies have associated some of these risk factors with MSSs in multiple body regions (Coggon et al., 2013; Guerreiro et al., 2020; Hallman et al., 2019; Subas Neupane et al., 2017; Punnett, 1998). For instance, in their systematic review Da Costa and Vieira (Da Costa & Vieira, 2010) reported that awkward postures were related with increased pain in the neck and lower back regions across several industries, whereas force application was associated with wrist and shoulder pain. All these body segments comprise the major regions reported as having musculoskeletal complaints in the automotive industry (Nordander et al., 2016). Moreover, among these biomechanical factors, manual material handling of heavy loads, vibrations and awkward postures are among the strongest predictors of MSSs, probably related with the high internal biomechanical loads (Mayer et al., 2012; National Institute of Occupational Safety and Health, 2000; Punnett & Wegman, 2004). Nonetheless, all these studies have focused on the long-term relationship between musculoskeletal complaints and exposure to risk factors without exploring the acute changes on self-reported pain in the short-term, which may have important information on the early symptoms and development of MSDs. Since the sooner a MSD is managed, the less likely it will develop into a chronic condition that leads to a loss of productivity and reduced wellbeing (De Kok et al., 2019), it is important for industries and companies to study the short-term relationship between known risk factors and musculoskeletal complaints and analyze which solutions may better suit their assembly lines.

Job rotation plans and relationship with MSDs

The science of Ergonomics plays a pivotal role in mediating the working conditions of workers to improve their health and well-being, while accounting for the needs of industries and companies to maintain their levels of productivity (Macdonald & Oakman, 2022). In the automotive industry, several approaches have been pursued with the goal to eliminate or mitigate the exposure to potential risk factors, such as changes in tools, workplace conditions, and manufacturing processes, either on the early or ongoing stages of product development (Figure 2.2). However, these changes are dependent on the feasibility of their implementation and may face significant roadblocks due to logistical or financial reasons. In such scenarios, companies tend to rely on more cost-effective solutions such as organizational measures, where the job rotation solution is often seen as a more viable approach (Padula et al., 2017).

Figure 2.2 – Measures to reduce MSD risk in the workplace

The emergence of the term job rotation dates to the 1940s and 1950s, when work design methods began to counteract the simplification, specialization, and repetitiveness that dominated early 20th-century Taylorist work design (Morris, 1956; Tucker, 1941). Job rotation plans were first introduced as organizational strategies with the aim of improving the production time, costs, and quality of existing manufacturing assembly lines by increasing the flexibility and know-how of their workers (Padula et al., 2017). According to the European Foundation for the Improvement of Living and Working Conditions (2017) (Eurofound, 2017), 45% of workers in the EU practiced job rotation in 2015. Although the original reason was related to lean production, job rotation plans were also designed to have a reduction in MSDs in mind through mitigating ongoing exposure to risk factors (Comper & Padula, 2014; Padula et al., 2017). Job rotation plans have been implemented in several industries to improve work diversity, ensure an equal workload among workers, (Aryanezhad et al., 2009) and reduce work monotony and the accumulation of fatigue (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012). The concepts of diversity and variability are important constructs to ensure the safety, health and well-being of workers, while simultaneously improving the sustainability and resilience of the workforce (Mathiassen, 2006). For example, the establishment of a job rotation strategy encourages the worker’s ability to perform multiple work tasks at multiple workstations, thus providing the manufacturing industry with greater flexibility to counteract the effects of absenteeism (Padula et al., 2017). Therefore, it is with no surprise that job rotation plans are recommended as an organizational measure to reduce workplace exposure to multiple risk factors and thus increase variability and reduce worker fatigue and monotony (Jorgensen et al., 2005; Rodriguez & Barrero, 2017; Yung et al., 2012).

Job rotation plan as a solution

Despite the aforementioned benefits of job rotation plans, conceiving one can be complex due to the number of variables and combinations that have to be considered during the design and conception phases. Moreover, the greater the number of variables included in the job rotation, the higher the amount of combinations possible, which represents an increase in the complexity of this combinatorial problem (Carnahan et al., 2000). When looking at the current scenario of manufacturing plants of the automotive industry, job rotation plans are widely disseminated in their production lines, however, the majority are conceived by the team leaders (or through management) by hand and on their own working schedule (Eurofound, 2017). This process can raise different implications, such as:

- Additional work burden to the team leaders who already have other responsibilities, and where the design of the job rotation plan can be seen as a complex and demanding chore distracting them from their main tasks;
- Despite their working experience, team leaders do not have the know-how and expertise to establish consistent and objective decision criteria to support and help their decision-making process in designing job rotation plans, while accounting for occupational exposure to biomechanical risk factors of each workstation, the diversity of the working sequence and the workload balance of their team;
- Finally, in cases where an immediate solution is needed due to external factors, such as unscheduled absenteeism, job rotation plans are redesigned without a supportive assessment of the implication of sudden changes in the occupational exposure of workers and workload balance of the teams.

Therefore, a computer assisted method to support the decision tasks of team leaders and other professionals in the design of job rotation schedules would be valuable and of great importance. Several studies have proposed solutions for the automatic design of job rotation plans with all of the solutions presenting optimization algorithms to solve this combinatorial problem (Bhasin et al., 2016; Digiesi et al., 2018; McDonald et al., 2009; Rajabalipour Cheshmehgaz et al., 2012). In the following sub-chapter, we will address some of these solutions and both their strengths and limitations.

The design of job rotation plans

The current body of literature has proposed several solutions for the automatization of job rotations plans (Bhasin et al., 2016; Digiesi et al., 2018; McDonald et al., 2009; Rajabalipour Cheshmehgaz et al., 2012). Various types of methodologies have been identified so far, adopting different taxonomies that can depend on the available variables, the organizational context and the purpose of optimization. Regardless, all the solutions present optimization algorithms to solve this combinatorial problem, such as: mixed-integer programming to upper extremities (Boenzi et al., 2013; Digiesi et al., 2018; Xu et al., 2012), minimizing net present cost within a lean manufacturing cell (McDonald et al., 2009), multi-criteria fuzzy-genetic algorithms for assembly line balancing (Rajabalipour Cheshmehgaz et al., 2012) and a diploid genetic algorithm (GA) in dynamic environment (Bhasin et al., 2016).

When looking at examples in the automotive industry, a heuristic was proposed to maximize diversification by setting criteria that characterizes the workplace by movements, general capacities, mental and communication capacities (Diego-Mas et al., 2009). In this model, GA is selected as the optimization method and diversification is mostly accomplished by including penalizations when subsequent rotations have similar characteristics. The same authors presented another GA to design job rotation plans (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012). In this case, in addition to ergonomic variables derived from the Occupational Repetitive Action (OCRA) method (Colombini & Occhipinti, 2016), a competence criterion, related with product quality and employee satisfaction, was used as well. All of these environmental and organizational factors were integrated in the fitness function and optimized by means of the GA (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012). In a different investigation, the focus was to reduce the accumulated risk by enhancing posture diversity by a multi-criteria methodology (Rajabalipour Cheshmehgaz et al., 2012). In this case, the model relies on the cycle time, overall physical workload and accumulated risk of posture based on the Ovako Work Assessment System (OWAS) (Karhu et al., 1977) scores for each body segment, and uses a fuzzy GA as the search algorithm (Rajabalipour Cheshmehgaz et al., 2012).

Based on these previous investigations, several risk assessment methods (e.g., OCRA and OWAS) have been used in the mathematical models to improve the fitness function and the job rotation plans. Another example of a risk assessment method lies with the European Assembly Worksheet (EAWS) method (Appendix 1), which is also used in the literature as an integral of the fitness function (Schaub et al., 2013). For instance, the variables of the EAWS method were used to characterize the risk factors of each workstation and implemented as an objective function as the sum of time-weighted period scores (Otto & Scholl, 2013). In this scenario, the methodology implements a naive construction procedure and a smoothing heuristic (Otto & Scholl, 2013). Another example can be observed in a job rotation plan, where a linear programming-based heuristic is proposed to search for short-term staff planning. The methodology uses the workplace's exposure from EAWS, the workers' qualifications and the most recent allocation of each worker (Hochdörffer et al., 2018).

There are several investigations that developed heuristics that use occupational variables based on risk assessment methods and organizational variables that include qualifications, absenteeism and/or impairment restrictions (Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012; Carnahan et al., 2000; Diego-Mas et al., 2009; Hochdörffer et al., 2018; Otto & Scholl, 2013; Rajabalipour Cheshmehgaz et al., 2012). In addition, regarding occupational variables, there is an increased interest in including diversity and variability factors in the methodologies (Mathiassen, 2006). In fact, regardless of the method chosen to conceive a job rotation plan (e.g., GA, mixed-integer programming to upper extremities) and the use of different criteria and risk factors (i.e., biomechanical, organizational, and psychosocial) to establish the fitness function, the concept of diversity is a common feature for most mathematical formulations addressed in these studies.

Despite the known importance of diversity in the conception of job rotation plans, there are also other criteria that may have a significant impact in the reduction of MSDs and that should not be overlooked, such as the homogeneity (i.e., balanced effort) between workers and the overall exposure (i.e., daily demand) to risk factors. On this topic, there are currently no suitable solutions in the automotive industry that encompass diversity, homogeneity, and exposure, while using objective ergonomic indicators to build a job rotation plan. In the next sub-chapter, the main objectives for the current dissertation will be addressed that will help overcome the referred shortcomings in the literature review of this dissertation.

2.2. Thesis goals

The present dissertation presents three research studies conducted under the framework of MSDs in the automotive industry and possible strategies to mitigate the exposure of known biomechanical risk factors.

In **Study 1** (chapter 3) we set forward a short-term prospective study aimed to determine the associations between biomechanical risk factors and MSSs in the upper limbs and low back in a production line of an automotive company. This is particularly important given that most studies were designed having in mind the long-term associations of MSS and biomechanical risk factors, whereas we focused on the acute changes of MSS reported in the morning and afternoon period throughout a workweek.

Study 2 (chapter 4) was conducted with a two-fold objective: 1) to conceive a mathematical formulation based on objective ergonomic indicators and a worker's qualifications to generate a job rotation plan solved by means of a GA in the automotive industry; and 2) provide an industrial case study where the GA was tested and applied on a single team of the assembly line, in order to be compared to team leaders' job rotation plan. This investigation overcomes the shortcomings presented in the literature by integrating the diversity, homogeneity, and exposure criteria in the fitness function whereas most of the previous investigations focused only on the diversity issue.

Study 3 (chapter 5) expands the objectives established in Study 2 by comparing the results of the GA with those provided by the team leader in a larger sample of teams of the assembly line. Therefore, this study aimed to evaluate and compare the effectiveness of the GA and the team leader to develop a job rotation plan.

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CHAPTER 3

Predictive Factors of Short-Term Related Musculoskeletal Pain in The Automotive Industry[1]

[1]**Based on:** Ana Assunção, Vera Moniz-Pereira, Carlos Fujão, Sarah Bernardes, António P. Veloso, Filomena Carnide (2021) *Predictive factors of short-term related musculoskeletal pain in the automotive industry*. International Journal of Environmental Research and Public Health. 18, 13062. https://doi.org/10.3390/ierph182413062

Abstract

To determine the short-term associations between biomechanical risk factors and musculoskeletal symptoms in the upper limbs and low back in an automotive company, a longitudinal study with a follow-up of 4 days was conducted in a sample of 228 workers of the assembly and paint areas. Data were analyzed using generalized estimating equations, calculating the crude and adjusted model for age, sex, seniority, and intensity of pain at baseline. The interactions found were the same for both models. Workers were divided in low-risk and high-risk group for posture, force, exposure, percentage of cycle time with the arm at/above shoulder level, and with the trunk flexed or/and strongly flexed. The predictive factors showed by time x group effect were found between pain intensity on the left shoulder for posture ($\beta = 0.221$, $p < 0.001$), percentage of time with the trunk flexed ($\beta = 0.136$, $p = 0.030$) and overall exposure ($\beta = 0.140$, $p = 0.013$). A time x group interactions were observed, namely between neck pain and posture ($\beta = 0.218$, $p = 0.005$) and right wrist and force ($\beta = 0.107$, $p = 0.044$). Workers in the high-risk group were more prone to report unfavorable effects on their self-reported musculoskeletal pain, across a workweek when exposed to specific risk factor, being posture important to neck, right wrist, and left shoulder pain.

Keywords: *short-term musculoskeletal pain; biomechanical factors; posture; force; exposure*

3.1. Introduction

Musculoskeletal disorders (MSDs) and symptoms (MSSs) are the most common work-related health problem in the European Union, impacting workers and employers across all economic sectors and occupations. Besides, MSDs have a high economic and social burden, affecting not only companies and businesses but also society's health care systems (De Kok et al., 2019).

Data from 31,612 workers reported in the 2015 sixth wave of the European Working Condition Survey showed that three out of five workers in the European Union-28 had MSDs (De Kok et al., 2019). The most common complaints were back (43%) and the upper limbs (41%) pain. Moreover, when questioned about the pain during the previous 12-months, 47% of the plant and machine operators and assemblers reported MSSs in the shoulders, neck, and/or upper limbs, whereas 55% reported back pain (De Kok et al., 2019). Thus, this is one of the occupations with the highest prevalence of reported musculoskeletal complaints (De Kok et al., 2019). Simple tasks such as tightening, picking up, and material handling, performed in the automotive production line have been suggested as the culprit behind the high incidence of MSDs (Zare et al., 2016). These types of operations have highly repetitive tasks, forceful exertion, and awkward postures, among other known biomechanical risk factors (Ohlander et al., 2019; Punnett, 1998; Spallek et al., 2010). Furthermore, short work cycles and insufficient recovery time related to the assembly line have often cumulative effects on mechanical load in the exposure during the work shift (Punnett, 1998; Visser & Van Dieën, 2006; Winkel & Mathiassen, 1994).

Among the most subjective symptoms of MSDs are sensations of constant muscle fatigue and stiffness accompanied by radiating pain (Visser & Van Dieën, 2006). Despite the fact that MSDs are one of the most common health problems in the automotive industry (Bernard, 1997; Nordander et al., 2016), where heterogeneous work tasks may be found (Neupane et al., 2017), short-term pain trajectory (e.g., one week) has received limited attention in the workplace. Most of the literature addressing the importance of perceived symptoms has focused on the cross-sectional (Coggon et al., 2013; Punnett, 1998) and long-term longitudinal (Da Costa & Vieira, 2010; Guerreiro et al., 2020; Hallman et al., 2019; Neupane et al., 2017) associations between physical and psychosocial factors, and MSSs with no studies addressing the short-term associations in the automotive industry. Understanding how early MSSs, before or after a work shift, evolve throughout a workweek, while exposed to different biomechanical risk factors, may provide valuable insight on the progression of symptoms and prevention of MSDs, such as which time of the day may be more sensitive to detect differences in pain reporting (Punnett & Wegman, 2004; Thi Thu Tran et al., 2016). In fact, when looking at exposure-response models, mainly on the short-term effects, the repercussions of the external exposure (i.e., biomechanical risk factors such as posture, force, etc.) on internal exposure (acute responses at system, tissue, cellular, and molecular level) during the working day and some hours after, may have serious medium to long-term implications on workers' health if not followed by a proper recovery (van der Beek & W Frings-Dresen, 1998). This issue is of utter importance, since these short-term effects may lead to more permanent symptoms and/or clinical disorders, most of the time accompanied by a decrease in work capacity and a negative impact in the productivity (Stigmar et al., 2013).

Therefore, this study aims to determine the prospective associations between biomechanical risk factors and MSSs in the neck, upper limbs, and low back in a production line of an automotive company throughout a workweek.

3.2. Materials and Methods

Study Design

This research has a prospective study design, which was conducted between June and July 2019 among a production line of a large automotive company.

Participants

A total of 302 workers (α = 5%, β = 0.20, d = 0.5, 20% of MSSs prevalence in the automotive industry, and a 15% drop-out) (Charan & Biswas, 2013) divided into 16 randomly selected teams from the assembly and paint areas, were invited to participate in this study. This sample was initially selected from a broader project aiming to develop a mathematical formulation to generate job rotation plans to teams in the production line of an automotive industry.

The study involved one week of work, which started after two days off, followed by 5 consecutive days of work. The eligibility criteria included having a contract with the company, being allocated to assembly and paint areas, having at least 3 months of seniority, not have any medical restrictions to perform the job assessed by the plant medical doctor, and not being a temporary worker. Workers and management in the company were informed at the organizational level first. The week before starting the data collection, the researcher met with all the workers from each team to explain the study aim, protocol, and provide detailed information on how to proceed during the data collection period. All participants gave their written informed consent before their participation in the study.

Self-Reported Musculoskeletal Symptoms

During the workweek (4 consecutive days), workers were asked to report their daily symptoms intensity in 10 body regions (neck, right and left shoulder, right and left elbow, right and left wrist, right and left hand/finger, and low back) using a numeric rating scale (Jensen et al., 1986). In this scale, workers reported a number between 0 and 10 that fitted their MSSs intensity, where 0 represents "no pain" and 10 "the worst pain" (Jensen et al., 1986). On the first day, the researcher individually handled the questionnaires to workers and explained how to fill them out throughout the week. Every day the workers reported their symptoms intensity immediately before and after the shift. The symptoms intensity reported at the beginning and at the end of the shift was used in the analysis.

The job rotation plan and the workstations assigned for each worker, during the data collection week, were provided by each Team Leader. The job rotation plan of each worker was collected to provide information about their individual daily and weekly exposure from each workstation.

Biomechanical Risk Factors

The biomechanical risk factors were assessed using the European Assembly Worksheet (EAWS), by certified ergonomists working within the company. This method is often used and validated in the automotive industry (Schaub et al., 2013). The theoretical model that supports this method overcome the traditional concept of limiting values of NIOSH (recommended weightlifting) (National Institute for Occupational Safety and Health, 2007) and in the ISO 11226, ISO 11228-1, ISO 11228-2, and ISO 11228.

The EAWS method results in a traffic light scheme point to classify the exposure severity level of each workstation evaluated. EAWS is divided in four sections for the evaluation of (1) working postures and movements with low additional physical efforts; (2) action forces of the whole body or hand-finger system; (3) manual material handling (>3 kg); (4) repetitive loads of the upper limbs.

Posture

In the first section, static working postures and high frequent movements were estimated. Working postures for standing, sitting, bending, kneeling, crouching, lying, and climbing were rated. Asymmetric postures for the trunk, such as trunk rotation, lateral bending, and far reach, were also evaluated. For this section the longer the time spent in unfavorable conditions, the higher the score for this risk factor.

Posture—Percentage of Cycle Time

Within the partial scores for posture, the variables percentage of cycle time with the arm at/above shoulder level (%CT shoulder), and percentage of cycle time with the trunk bent or strongly bent (%CT bent) were defined as the percentage of time that each worker is exposed to these awkward postures during the cycle time of that workstation.

Force

Whole body and hand-finger action forces above 30 to 40 N, respectively, were considered in the second section of the EAWS method. A total score for force was derived by multiplying the intensity and the duration (static)/frequency (dynamic) of force exertions. Finally, the variable exposure represents the total score for a specific workstation and the variables posture and force were defined by the partial scores for each of these risk factors.

Demographic Data

Demographic data concerning age, sex, and seniority for all workers was collected by documental search from Human Resources Department and was provided by the company before the assessments.

Statistical Analysis

Given the high drop-out rate on the 5th day of assessments, only the first 4 days were considered in the analyses. A descriptive analysis was carried out to present sample baseline characteristics and mean scores for MSSs over the 4 days follow-up period. Mean scores and standard deviation were calculated for the whole population and for the sub-groups that were defined according to the different risk factors: posture, force, %CT shoulder, and %CT bent. These sub-groups were established based on the tertiles of the EAWS results. The low-risk sub-group included the first 2 tertiles and the high-risk group, the upper tertile. Thus, the cut-offs to be allocated in each of the high-risk groups were: having a total exposure score above 33.63; a posture score above 20.39; for force risk factor a score above 8.21 points; for the risk factor %CT shoulder a score above 10.18, and the %CT bent risk factor a score above 10.59.

Comparisons between groups (low risk and high-risk groups for each of the EAWS variables) at baseline were performed using the parametric independent sample t-tests for those normally distributed outcomes (i.e., age, seniority) and the non-parametric Mann–Whitney test in the absence of normality distribution on the variables (i.e., self-reported symptoms).

Generalized estimating equations (GEE) were used to analyze the between-group and within-group changes for MSS and the least significant differences were used for post hoc test (Ballinger, 2004; Lipsitz et al., 1994). Unadjusted models were performed as well as models adjusted for potential confounding factors including age, seniority, gender, and baseline symptoms if differences between groups at baseline were observed. A linear distribution for the response was assumed and an autoregressive correlation matrix was set to the data (Ballinger, 2004; Lipsitz et al., 1994).

Statistical analysis was performed using IBM SPSS Statistics version 25.0 (SPSS Inc., an IBM company, Chicago, IL, USA). For all tests, statistical significance was set at $p < 0.05$.

3.3. Results

Sample Characteristics and Exposure

All the 302 workers, who were invited to participate in the study, filled the baseline questionnaire. However, the final sample included 228 workers, since 74 had to be excluded given the lack of ID in the follow-up questionnaires. The decision to remove the fifth day was justified by the dropout rate on the final day of the workweek.

The baseline characteristics of workers are presented in Table 3.1. The workers' mean age was 30.0 ± 7.1 years, the seniority was 2.0 ± 3.8 years and 39.5% were females. In the total exposure and posture groups, statistically significant differences were found in seniority between groups. There were no statistical differences in the workers' mean age and between genders across the exposure groups.

Table 3.1 - Sample characteristics, according to each of the risk factors and low-risk and high-risk groups

	Exposure		Posture		Force		%CT Shoulder		%CT Bent		Total Sample (n=228)
	Low Risk (n=152)	High risk (n=76)	Low Risk (n=152)	High risk (n=76)	Low Risk (n=152)	High risk (n=76)	Low Risk (n=152)	High risk (n=76)	Low Risk (n=152)	High risk (n=76)	
Age (years)	30.3±7.4	29.7±6.5	30.4±7.3	29.4±6.7	30.1±6.8	29.8±7.6	29.7±6.9	30.7±7.4	30.2±7.2	29.6±6.9	30.0±7.1
Seniority (years)	2.3±4.5	1.2±1.6*	2.9±4.4	1.3±2.2*	2.0±3.9	1.8±3.6	1.9±3.9	2.0±3.7	2.1±4.0	1.6±3.4	2.0±3.8
Gender (% female)	39.1	40.8	39.5	39.5	38.4	42.1	44.1	30.3	36.8	44.7	39.5

*significance $p<0.05$

%CT shoulder – percentage of cycle time with the arm in extreme posture (at/above shoulder level); %CT bent - percentage of cycle time with the trunk bent or strongly bent.

Musculoskeletal Symptoms Tendency according to Work Exposure

Figures 3.1 and 3.2 depict the information of the within-group changes throughout the workweek on the symptoms reported in different body segments assessed at the beginning and the end of the shift, in workers categorized in the high vs low-risk group according to exposure, force, posture, %CT shoulder and %CT bent risk factors. We found a within-group changes with a negative trend for the symptoms reported on both shoulders and right wrist in those categorized as the low-risk group in all the risk factors ($p < 0.05$). Similarly, we observed a negative trend throughout the week for neck symptoms reported by the low-risk group in what concerns posture and %CT bent risk factors, and for low back symptoms in the posture low-risk group. Conversely, we observed no within-group changes in the MSS reported at the beginning of the shift throughout the week.

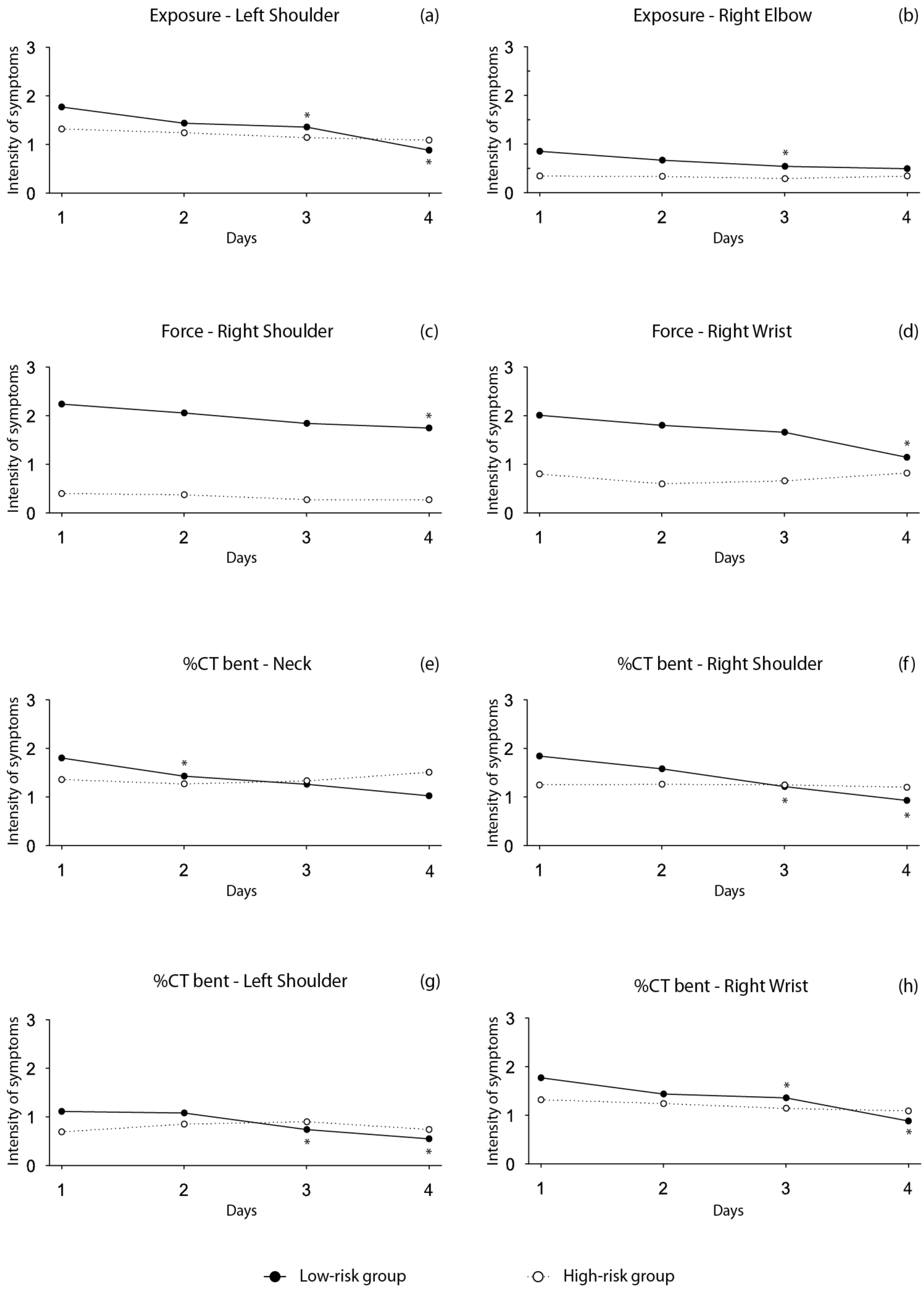

Figure 3.1 - Trajectory of MSS reported at the end of the shift during the 4 days of data collection. **(a)** Within-group changes are shown for exposure and left shoulder; **(b)** within-group changes are shown for exposure and right elbow; **(c)** within-group changes are shown for force and right shoulder; **(d)** within-group changes are shown for force and right wrist; **(e)** within-group changes are shown for %CT bent and neck; **(f)** within-group changes are shown for %CT bent and right shoulder; **(g)** within-group changes are shown for %CT bent and left shoulder; **(h)** within-group changes are shown for %CT bent and right wrist. * Within-group changes for afternoon group significant at $p < 0.05$.

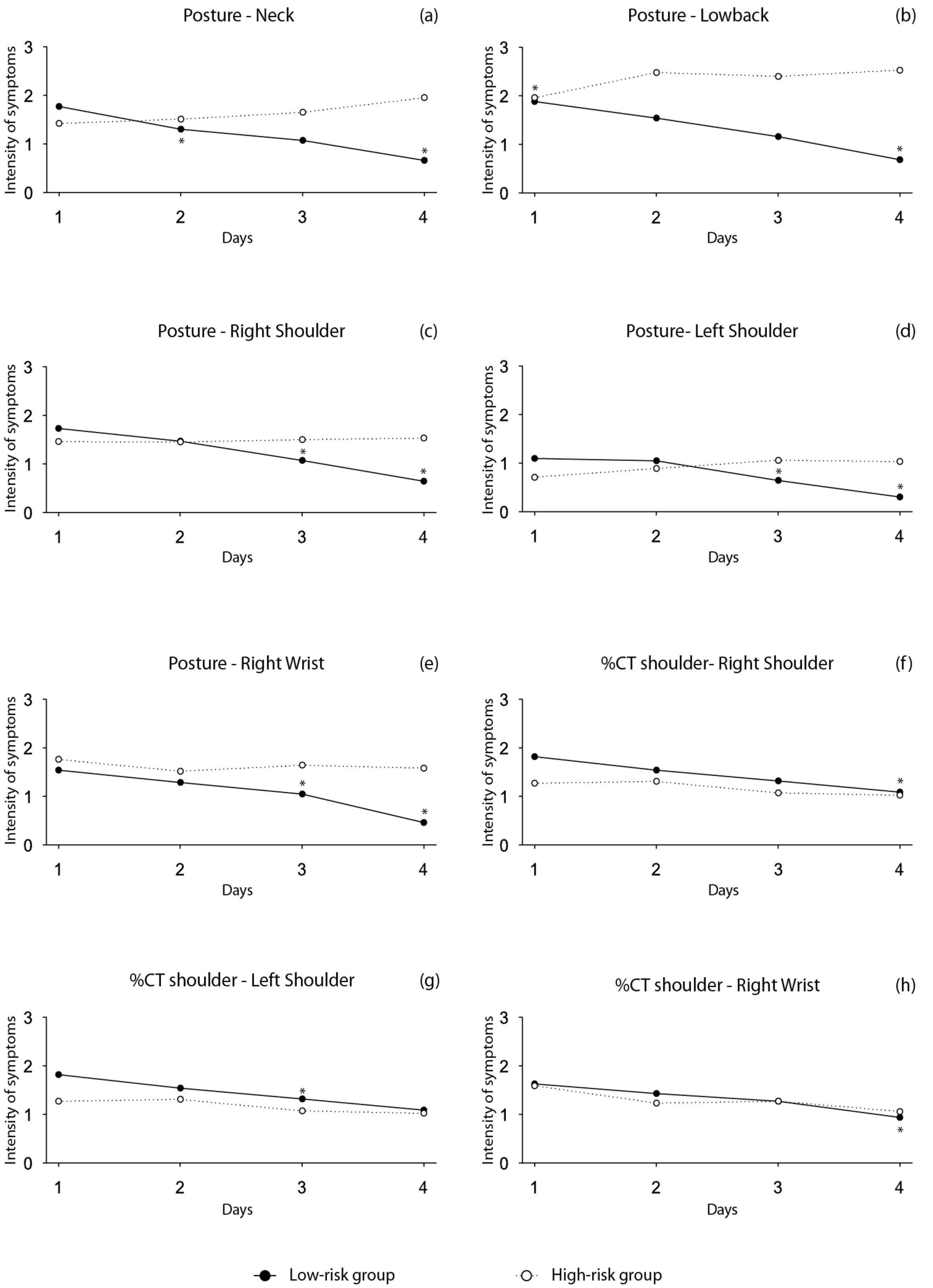

Figure 3.2 - Trajectory of MSS reported at the end of the shift during the 4 days of data collection. **(a)** Within-group changes are shown for posture and neck; **(b)** within-group changes are shown for posture and low back; **(c)** within-group changes are shown for posture and right shoulder; **(d)** within-group changes are shown for posture and left shoulder; **(e)** within-group changes are shown for posture and right wrist; **(f)** within-group changes are shown for %CT shoulder and right shoulder; **(g)** within-group changes are shown for %CT shoulder and left shoulder; **(h)** within-group changes are shown for %CT bent and right wrist. * Within-group changes for afternoon group significant at $p < 0.05$.

Predictive Models of Musculoskeletal Symptoms

Table 3.2 summarizes the results for the within and between-group interaction effects with each biomechanical risk group, adjusted for age, gender, seniority, and baseline values whenever differences were found between groups for baseline measurements. Following adjustments, most of the between-group effects were found at the end of the shift. As a result, those the predictive factors are allocated to the high-risk group for the exposure (β = 0.140, p = 0.013), posture (β = 0.221, p < 0.001), and %CT bent (β = 0.136, p = 0.030) had a significant interaction for symptoms reported in the left shoulder when compared to those in the low-risk group. For the symptoms reported in the neck and right wrist region, we can conclude that the predictive factors with significant interaction effect in the high-risk group were posture (β = 0.218, p = 0.005) and force risk factors (β = 0.107, p = 0.044), respectively. Finally, at the beginning of the shift, the left shoulder region also had an interaction effect for posture in those in the high-risk group (β = 0.053, p = 0.008), when compared to those in the low-risk group.

Table 3.2 - Within and between-group changes in MSS in different body regions for different biomechanical risk factors, after a workweek. Betas (β) are presented as unstandardized coefficients adjusted. The model is adjusted for gender, age, seniority, and baseline whenever differences were found between the low-risk and high-risk groups, with the respective 95% confidence intervals.

Symptoms at the beginning of the shift					
	Exposure	**Posture**	**Force**	**%CT Shoulder**	**%CT Bent**
Body regions	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)
Neck	0.010 (-0.103-0.123)	0.089 (-0.015-0.193)	-0.049 (-0.156-0.058)	-0.046 (-0.172-0.081)	0.028 (-0.085-0.141)
Low Back	0.020 (-0.112-0.152)	0.124 (-0.001-0.249)	0.007 (-0.106-0.120)†	-0.002 (-0.147-0.143)	0.044 (-0.084-0.173)
Right Shoulder	0.010 (-0.107-0.126)	0.093 (-0.021-0.208)	0.013 (-0.085-0.111)†	-0.047 (-0.178-0.084)	0.014 (-0.107-0.136)
Left Shoulder	0.055 (-0.010-0.119)†	**0.053 (0.002-0.104)* †**	-0.033 (-0.097-0.030)†	0.035 (-0.035-0.104)	0.054 (-0.021-0.129)
Right Elbow	0.018 (-0.036-0.072)	0.013 (-0.042-0.067)	0.012 (-0.039-0.064)	0.011 (-0.042-0.064)	-0.010 (-0.070-0.050)
Left elbow	0.040 (-0.009-0.089)†	0.026 (-0.014-0.067)†	0.018 (-0.036-0.072)	0.000 (-0.054-0.054)	-0.015 (-0.083-0.054)
Right wrist	0.008 (-0.116-0.106)	0.050 (-0.058-0.159)	0.068 (-0.017-0.153)†	-0.029 (-0.149-0.091)	0.035 (-0.075-0.144)
Left wrist	-0.012 (-0.091-0.068)	0.064 (-0.019-0.147)	-0.009 (-0.087-0.070)	0.006 (-0.081-0.093)	0.017 (-0.068-0.102)
Right hand/fingers	0.005 (-0.107-0.117)	0.038 (-0.075-0.1519	-0.027 (-0.130-0.076)	-0.050 (-0.177-0.076)	0.003 (-0.112-0.118)
Left hand/fingers	0.002 (-0.091-0.094)	0.025 (-0.039-0.089)	-0.019 (-0.103-0.064)	-0.040 (-0.147-0.067)	0.051 (-0.046-0.147)

Symptoms at the end of the shift					
	Exposure	**Posture**	**Force**	**%CT Shoulder**	**%CT Bent**
Body regions	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)	**High risk * Low Risk** β (95%CI)
Neck	0.002 (-0.150-0.154)	**0.218 (0.067-0.368)***	-0.002 (-0.129-0.126)†	0.015 (-0.131-0.162)	0.113 (-0.041-0.267)
Low Back	0.063 (-0.107-0.233)	0.143 (-0.026-0.311)	0.108 (-0.036-0.252)†	-0.008 (-0.180-0.164)	0.054 (-0.111-0.220)
Right Shoulder	-0.027 (-0.169-0.115)†	0.092 (-0.060-0.245)	0.030 (-0.106-0.167)†	0.030 (-0.127-0.188)	0.080 (-0.066-0.227)
Left Shoulder	**0.140 (0.030-0.251)*†**	**0.221 (0.102-0.339)***	0.004 (-0.108-0.117)†	0.075 (-0.049-0.199)†	**0.136 (0.013-0.260)***
Right Elbow	0.007 (-0.068-0.082)†	0.055 (-0.042-0.152)	0.015 (-0.057-0.088)†	-0.010 (-0.117-0.098)	0.011 (-0.060-0.081)†
Left elbow	0.031 (-0.040-0.102)†	0.067 (-0.016-0.150)	0.007 (-0.064-0.078)†	-0.008 (-0.092-0.077)	0.016 (-0.071-0.102)
Right wrist	0.005 (-0.131-0.141)	0.020 (-0.114-0.153)	**0.107 (0.003-0.211)*†**	-0.050 (-0.191-0.090)	0.084 (-0.049-0.218)
Left wrist	0.056 (-0.071-0.183)	0.103 (-0.029-0.235)	0.081 (-0.041-0.203)	0.039 (-0.107-0.186)	0.065 (-0.060-0.191)
Right hand/fingers	-0.084 (-0.299-0.061)	-0.013 (-0.157-0.130)	-0.001 (-0.126-0.125)†	-0.046 (-0.199-0.107)	-0.094 (-0.239-0.052)
Left hand/finger	-0.062 (-0.175-0.050)	0.051 (-0.070-0.172)	0.047 (-0.057-0.150)†	-0.014 (-0.142-0.114)	0.063 (-0.055-0.180)

*Between-group changes significant at $p < 0.05$; † within-group changes significant at $p < 0.05$
95% CI – 95% confidence interval; %CT shoulder – percentage of cycle time with the arm in extreme posture (at/above shoulder level); %CT bent - percentage of cycle time with the trunk bent or strongly bent.

3.4. Discussion

This study aimed to determine the prospective associations between biomechanical risk factors and MSSs in the upper limbs and low back in a production line of an automotive company throughout a workweek.

To our knowledge, this is the first study to analyse the prospective short-term associations between biomechanical risk factors and MSS in the upper limbs and low back, in a production line of an automotive company during a workweek. The main findings were that during this period the intensity of self-reported MSS was less favorable in the high-risk group, for selected biomechanical risk factors, such as overall exposure, force, posture, and %CT bent, specifically on neck, shoulder, and wrist segments, when compared with the low-risk group. These associations were more pronounced after the shift when compared to the beginning of the shift. These results suggest that workers in the high-risk groups of these specific risk factors may be more susceptible to have increased MSS. Thus, if continuous exposure to such conditions is maintained, these workers will have greater odds for future MSDs.

Given the MSDs' impact in the occupational context, more specifically in the automotive industry, it is paramount to understand which specific risk factors increase the incidence of MSDs and how to assess and detect early signs and symptoms of this condition. Our results add upon the current literature by showing that one week of work can alter the self-reported MSS of workers in the automotive industry depending on the exposure to a given risk factor and the body segment analyzed. For instance, and considering the posture risk factor, workers who were categorized in the high-risk group had higher MSSs scores for both neck and left shoulder body regions. Moreover, the shoulder region was also identified as a specific region of interest, since a time x group interaction was also found for exposure, and the %CT bent risk factors, favoring the low-risk group. Likewise, we also observed time x group interaction in the force risk factor for the right wrist region. Given that posture has been identified as an established risk factor for MSDs (Bernard, 1997; Hoogendoorn et al., 1999; National Research Council & Institute of Medicine, 2001; van der Windt et al., 2000) and since it is composed by %CT shoulder and %CT bent, there was either a within-group changes alone or time x group interaction for the left shoulder, special attention should be given to this risk factor, on the short-term management of workers exposure. The literature on the MSDs incidence and the connection between self-reported symptoms for the neck and posture risk factor (Christensen & Knardahl, 2010; Heuvel et al., 2006), as well as wrist symptoms and force risk factor has also been established (Silverstein et al., 1986), and hence should also be monitored. Beyond the be-tween-group effects, within group changes were also found between different body regions and all risk factors, reinforcing the notion that those in the low-risk group may also benefit from the decreased intensity of self-reported symptoms over the working week. These changes can be observed across all risk factors, being the right wrist, right shoulder, and left shoulder the most affected regions. Even though it was absent from the between group changes, the low back region had a time-effect for the low-risk group in the posture risk factor. This region has been previously identified as one of the body segments with a high prevalence for MSSs (Bláfoss et al., 2019), in which posture is considered a risk factor (Bernard, 1997). In fact, when considering other industries, frequent occupational lifting has been associated to short-term increase in reported low back symptoms. Our study found similar results to those of Andersen at al. (Andersen et al., 2017) where the increase in symptoms intensity was of small magnitude during the study period. Nonetheless, our study did not assess occupational lifting, but unfavorable postures adopted by workers during the workday may be the underlying cause of low back symptoms (Zare et al., 2016).

Our results are in accordance with previous studies, some with cross-sectional (Punnett, 1998), others with long-term prospective designs (Da Costa & Vieira, 2010; Punnett & Wegman, 2004) showing that disorders in the upper limbs such as shoulders, and wrists increased markedly with overall exposure scores, composed by biomechanical risk factors such as awkward postures and forceful exertions. Regarding neck self-reported symptoms, Da Costa et al. (Da Costa & Vieira, 2010), in a systematic review of prospective studies, also provided evidence on the connection between awkward postures and increased symptomatology in this body region, across several industries and workplaces. However, none of these studies accessed self-reported symptoms in the short-term (i.e., such as during a workweek), which might provide valuable insight into early symptoms, since a shorter duration of shoulder MSS, among others, is a predictor of greater improvement in disability (Kennedy et al., 2006). Therefore, assessing MSS during a shorter period could be a way to prevent or help improve the outcomes of an injury, thus affecting the incidence of long-term MSDs.

In this study, even though the average intensity of the self-reported MSSs were scored as mild (1–3) (Krebs et al., 2007), it is still noteworthy that the interaction observed on the exposure to these specific risk factors might help, through a cumulative manner, on the management of long-term risk for MSD (Kennedy et al., 2006). For instance, for the left shoulder to be in the high-risk group for the overall exposure, posture and %CT bent was associated with increased self-reported symptoms intensity, during a 4-day work period, which in the long-term may accrue the symptoms' intensity to a cut-off value closer to three (scale: 1–10). In fact, this value was identified in the literature as a criterion in the diagnosis of rotator cuff tendonitis (Sluiter et al., 2001). On this topic, the work developed by the team leaders at the production line on managing the rotation plans may prevent or aggravate the exposure to these risk factors. The team leaders' rotation plans are made empirically, and without considering the evaluation carried out by the validated evaluation method EAWS (Schaub et al., 2013). Nonetheless, they are trained to actively pursue weekly changes in diversity and variability in overall exposure and thus, mitigate the effects of the cumulative exposure to the biomechanical risk factors, reducing the incidence of the MSSs. Another important factor concerns the initial condition of all workers, regardless of their previous week, where they start their workweek following a resting period of 2 days. We can speculate that both the rotation plan and the 2-day rest period may impact the symptoms intensity reported by the workers and reset their perceived symptomatology at the beginning of each week. However, even if there is residual symptoms from the workweek prior to the assessment, we adjusted all models when baseline differences were observed for self-reported MSS. Therefore, the time x group interactions between the high and low risk group for each of the body segments were irrespective of the worker's baseline values.

Another finding from this investigation concerns the results obtained at the end and the beginning of the shift, throughout the workweek. Most of the associations found for the within-group changes and time x group interactions were observed at the end of the shift, which could be explained by the fact that workers had already undergone their shift, thus were already exposed to all the risk factors. Interestingly, there was no within-group changes for the MSS reported at the beginning of the shift throughout the week, suggesting that workers always started on average with the same intensity of self-reported symptoms. Therefore, self-reported symptoms at the end of the shift may provide more valuable information, especially if looking at the short-term cumulative effects for exposure. To our knowledge, most of the literature does not report the time of the working day when the symptoms was reported. In fact, one study in a seafood processing factory indicated that the data collected was performed after the shift, also found that 80% of their workers reported symptoms after the shift on upper and lower extremities, neck, and shoulders (Thi Thu Tran et al., 2016).

This study is not without limitations. For instance, we did not control the models for the risk factors that workers were exposed in the week prior to data collection, and other important determinants, such as physical activity level and the handedness of the participants. However, when baseline differences between groups were observed for musculoskeletal intensity symptoms, we adjusted the models for baseline values in each of the groups (Podsakoff et al., 2003). Regardless of the initial briefing on how to fill the questionnaires, self-reporting data on MSS can always be biased depending on workers' mood and on a higher frequency of data collection. Despite the dropout being higher than expected (~30%), the 228 subjects included in the final sample still have a high variability of exposure to the risk factors, given the tasks performed in the production line. Moreover, the results obtained in the intention to treat analysis (data not shown) did not differ from those presented in this study.

One of the methodological strengths of our study is the short-term longitudinal approach, which might provide valuable insight into how MSS may be related to biomechanical risk factors. Additionally, we provide information in several body segments, while also accounting for different biomechanical risk factors in both the beginning and end of the shift using a significant sample size.

3.5. Conclusions

In conclusion, this work suggests that workers in the high-risk groups to biomechanical risk factors such as posture, force, and the overall exposure had unfavorable effects on their self-reported MSSs throughout a workweek. More specifically, the risk factor posture seems to have an increased contribution to the MSSs in the neck and left shoulder regions. Therefore, alternating exposure to such risk factors may be of relevance to the short-term period to possibly prevent or help improve the MSSs, thus affecting the incidence of long-term MSDs in the automotive industry.

Author Contributions

Conceptualization, A.A. and F.C.; methodology, A.A. and F.C.; software, A.A.; validation, A.A. and F.C.; formal analysis, A.A. and S.B.; investigation, A.A., V.M.P., A.P.V. and F.C.; resources, A.A.; data curation, A.A. and S.B.; writing—original draft preparation, A.A.; writing—review and editing, A.A., V.M.P. and F.C.; visualization, A.A.; supervision, F.C. and C.F.; project administration, A.A.; funding acquisition, A.A. and S.B. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The study was carried out following the recommendations of the Declaration of Helsinki for Human Studies. The protocol was approved by the Ethics Committee of the Faculty of Human Kinetics, from the University of Lisbon (CEFMH Nº8/2019) (Appendix B).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available from the corresponding author on reasonable request.

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Conflicts of Interest

The authors declare no conflicts of interest.

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CHAPTER 4

A Genetic Algorithm Approach to Design Job Rotation Schedules Ensuring Homogeneity and Diversity of Exposure in The Automotive Industry[2]

[2] **Based on:** Ana Assunção, Nafiseh Mollai, João Rodrigues, Carlos Fujão, Daniel Osório, António P. Veloso, Hugo Gamboa, Filomena Carnide (2022) *A genetic algorithm approach to design job rotation schedules ensuring homogeneity and diversity of exposure in the automotive industry*. Heliyon. 8, e09396. https://doi.org/10.1016/j.heliyon.2022.e09396

Abstract

Job rotation is a work organization strategy with increasing popularity, given its benefits for workers and companies, especially those working with manufacturing. This study proposes a formulation to help the team leader in an assembly line of the automotive industry to achieve job rotation schedules based on three major criteria: improve diversity, ensure homogeneity, and thus reduce exposure level. The formulation relied on a genetic algorithm, that took into consideration the biomechanical risk factors (EAWS), workers' qualifications, and the organizational aspects of the assembly line. Moreover, the job rotation plan formulated by the genetic algorithm formulation was compared with the solution provided by the team leader in a real life-environment. The formulation proved to be a reliable solution to design job rotation plans for increasing diversity, decreasing exposure, and balancing homogeneity within workers, achieving better results in all the outcomes when compared with the job rotation schedules created by the team leader. Additionally, this solution was less time-consuming for the team leader than a manual implementation. This study provides a much-needed solution to the job rotation issue in the manufacturing industry, with the genetic algorithm taking less time and showing better results than the job rotations created by the team leaders.

Keywords: *automotive industry, musculoskeletal disorders, prevention approach, workplace intervention, genetic algorithm, occupational risk factors*

4.1. Introduction

Musculoskeletal disorders (MSD) are the most common work-related health problem worldwide (Sebbag et al., 2019), being considered one of the top reasons for work absenteeism (Durand et al., 2014). Within this context, work-related musculoskeletal disorders (WRMSDs) have a significant impact on the declined working capacity and quality of life of workers, as well as high costs for companies and society due to productivity loss and healthcare services (De Kok et al., 2019). Preventing WRMSDs is especially important in repetitive jobs with less exposure variation, fewer breaks, and prolonged low-level exertions, such as that in the automotive industry (Mossa et al., 2016), since these jobs tend to be the reason behind the higher number of WRMSDs on the long term (Aryanezhad et al., 2009).

Alongside other measures to reduce the incidence of WRMSD (i.e., engineering, processes, and product changes on the assembly line), the job rotation plans have been recommended as an organizational measure to reduce the exposure in workplaces to several risk factors and, thus, increase the variability and reduce worker fatigue and monotony (Jorgensen et al., 2005; Rodriguez and Barrero, 2017; Yung et al., 2012). Within the several solutions found in the literature to optimize job rotation plans, there are mixed-integer programming to upper extremities (Boenzi et al., 2013; Digiesi et al., 2018; Xu et al., 2012), minimizing net present cost within a lean manufacturing cell (McDonald et al., 2009), multi-criteria fuzzy-genetic algorithms for assembly line balancing (Rajabalipour Cheshmehgaz et al., 2012), and diploid genetic algorithm (GA) in dynamic environments (Bhasin et al., 2016).

The GA stands out from the remaining solutions since it can solve complex mathematical problems in situations where there are a large number of possible outcomes and the environments are dynamic (Carnahan et al., 2000). In fact, the GA have already been implemented in different automotive industry scenarios with several studies using this approach to reduce the risk of MSDs and maximize the diversification of the job rotation plans (Asensio-Cuesta et al., 2012b, 2012a; Diego-Mas et al., 2009). For instance, the GA solution provided by Diego et al. for an automotive parts supplier assembly plant (Diego-Mas et al., 2009), focused on maximizing the diversification while using a multi set of criteria that characterized the workplace by physical, mental, and communication capacities. The same authors also used a GA approach to design a job rotation in environments characterized by high repeatability of movements (Asensio-Cuesta et al., 2012a). Compared to their previous work, authors added information from the Occupational Repetitive Action (OCRA) screening tool, in which they assessed the presence of risk factors when performing repeated movements. The solution was able to diversify the tasks in order to aid the recovery of workers in between jobs. In a different take on this topic, Asensio-Cuesta and colleagues (Asensio-Cuesta et al., 2012b) developed another GA solution that considered the competence criterion related with product quality and employee satisfaction as a measure for the goodness of solutions. Although the method used is the same, the choice, the number, and the diversity of variables included in the model (e.g., movements, general capacities, task time) as well as the criteria used to establish the GA (e.g., capacity to perform the movement, frequency of movement per minute) differ between studies, which leads to different results and amplifies the lack of consensus in the literature regarding the effectiveness of rotation plans (Comper and Padula, 2014).

Although most of the studies have focused on the issue of diversity for the development of the job rotation plans, other criteria may have a significant impact in reducing the risk of MSDs, and should not be overlooked, such as the homogeneity (i.e., balanced effort) between workers and the overall exposure (i.e., daily demand) to risk factors. Moreover, the majority of the GAs used in the literature relied on changes in the intensity of the task to increase the diversity of the job rotations, which was achieved by using specific or general ergonomic risk assessment metrics, differing in respect to the level of detail regarding evaluation sections they cover (Carnahan et al., 2000; Diego-Mas et al., 2009). Moreover, most of the studies covered the issue of job rotation plans in an automobile parts supplier industry, with a lack of information on assembly lines of big automotive plants, where the specificities of the tasks performed may have different implications for WRMSDs. To the best of our knowledge, currently there is no suitable solution to tackle the job rotation issue in the automotive industry that focuses not only on the diversity criteria, but also ensures the reduction of exposure throughout the working shift, and safeguards the homogeneity within the team, while using objective ergonomic indicators to build a job rotation plan.

This study's aims were two-fold: 1) to develop a formulation based on objective ergonomic indicators and workers qualifications to generate a job rotation plan based on diversity, homogeneity, and exposure criteria for an assembly line in the automotive industry, solved by means of a GA; and 2) provide an industrial case study where the GA was tested and applied to a randomly selected team from the automotive assembly area in a real life-environment, in order to compare the performance of the job rotation plan formulated by the new GA versus that of the team leader.

Given the length and detail of the GA, and to guide the reader, the manuscript is organized into the following sections: In section 2, we address the modelling assumptions used to apply the GA, provide a detailed description of the job rotation variables included in the GA and explain the respective mathematical formulation. In section 3, we describe the GA architecture and the several steps needed to provide the best closing condition. Section 4 presents the results of an industrial case study, where the GA was tested in a real life-environment. Finally, in section 5, the results are discussed and wrapped up by a conclusion in section 6.

4.2. Methods

4.2.1. Modelling assumptions

To apply the GA in this study, several assumptions were considered, including organizational conditions, workforce, and workstation characteristics, which were made to cope with real-life environments constraints of this assembly line, including:

- Workers perform the workstations that they are qualified to, according to the versatility matrix of the respective team.
- In each rotation period, only one workstation could be assigned to each worker.
- During a shift, the same workstation should not be assigned to a worker more than once.
- Workstations with high demands on the same body region should not be consecutively assigned to the same worker.
- Any workstation can be assigned in the first period of the shift, as full recovery from one day to the next is assumed.

• All variables of the formulation are deterministic and constant during the planning horizon.

• The allocation of workers to workstations is independent of gender, efficiency, and quality.

4.2.2. Notation

The notation used in the proposed model is available in Table 4.1.

Table 4.1 - Index and parameters definition

Index	Definition
ws	Index of workstations, where ws=1,2,…,WS
w	Index of workers, where w=1,2,…,W
rot	Index of rotation periods, where rot=1,2,3,4
i	Index of categories of each risk factor or risk factor layers, where i=1,…,N
l	Index of layers of the force risk factor categories, where l=1,2,…,L
t	Index of the workplace transition period, where t=1,2,…,$R-1$
rf	Index of risk factors of the EAWS, where rf=p, mmh or f
Parameters	
OE_{rot}	Score of a workstation on a rotation period rot (See Eq.1)
AP_{ws}	Overall score of a workstations ws
$\Delta t\%_{rot}$	Percentage of time of rotation period rot
OE_w	Occupational exposure score of a sequence of workstations attributed to a worker w (See Eq.2)
NOE_w	Normalized occupational exposure score of a sequence of workstations attributed to worker w (See Eq.3)
min_w	Minimum occupational exposure score of worker w
max_w	Maximum occupational exposure score of worker w
tsA_t	Transition score of the risk factor group A (e.g., ts_p - posture and ts_{mmh} - Manual Material Handling) for the transition period t (See Eq.4)
$tsA_{t,i}$	Transition score given to the category i of the risk factor (group A) for the transition period t
tsB_t	Transition score of the risk factor group B (ts_f - force) for the transition period t
$tsB_{t,l}$	Transition score given to the layer l of the risk factor (group B) for the transition period t (See Eq.5)
$tsB_{t,l,i}$	Transition score given to the layer l and category i of the risk factor (group B) for the transition period t
$ts_{w,rf}$	Transition score of a sequence for risk rf and worker w (See Eq.6)
ts_t	Transition score for the transition period t
Ts_w	Transition score of a sequence for worker w (See Eq.7)
W_{rf}	Weight of risk factor rf
σ_{oe}	Standard deviation of the NOE scores of the team (See Eq.8)
σ_d	Standard deviation of the T_s scores of the team (See Eq.10)
$\overline{NOE}$	Mean NOE score for the team
$\overline{Ts}$	Mean transition score of the team
$SWSQ_w$	Shift working sequence quality for worker w (See Eq.13)
$\overline{SWSQ}$	Mean shift working sequence quality (See Eq.14)
Hom	Homogeneity score (See Eq.12)
Hom_d	Homogeneity score for diversity
Hom_{oe}	Homogeneity score for occupational exposure
MQ	Matrix quality index of the job rotation plan (See Eq.15)

4.2.3. Job rotation plan variables

Two main types of variables were considered to design the job rotation plan: (1) biomechanical variables; and (2) organizational variables.

Biomechanical Variables

The main variables used to define the quality assessment of a job rotation schedule were: (1) the overall risk score of each workstation, resulting from the assessment of the biomechanical and organizational work conditions; (2) the duration and intensity of the biomechanical risk factors present in each workstation such as posture, force, and manual material handling (MMH).

Data on biomechanical work conditions (intensity, duration, and frequency) were collected from the ergonomics evaluation made through the European Assembly Worksheet method (EAWS) (Schaub et al., 2013) performed by certified ergonomists. The corresponding methods evaluated the movements made by a worker while performing the workstation. This method assessed:

- working postures and movements with low additional physical efforts;
- action forces of the hand-finger system and/or whole body;
- MMH;
- repetitive loads on the upper limbs.

As a result, a combined score of all these risk factors was used and an overall exposure score was assigned to the workstation characterized by a traffic light color scheme: green - no risk or low risk (0-30 points); yellow - possible risk (31- 49 points); and red - high risk (>50 points) (Schaub et al., 2013).

Organizational variables

The team's versatility matrix was obtained from the Team Leader. The matrix indicates the qualifications of workers. In other words, it provides which workstations can be assigned to which workers according to their skills. The duration of each rotation period differs between shifts (early, late, and night shifts) and even between teams within the same area. Also, a common approach in practice is to estimate ergonomic risks as a time-weighted average of the respective ergonomic points for the different jobs. Thus, this data was also included to calculate the occupational exposure score for the quality assessment metric.

4.2.4. Defining the Fitness Function

The fitness function is the core of this work. In this function, the mathematical formulation that guides optimization algorithms, such as the GA, was integrated to reach the solutions that were desired. In this section, we describe how this mathematical formulation was created based on the aforementioned variables.

The quality of the job rotation schedule was estimated with variables that are present in the working day of each worker. The EAWS data was used to characterize the occupational environment. These scores quantify the risk of each workstation and provide an individual picture of each of the risk factors that were used for the global score. The way these variables are combined to give a representative score of the job rotation schedule should maximize its purpose, which is to assign a sequence of workplaces that promotes the variation in posture, load, and muscle activity (Mathiassen, 2006).

Furthermore, the proposed mechanism for building the fitness function was composed of three layers of analysis: (1) overall averaged occupational exposure score, (2) diversity calculated for the sequence of workstations considering the risk factors, and (3) a homogeneous rotation schedule, so that the scores assigned to the team were balanced between workers.

Exposure

The first layer of assessment involved calculating the average *occupational exposure* score from the sequence of workstations assigned to each worker. The *occupational exposure* score of a workstation (OE_{rot}) in a given rotation period *rot* was calculated according to Eq. 1, considering the network shift time:

$$OE_{rot} = AP_{ws} \times \Delta t\%_{rot} \tag{1}$$

The time was fixed according to the rotation period in which the workstation was allocated. Finally, the resulting score for a sequence of workstations (OE_w) performed by a worker over the set of rotation periods (n_{rot}=4) was given according to Eq. 2:

$$OE_w = \sum_{rot=1}^{n_{rot}} OE_{rot} \tag{2}$$

The OE_w has to be normalized to obtain a value between 0 and 1 as an output. A sequence with a score of 0 was the best possible sequence of workstations considering the qualification matrix. On the other hand, the score of 1 represents the worst possible sequence of workstations. The lowest exposure score (min_w) was therefore associated with 0, while the highest (max_w) was associated with 1. Before the algorithm was applied, the worst and best reference exposure sequences for each worker were calculated. The normalization was made taking into consideration these reference values (min_w and max_w):

$$NOE_w = \frac{OE_w - min_w}{max_w - min_w} \tag{3}$$

where NOE_w was the normalized *occupational exposure* score for a given worker's (w) sequence.

Diversity

The second layer of assessment consisted of calculating the diversity in the sequence of workstations. Diversity is the amount of change in the exposure score between successive workstations for each one of the following risk factors: posture, force, and MMH. Therefore, this measure should guide the algorithm to reach solutions that have a high diversity. Generally, diversity was calculated through a score for the transitions between categories of exposure in successive workstations (in a multi-layered process). It is relevant to mention that the term *transitions* was intended to represent the change in the presence of a risk factor between successive workstations. Since there were 4 working periods, there were 3 transitions evaluated. Independent of the risk factor, each transition can be categorized, based on the presence (1) or absence (0) of a risk factor, as one of the three possible types of transitions showed in Figure 4.1, namely Type 1, 2 or 3:

Type 1 transitions - there is a change between the presence and absence of risk factor in two consecutive workstations (presence to absence, or vice-versa). The score for this transition is 1, as it is the type of transition preferred to be searched.

Type 2 transitions - the risk factor is absent in two consecutive workstations, so the score is ⅓ (absence to absence). This value was given because the absence of a risk factor in two consecutive workstations should not be evaluated as bad, but the algorithm should be guided in searching for solutions that have diversity, therefore it should be scored under 1. This way, type 2 transitions are favored against type 3 transitions, but not with regard to type 1 transitions.

Type 3 transitions - the risk factor is present in two consecutive workstations, thus being the non-desirable transition. The score attributed to this type of transition was dependent on the risk factor evaluated.

The process to calculate the score of a transition depends on the risk factor category. For posture and MMH, the process is showed in Figure 4.1, while for force, the process is showed in Figure 4.2.

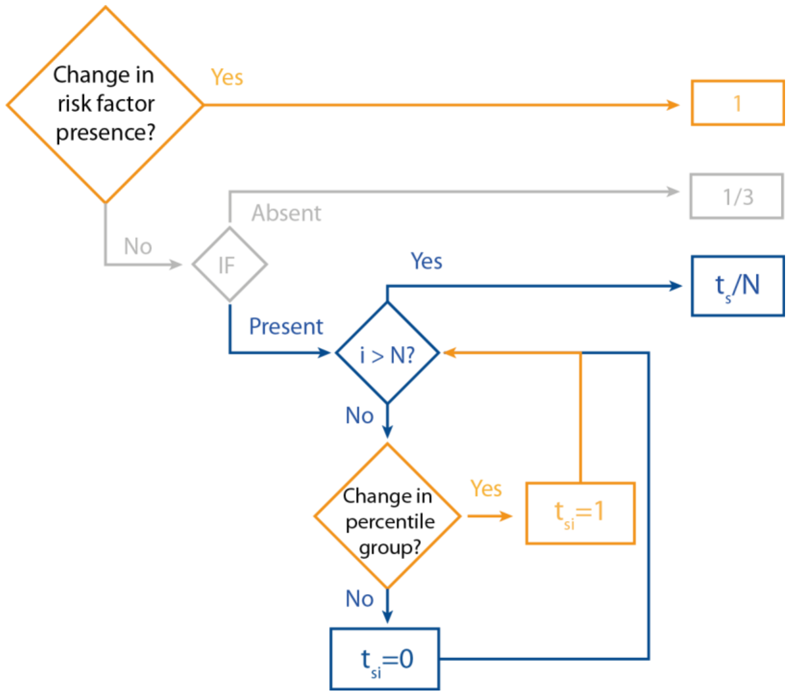

Figure 4.1 - Diversity in posture and manual material handling. The process is depicted as a flowchart. When the risk factor is present in both workstations, the process iterates over the categories of the risk factor, being i the iterator variable.

Diversity in Posture and Manual Material Handling

The diversity in posture and MMH was calculated following the same rationale. The first step was to verify the presence of a risk factor in the next workstation. Therefore, if the risk factor was present in the first workstation (1) but not in the next one (0) (or vice versa - type 1 transitions), then the score for the transition was calculated for the risk factor between these two workstations was 1. However, if the risk factor was absent in both (type 2 transitions), then the transition score was 1/3. If the risk factor was present in the first two workstations, which means that no transition existed, then a second step was needed.

EAWS evaluates posture according to time spent in an awkward posture during the cycle time. A transition in the sequence would mean that the difference in the scores of the following workstations was significant. To establish significance levels, the distributions of the risk factor scores for each posture category, and each worker were divided into four percentiles (0-25%, 25-50%, 50-75%, and 75-100%). Transitions were considered significant when consecutive workstations had scores belonging to different percentiles. If there was a change in the percentile, the score was 1, and if not, the score was 0. Although the body region was recruited in two consecutive workstations, the intensity with which this recruitment took place was different, and, therefore, there was diversity. This diversity was sought with this algorithm.

The process to calculate the diversity score for MMH was the same as posture. In the case of posture, a diversity score for each body region (N=3) (i.e., elbow, trunk, and shoulder/neck) was calculated. In the case of MMH, 4 categories (N=4) were considered: repositioning, carrying, holding, and pushing and pulling.

Equation 4 shows the process to calculate the transition score (tsA_t) for posture and MMH:

$$tsA_t = \sum_{i=1}^{N} \frac{tsA_{t,i}}{N} \tag{4}$$

$$tsA_{t,i} = \begin{cases} \mathbf{1}\ if\ Q_a \neq Q_{b,}\ ws_{rot} \in Q_{a,} ws_{rot+1} \in Q_b \\ \mathbf{0}\ if\ Q_a = Q_{b,}\ ws_{rot} \in Q_{a,} ws_{rot+1} \in Q_b \end{cases}$$

Here, the tsA_t is the score for the transition of the risk factor; i represents the categories of the risk factor; $tsA_{t,i}$ is the score for the transition t and the category i for the risk factor (body region and MMH categories), and Q_a is the percentile where the workstation ws on the rotation period rot belongs to, with Q_b being the percentile belonging to where the workstation ws is on the next rotation period $rot + 1$. To have an output between 0 and 1, a denominator factor N was used, which is equal to the number of categories in each factor.

Diversity in Force

The calculation of diversity in force follows the same logic as in the previously mentioned risk factors. However, when facing a transition of type 3, the process was made in more layers and differently. The first step, like posture and MMH, was checking if a risk factor was present in consecutive workstations and if so, the following layers were evaluated: (1) the presence of that risk in one or both systems “whole-body” and/or “hand-arm-finger”; (2) if present, at what intensity and, (3) in what type, dynamic or static. Figure 4.2 represents the calculation of diversity for force.

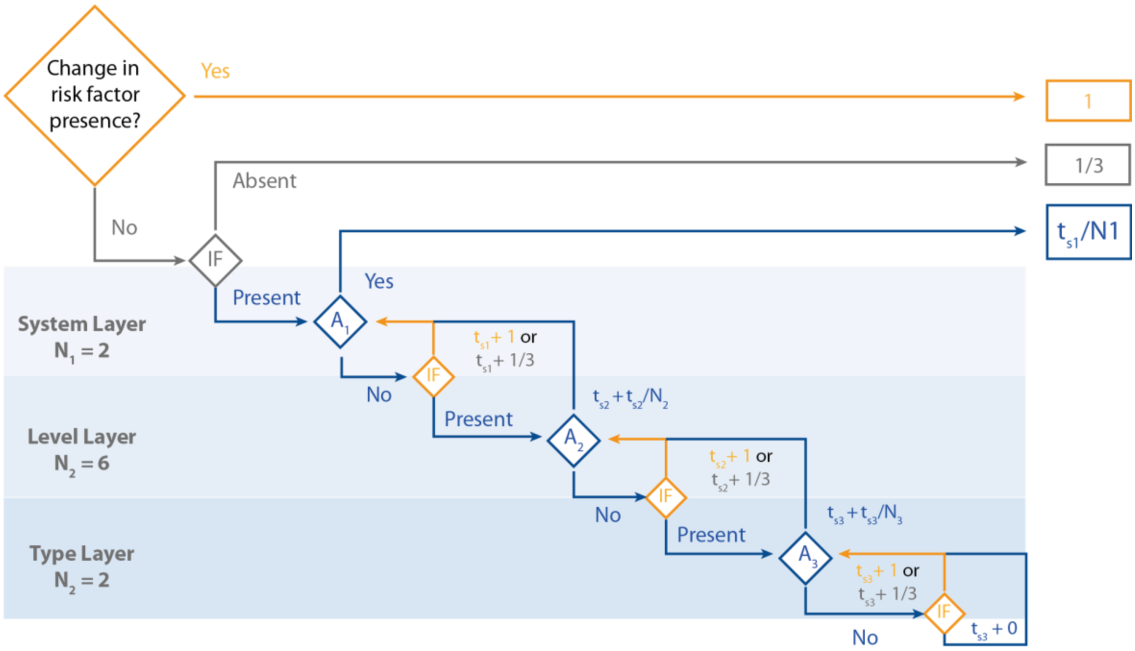

Figure 4.2 - Flowchart to calculate force diversity. In each layer, on the left, it is indicated the number of categories (N). On the right side, the possible scores attributed to type 1 (top), type 2 (middle), and type 3 (down) transitions are presented.

Looking at Figure 4.2, the rationale followed in a downward direction until the transition was verified or until the last layer was met (the type of force).

In the case of being present in two consecutive workstations, the score was calculated in the next layer to verify the change in the presence or absence of the risk factor in the *whole body* or *hand-arm finger* system. Next, the process was repeated, and if the risk factor was presented in both workstations in the *system layer*, the presence and absence of the risk factor was checked for each *intensity level* (light, medium, high, stressed, maximum, or > maximum). If the risk factor was observed in both workstations at a specific *intensity level*, the calculation of the score goes deeper and the change of presence and absence of the risk factor was evaluated for the force mode (dynamic or static). Finally, in that layer, if the presence of the risk factor was verified in both workstations, then the output was 0.

The details in Eq. 5 show how to calculate the diversity in force:

$$tsB_{t,l} = \sum_{i=1}^{N_l} \frac{tsB_{t,l,i}}{N_l} \tag{5}$$

$$tsB_{t,l,i} = \begin{cases} \mathbf{1} : for\ type\ 1\ transitions \\ \dfrac{\mathbf{1}}{\mathbf{3}} : for\ type\ 2\ transitions \\ \boldsymbol{tsB_{t,l}} : for\ type\ 3\ transitions, \\ with\ l\ = l + 1\ \ and\ if\ l\ < 3 \\ \mathbf{0} : for\ type\ 3\ transitions, \\ if\ l\ = 3 \end{cases}$$

In this case, $tsB_{t,l}$ is the transition score given to layer l, $tsB_{t,l,i}$ is the transitions score for the category i in that layer l. N_l is the number of categories of layer l and i is the iterator over the categories.

Total diversity score

For each one of the risk factors described in the previous sections, the transition score t_s had to be accounted for all rotation periods during the working day. Therefore, the diversity score of each risk factor was calculated with Eq. 6:

$$ts_{w,rf} = \sum_{t=1}^{R-1} ts_t \tag{6}$$

Note that, $ts_{w,rf}$ is the transition score for risk factor rf for worker w in the transition period t, resulting from the sum of the transition score ts_t for the transition period t.

The total diversity score, considering all risk factors was calculated. As the effect of the risk factors on occupational exposure was not equal, the relevance of the transition score of each risk factor was weighted (W_{rf}) differentially: 3 for posture, 2 for force, and 1 for MMH. The rationale for this choice was based on the ergonomics assessment and the weight of each risk factor to the total score (Bao, 2015). The score of each change in the workplace was then the sum of the transition score for each risk factor normalized between 0 and 1. The final score value was calculated according to Eq 7:

$$Ts_w = \frac{\sum_{rf} W_{rf} \times ts_{rf}}{6} \tag{7}$$

In this formulation, rf is the risk factor considered: posture, force, or MMH.

Homogeneity

The homogeneity was the last variable included in the *fitness function*, and our formulation. In order to guarantee the balance between the team, homogeneity aimed to guide the algorithm to avoid favoring workers differently. The homogeneity score was calculated after the occupational exposure and diversity score were calculated for all of the team workers. The standard deviation of occupational exposure (Eq. 8) and diversity scores (Eq. 10) was calculated. Then, the homogeneity contribution of occupational exposure (Eq. 9) and diversity (Eq. 11) was determined.

$$\sigma_{oe} = \sqrt{\frac{1}{W}\sum_{w=1}^{W}\left(NOE_w - \overline{NOE}\right)^2} \tag{8}$$

$$Hom_{oe} = 1 - \sigma_{oe} \tag{9}$$

where: the σ_{oe} is the standard deviation of occupational exposure, W is the number of workers on the team, w is the iterator over the workers, NOE_w is the occupational exposure score for the worker w and $\overline{NOE}$ is the mean occupational exposure score of the team. Hom_{oe} is the homogeneity contribution of the exposure.

$$\sigma_{d} = \sqrt{\frac{1}{W}\sum_{w=1}^{W}\left(Ts_w - \overline{Ts}\right)^2} \tag{10}$$

$$Hom_{d} = 1 - \sigma_{d} \tag{11}$$

Here σ_d is the standard deviation of occupational exposure, W is the number of workers on the team, w is the iterator over the workers, Ts_w is the diversity score for the worker w and $\overline{Ts}$ is the mean diversity score of the team. Hom_{oe} is the homogeneity contribution of diversity.

Since the standard deviation is a measure of dispersion, the higher the value the worse the balance is of the job rotation plan between workers. As a mean to have a value with a positive trend (the higher the better), the homogeneity score (Hom) results from an inverse sum of both standard deviations. The final homogeneity score is given by Eq. 12:

$$Hom = Hom_d + Hom_{oe} \tag{12}$$

4.2.5. Formulation of the Fitness Function

The *fitness function* is the combination of *occupational exposure*, *diversity,* and *homogeneity*. For each worker sequence, a score was calculated for *occupational exposure* and *diversity*, normalized between 0 and 1. The index that characterizes the quality of this worker sequence was the weighted sum of both scores, 2 for diversity, and 1 for occupational exposure (Eq. 13).

$$SWSQ_w = 1 - scoreOE_w + 2 \times scoreD_w \tag{13}$$

In this case, $SWSQ_w$ is the quality of the shift working sequence index for worker w. Note that the *occupational exposure* score has a negative trend (the lower the better), therefore the subtraction in the equation was used to invert the trend of the parameter.

The shift working sequence quality ($SWSQ$), which means the quality of the job rotation plan for the entire team (i.e., characterizes the job rotation plan in terms of *occupational exposure* and *diversity*), was calculated by averaging the set of indexes (Eq. 14).

$$\overline{SWSQ} = \sum_{w=1}^{W} \frac{SWSQ_w}{W} \tag{14}$$

Finally, the homogeneity score was added, resulting in the matrix quality index (MQ) (Eq. 15):

$$MQ = \overline{SWSQ} + 0.25 \times Hom \tag{15}$$

Since the search should favor job rotation schedules with reduced exposure and high diversity above homogeneous schedules, a weight of 0.25 was calculated for the homogeneity score to adjust its influence in the guidance of the algorithm.

The fitness function is then the MQ index, which has to be maximized to reach solutions that increase the diversity, reduce the exposure and increase homogeneity, as presented in Eq. 16:

$$max\ MQ = \overline{SWSQ} + 0.25 \times Hom \quad (16)$$

4.3. Heuristic approach for job rotation scheduling

The fitness function (Eq. 15) represents the quality of the job rotation plan regarding occupational exposure, diversity, and homogeneity. This function guides the algorithm in generating a job rotation plan that maximizes the MQ function (Eq. 16). From this formulation, any optimization algorithm can be applied to reach a desired solution. In this case, the proposed algorithm was based on a GA, which was already applied in similar contexts by Diego-Mas et al. (Diego-Mas et al., 2009). In this section, we describe the several steps that comprehend the GA's architecture (Figure 4.3). The GA relies on the *natural selection* theory, in which evolution of the overall population into better offspring was expected over several iterations.

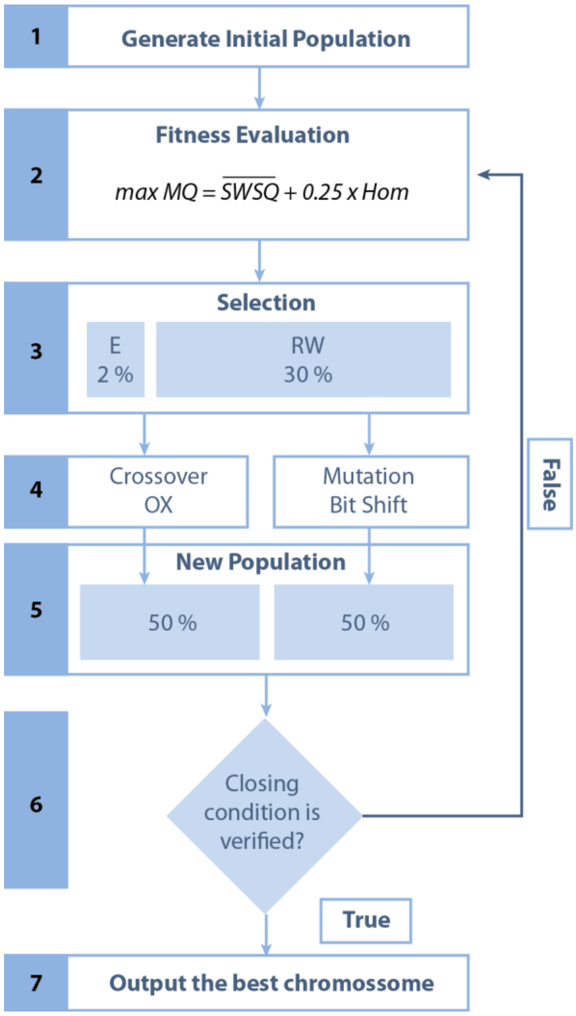

Figure 4.3 - Flowchart of the genetic algorithm architecture: Step (1): Creating initial population with valid chromosomes - randomly generated. Step (2): Evaluating the fitness of population members applying Equation 13, which considers exposure, diversity, and homogeneity. Step (3): Selection of the individuals that will undergo crossover and mutation with 2% Elitism (E), and 30% Rank-Based Wheel (RW). Step (4): Apply Crossover and Mutation methods. Step (5): Generate an offspring population from the selected chromosomes. Step (6): If the closing condition is met, return the best offspring (Step 7), otherwise, return to step 2.

Abbreviations: $\overline{SWSQ}$ – Mean shift working sequence quality; Hom – Homogeneity; OX – ordered crossover.

The algorithm starts by generating the initial population. Thereafter, in each iteration, a selection of a set of chromosomes that belonged to the population pool were selected to perform a crossover with their genes and/or were mutated, expecting that better chromosomes would be created over the iteration process that ended when a closing condition was verified. The proposed genetic algorithm followed the same architecture.

In this case, the nomenclature is defined in Figure 4.4, showing that the population is the overall set of possible job rotation plans; the chromosome belonging to the population is a valid job rotation plan; and the gene belonging to the chromosome is a workstation of the job rotation plan.

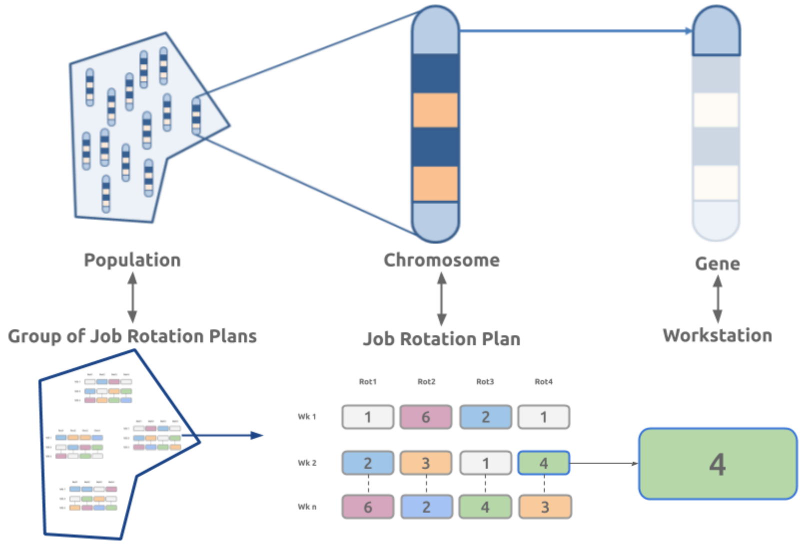

Figure 4.4 - Nomenclature of the genetic algorithm. The population is regarded as the group of possible job rotation plans; the chromosome is a valid job rotation plan, and the gene is a workstation.

The way a GA is structured can vary extensively and several approaches were found in the literature for the selection, crossover, and mutation steps. The chosen methods depend on the type of problem itself and the restrictions that the problem implies. In this case, the main restrictions were related to the definition of a valid job rotation plan. The structure of the proposed algorithm will be explained further, namely which methods were used for the selection, crossover, and mutation, as well as what comprised was the closing condition.

4.3.1. Population Generation

The GA started by randomly generating a primary population pool that contained a set of chromosomes. Each of these chromosomes is valid and cannot be generated against the constraints defined. Thus, a chromosome had a size of $n_w \times n_{rot}$, with n_w being the number of workers (equal to the number of workstations) and n_{rot} the number of rotation periods. One workstation was randomly assigned to each of the cells in the matrix, and no workstations was repeated on the same row. The initial number of chromosomes in the population can vary. The value of 100 individuals was considered, after obtaining satisfactory results for the case of 12 workstations and 4 rotation periods. Each of the chromosomes belonging to the population was evaluated by the fitness function to get a score that characterized their fitness.

4.3.2. Selection

Having the starting population, the next step was to select a set of chromosomes for the search space exploration with crossover and mutation. The selection had several criteria. The main idea was that the population should be able to evolve, and chromosomes should have better scores over the iteration process. First, it was necessary to guarantee the presence of 2% of the best chromosomes of the population for the next iteration, a process called elite selection. Second, for this process, a rank-based *roulette wheel selection* (Goldberg, 1989) was used to select 30% of the population pool. It is important to note that a chromosome selected was excluded from the population set to avoid further repetitions in the selection.

4.3.3. Crossover

The selected chromosomes were the base individuals that origin the new population for the next iteration. The crossover was responsible for 50% of the new population. During crossover, the selected chromosomes were merged based on a specific method. When merging the information of two chromosomes, the sequences of workstations attributed to each worker based on the information of two job rotation plans was expected to be reordered. The problem in swapping information from one job rotation plan to the other was that the offspring would probably be invalid, because: (i) it would have repeated workstations on the same rotation period; and (ii) the workstations assigned to a worker might not be present in his/her qualification matrix. To tackle these constraints, the proposed solution was to use a permutation-based crossover method applied column-wise to the chromosomes. In this case, the method considered was the *ordered crossover* (OX) (Moscato, 1989). Consider the example presented in Figure 4.5. For this example, we assumed that there were six different workstations and six different workers. The color and the corresponding number represent each workstation. The corresponding qualification matrix is presented in Figure C.1 Supplementary Material.

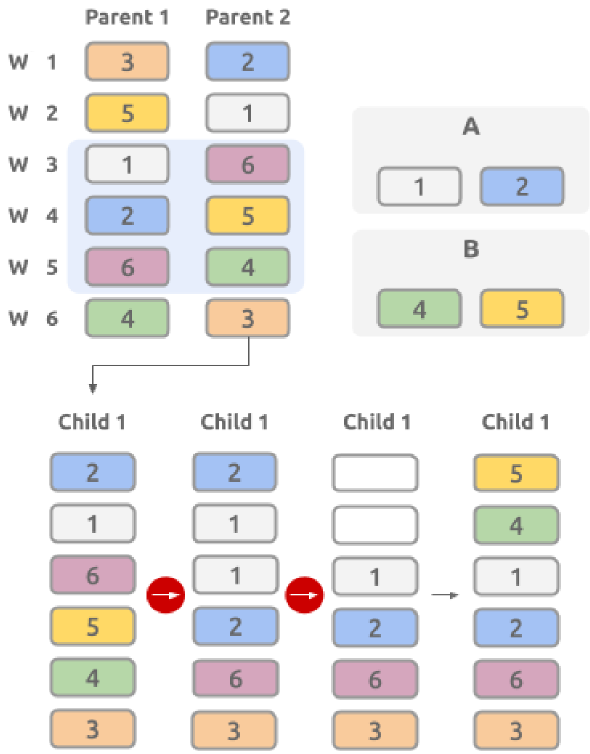

Figure 4.5 - Example of the ordered crossover method applied to this problem. From two parents (one rotation of a job rotation plan for each parent) a child was created. The child was based on a variation of parent 2, which has received the selection from parent 1, in the same positions. The genes that were now repeated in the child (group A) are erased, and the ones that are not present in the child will be added by the order they appear in parent 2. For those who belong to the map, the shift of genes will go through a qualification check. The red points indicate the checkpoint because of the workstation shift.

Abbreviations: w – worker

From two job rotation plans ($matrix_1$ and $matrix_2$), a random number of rotation periods (column) were selected to go through the OX method. From $matrix_1$ a column was selected as the first parent ($parent_1$, and the same column from $matrix_2$ was selected as the second parent ($parent_2$). The OX method starts by selecting randomly a subsection of workstations from $parent_1$. The child was mapped by inserting into $parent_2$, on the same subsection positions, the subsection of $parent_1$. In Figure 4.5, $ws1$; 2 and 6 were shifted from $ws6$; $ws5$ and $ws4$. After that, the repeating workstations ($ws1$ and $ws2$ - group A) were deleted from $parent_2$. The now missing workstations (5 and 4 - group B) were added by order of appearance in the original $parent_2$. This new rotation period was $child1$ with $ws5$; $ws4$; $ws1$; $ws2$; $ws6$ and $ws3$.

Each row (worker) had a set of valid workstations. If during the OX method, a workstation was shifted into a row where it was not valid, the process searched for rows where this workstation could fit and made the exchange. This process was a checkpoint to ensure the child generated was a valid option.

4.3.4. Mutation

The mutation is the other operator used to generate the other 50% of the new population. The method used was a variation of the bit string mutation. The process comprised 3 steps and was done per column: (1) random selection of rotation periods; (2) random selection of a workstation for a given rotation period; (3) change of the workstation selected for another in the same period of rotation, as long as it ensures compliance with the qualification matrix.

Consider the example presented in Figure 4.6 and the qualification matrix (Figure C.1 – Appendix 3). The example shows a column of one of the selected job rotation plans. The column had randomly been selected (step 1). Then one workstation was randomly selected (step 2). After that, this workstation was shifted with workstations that would follow the requirements. In this case, $ws3$ from $w1$ was selected. The possible workers to shift this workstation with were $w3$, $w5$ and $w6$, because these have $ws3$ on their qualifications, and $w1$ is able to perform $ws3$, $ws5$ and $ws6$. The shift workstation was then chosen randomly from the valid group.

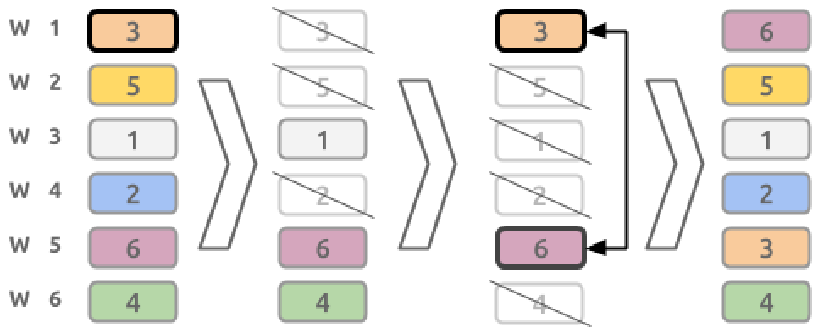

Figure 4.6 - Mutation example. A rotation period was selected and would be mutated to generate a variation of the rotation period.

Abbreviations: w – worker

4.3.5. Closing Conditions

When the closing condition is reach, the iterative process of the genetic algorithm ends, and a result is returned. Two conditions must be met: (1) "is the score of the best chromosome higher than the reference value?" and (2) "is the number of iterations above 100?”. The first condition guarantees that a job rotation plan with a referenced adequacy was returned. The reference value was the mean score of the weekly job rotation plan designed by the team leaders for their URQ. The second condition was meant to give the algorithm enough iterations to stabilize. This value had to be experimentally calculated by running the algorithm 1000 times and extracting the value that ensures a good margin to let the algorithm stabilize. When these two conditions are met, the algorithm stops and outputs the best chromosome of the population. If the conditions are not met, the algorithm is kept running to improve the offspring.

4.4. Industrial case study

A full detailed example on how the GA can be applied can be found in the Supplementary Material (Appendix C). The GA was also tested in a real life-environment, by being applied to a randomly selected team from the assembly area of an automotive industry with 12 workers, 12 workstations, and under the responsibility of (hereafter) a team leader. All workstations were close together and the standard rotation did not affect the normal operation of the production line (since rotation periods coincided with breaks). Although there was a standard job rotation at the company (provided by the Team Leader), the choice of the workstations was mostly based on empirical knowledge and experience.

In this study, the morning shift was considered. The working day was composed of 8h, with a lunch break of 30 minutes, and two breaks of 7 minutes each, before and after lunch. This translates into a mean network time of 466 minutes. Considering the network time, four working periods were already established with the following relative distributions: (1) 22.6%; (2) 30.7%; (3) 27.0%; and (4) 19.7%. Each worker performs 4 different workstations during the working day, according to their qualification. The versatility matrix was consulted to allocate workers to workstations that they were able to perform autonomously.

4.4.1. Workstations and workers

The evaluations of the 12 workstations belonging to the team are presented in Table 4.2. Most of the workstations were classified with medium risk, one workstation was classified as no risk ($ws10$) and two workstations were classified as high risk ($ws3$ and $ws11$).

Table 4.2 - Ergonomic evaluation and risk factors characteristics. Risk factor scores for all categories of the EAWS. The colors on the Action Forces section represent the type of force exerted: black - dynamic and static forces; dark grey - dynamic forces; light blue – static force; light grey - the risk factor is not present. The unit %t indicates the percentage of time spent in that risk factor during 1 cycle time, and n represents the number of times these risk factors appear in 1 cycle time.

	Posture (%t)							MMH (points)				Force (%t or n)												
	NS		T		E							WB						HAF						
	ASL	AHL	B	SB	GA 6	GA 8	GA 10	R	C	H	P	1	2	3	4	5	6	1	2	3	4	5	6	S
Ws1	0	0	15	0	53	11	10	0	0	0	0													42
Ws2	7	0	5	0	25	21	5	0	0	0	0													31
Ws3	0.2	0	19	0	39	18	9	0	0	0	0													59.5
Ws4	3	0	19	0	25	23	0	0	0	0	0													41
Ws5	0	0	31	0	18	16	3	0	0	0	0													48
Ws6	0	0	14	0	42	5	0	0	0	0	0													43
Ws7	0	0	0	2	33	8	0.5	0	0	0	0													35.5
Ws8	0	0	22	0	29	23	5	1	0	0	0													43
Ws9	0	0	3	0	40	10	0	0	0	0	0													35
Ws10	6	10	0	0	11	1	0	0	0	0	0													24.5
Ws11	9	24	0	0	13	0.9	2	0	0	0	0													56.5
Ws12	10	7	0	0	3	46	9	0	0	0	0													42.5

Abbreviations: Ws – Workstation; NS – Neck and shoulder; ASL – At/Above shoulder level; AHL – Above head level; T-Trunk; B-Bent; SB-Strongly bent; E – Elbow; GA6 – Arm reach at 60%; GA8 – Arm reach at 80%; GA10 – Arm reach at 100%; MMH – Manual material handling; R – Repositioning; C – Carrying; H – Holding; P – Pushing and Pulling; WB – Whole body force; HAF – Hand Arm Finger force; S - Score

Note that posture was evaluated considering the percentage of time that an awkward posture was observed during the cycle time (approximately 79 seconds), as well as the static force for the whole body and hand arm finger systems. The dynamic type of force was accessed according to the frequency of its presence in the cycle time. The presence or absence of MMH in the workstation was used to classify this risk factor.

The team’s qualification matrix is given in Table 4.3. From the 12 workers, eight had full versatility, i.e., they can perform autonomously all workstations, which was an advantage to the Team Leader.

Table 4.3 - Worker's versatility according to the workstations. The empty cells indicate that the worker does not have the competence to perform the respective workstation

	WS 1	WS 2	WS 3	WS 4	WS 5	WS 6	WS 7	WS 8	WS 9	WS 10	WS 11	WS 12
W 1	•	•	•	•	•	•	•	•	•	•	•	•
W 2	•	•	•	•	•	•	•	•	•	•	•	•
W 3	•	•	•	•	•	•	•	•	•	•	•	•
W 4	•	•		•	•	•			•	•	•	•
W 5	•	•	•	•	•	•	•	•	•	•	•	•
W 6	•	•	•		•	•	•	•	•	•	•	•
W 7	•	•	•	•	•	•	•	•	•	•	•	•
W 8	•	•	•	•	•	•	•					•
W 9	•	•	•	•	•	•	•	•	•	•	•	•
W 10	•	•		•		•	•	•	•	•	•	•
W 11	•	•	•	•	•	•	•	•	•	•	•	•
W 12	•	•	•	•	•	•	•	•	•	•	•	•

Abbreviations: W – Worker; WS - Workstation

4.4.2. Convergence of the algorithm

The fitness function guides the algorithm during the iterative process, and it is expected to improve all variables contributing to the quality score. Therefore, the occupational exposure score should decrease, and diversity and homogeneity scores should increase. Figure 4.7 shows a higher improvement for diversity and homogeneity as expected, but on the other hand, exposure did not change significantly during the entire process. Regarding the quality score, the best job rotation plan in the population over the iteration process was verified as an improvement.

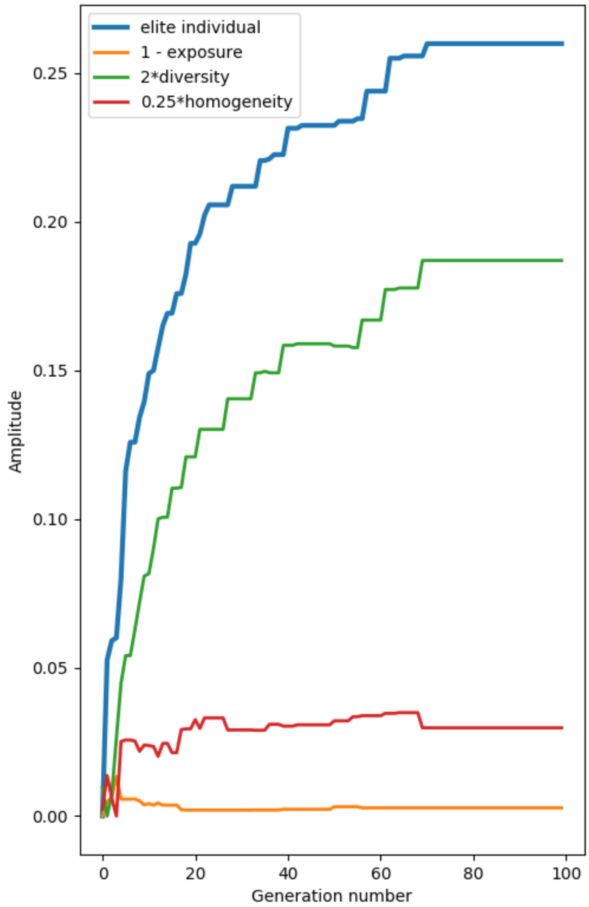

Figure 4.7 - Convergence of the algorithm considering exposure (orange), diversity (green), and homogeneity (red).

Figure 4.8 gives the evolution of the execution of the algorithm concerning exposure, diversity, and homogeneity and reflects the capacity of the algorithm to progressively generate better solutions by employing simulated evolution techniques.

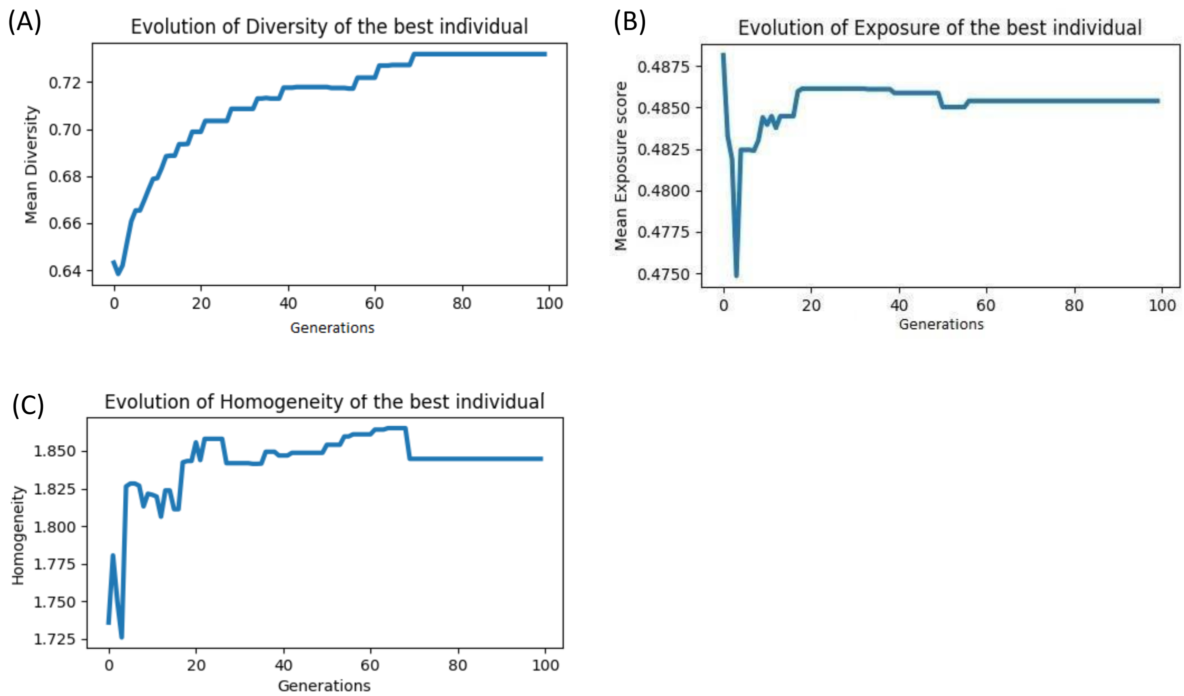

Figure 4.8 - Evolution of the fitness of the best individual throughout the generations, concerning exposure (A), diversity (B), and homogeneity (C).

The algorithm reaches a stable solution around the 70th iteration.

4.4.3. Job rotation schedule obtained

The algorithm took 53 seconds to generate the proposition of a job rotation plan for the problem proposed: 12 workers, 12 workstations, and 4 working periods. The working computer used an Intel i5 quad core processor with 3.2 GHz, 8 GB of RAM and ran on a Linux Ubuntu 18.0.1 operative system.

The best solution obtained is presented in Figure 4.9. In this solution, the allocation of workers to workstations satisfied the restrictions imposed on the problem and tried to decrease the prolonged time consumed by the same movement. During the working day, the workers were not assigned to the same workstations and did not occupy two red workstations. This happened mainly because diversity was highly promoted over the iteration process, resulting in working sequences with better diversity results. In the last 3 columns of Figure 4.9, the contribution of each worker to the fitness function is given with the values of exposure, diversity, and SWSQ.

	Rot 1	Rot 2	Rot 3	Rot 4	Exposure	Diversity	SWSQ
w1	ws 4 41.0	ws 8 43.0	ws 11 56.5	ws 1 42.0	0.63	0.75	1.86
w2	ws 1 42.0	ws 10 24.5	ws 7 35.5	ws 3 59.5	0.32	0.68	2.03
w3	ws 12 42.5	ws 6 43.0	ws 3 59.5	ws 7 35.5	0.62	0.71	1.81
w4	ws 6 43.0	ws 12 42.5	ws 9 35.0	ws 12 42.5	0.51	0.78	2.04
w5	ws 9 35.0	ws 3 59.5	ws 6 43.0	ws 4 41.0	0.66	0.78	1.89
w6	ws 3 59.5	ws 9 35.0	ws 4 41.0	ws 9 35.0	0.45	0.78	2.10
w7	ws 5 48.0	ws 2 31.0	ws 1 42.0	ws 11 56.5	0.51	0.73	1.94
w8	ws 8 43.0	ws 4 41.0	ws 5 48.0	ws 2 31.0	0.33	0.69	2.05
w9	ws 10 24.5	ws 1 42.0	ws 2 31.0	ws 5 48.0	0.30	0.69	2.09
w10	ws 7 35.5	ws 11 56.5	ws 8 43.0	ws 10 24.5	0.56	0.74	1.92
w11	ws 11 56.5	ws 7 35.5	ws 10 24.5	ws 8 43.0	0.41	0.71	2.01
w12	ws 2 31.0	ws 5 48.0	ws 12 42.5	ws 6 43.0	0.51	0.75	1.99

Figure 4.9 - Best scored job rotation schedule for the last iteration of the algorithm. Each cell is colored considering the color traffic light scheme used to classify the risk of the workstation. Scores: $Hom\ = 1.84$, $\overline{SWSQ}$ =1.98, $MQ\ = 2.44$. Abbreviations: w – Worker; ws – Workstation; Rot – Rotation period; SWSQ - Shift working sequence quality

The scores for the job rotation schedules obtained are presented in Table 4.4. As expected, the first matrix had the worst MQ score compared to the last matrix (2.02 and 2.44, respectively). This was due to the fact that the first matrix had the worst set of occupational exposure and diversity scores, and these scores were not homogenous. The final score had a better homogeneity score when compared to the initial score (1.84 and 1.74, respectively).

Table 4.4 - Results for job rotation schedules obtained in the first and last iteration.

	$\overline{SWSQ}$	Hom	MQ
Best scored job rotation for 1st iteration	1.80	1.74	2.23
Worst scored job rotation for 1st iteration	1.63	1.59	2.02
Best scored job rotation for the last iteration	1.98	1.84	2.44

Abbreviations: $\overline{SWSQ}$- Mean shift working sequence quality; Hom – Homogeneity; MQ – Matrix quality

An improvement in the results during the iteration process resulted in a better solution, i.e., in a better job rotation schedule for this specific team.

A job rotation plan designed by a team leader is presented in Figure 4.10.

	Rot 1	Rot 2	Rot 3	Rot 4	Exposure	Diversity	SWSQ
w1	ws 4 41.0	ws 8 43.0	ws 11 56.5	ws 1 42.0	0.63	0.75	1.86
w2	ws 1 42.0	ws 10 24.5	ws 7 35.5	ws 3 59.5	0.32	0.68	2.03
w3	ws 12 42.5	ws 6 43.0	ws 3 59.5	ws 7 35.5	0.62	0.71	1.81
w4	ws 6 43.0	ws 12 42.5	ws 9 35.0	ws 12 42.5	0.51	0.78	2.04
w5	ws 9 35.0	ws 3 59.5	ws 6 43.0	ws 4 41.0	0.66	0.78	1.89
w6	ws 3 59.5	ws 9 35.0	ws 4 41.0	ws 9 35.0	0.45	0.78	2.10
w7	ws 5 48.0	ws 2 31.0	ws 1 42.0	ws 11 56.5	0.51	0.73	1.94
w8	ws 8 43.0	ws 4 41.0	ws 5 48.0	ws 2 31.0	0.33	0.69	2.05
w9	ws 10 24.5	ws 1 42.0	ws 2 31.0	ws 5 48.0	0.30	0.69	2.09
w10	ws 7 35.5	ws 11 56.5	ws 8 43.0	ws 10 24.5	0.56	0.74	1.92
w11	ws 11 56.5	ws 7 35.5	ws 10 24.5	ws 8 43.0	0.41	0.71	2.01
w12	ws 2 31.0	ws 5 48.0	ws 12 42.5	ws 6 43.0	0.51	0.75	1.99

Figure 4.10 - Example of a job rotation plan designed by a team leader.

Abbreviations: w – worker; ws – Workstation Rot – Rotation; $SWSQ$ – Shift working sequence quality

For evaluation purposes, look at $w1$, $w7$, and $w11$. Besides the risk level of the workstations, scores for the sequence evaluation are presented, namely the exposure, the diversity, and the sequence quality score. The sequence of workstations attributed to $w1$ was medium levelled, except for the first workstation, which had a low-risk level. This fact was verified by the exposure score, which was 0.09, close to 0, reflecting that this sequence was near to the best possible sequence $w1$ could have. Nevertheless, the diversity score of $w1$ was not as good (0.58). This shows how different the evaluation made for the diversity was between the three workers. Regarding $w11$, the scores were different. In this case, the sequence had two red-labelled workstations, which increased the exposure score. On the other hand, the diversity score was the same as for $w1$. This demonstrates how different the measures of exposure and diversity were. A sequence of workstations with low-levelled scores might be good in terms of exposure, but might be bad in diversity, because it measures different outcomes. For instance, $w7$ had the worst diversity score of the team. This was a result of the two identical workstations at the end of the shift, therefore compromising the diversity score at the last transition.

When comparing the best results obtained by the GA for one day (Table 4.4), with a full week planned by the team leader (Table 4.5), we found that the algorithm provided better results in all the parameters, including homogeneity, diversity, and matrix quality, regardless of the day analyzed.

Table 4.5 - Scores for shift working sequence quality, homogeneity, and matrix quality for job rotation schedules for a week designed by a team leader. These schedules were scored with the formulation designed.

Team Leader Matrix	$SWSQ$	Hom	MQ
Day 1	1.72	1.77	2.16
Day 2	1.64	1.71	2.07
Day 3	1.72	1.73	2.15
Day 4	1.76	1.74	2.20
Day 5	1.69	1.70	2.12

Abbreviations: $SWSQ$ – Shift working sequence quality; Hom – homogeneity; MQ – Matrix quality

4.5. Discussion

The main purposes of this study were: (1) to develop a formulation based on objective ergonomic indicators and workers qualifications to generate job rotation schedules based on three main criteria: diversity, exposure and homogeneity for an assembly line of the automotive industry solved by means of a GA; and (2) provide an industrial case study where the GA was tested and applied to a randomly selected team from the automotive assembly area in a real life-environment, in order to compare the performance of the job rotation plan formulated by the new GA versus that of the team leader. The algorithm proposed showed a high diversity sequence during working hours, a lower overall exposure, and reassured homogeneity to balance the rotation within each team. These results also demonstrate that the time spent by the team leader organizing the weekly schedule was considerably higher when compared with the time that the algorithm took to deliver a job rotation plan for a week.

A job rotation plan is an essential tool to the automotive industry and its aim is to facilitate not only the work of the team leader but also, in the long run, to reduce the risk associated with musculoskeletal injuries by increasing diversity, decreasing exposure, and ensuring homogeneity. This investigation, through its resources and departments, namely the industrial engineering, the ergonomics, and the occupational health teams, built a job rotation plan using a GA. The algorithm had a good computational performance and generated a solution that took less time building a rotation plan, when compared with that of the team leaders. More specifically, it took the algorithm 53 seconds to generate a job rotation plan, where usually team leaders spend approximately 2-3 hours. Thus, the use of GA has the potential to spare the team leaders time for allocation to other important tasks. The reduction in the time to generate a job rotation plan is in accordance with other studies that also used this type of algorithms (Asensio-Cuesta et al., 2012a; Diego-Mas, 2020; Diego-Mas et al., 2009; Hochdörffer et al., 2018).

Our results also suggest that the repetition of the same workstation, followed by rotation periods, although allowed, was not promoted by the method. This is a result of the algorithm giving higher relevance to the diversity score. This score has a wide progression and is the major factor of convergence. It also demonstrates that the algorithm can improve the conditions from the first iteration to the last and give a result that reflects the need for increased diversity and homogeneity, and decreased exposure. Diego et al. applied a GA in an automotive parts supplier assembly plant considering the previous rotations, trying to minimize the performance with the same body region, but not quantifying it, as we did with diversity (Diego-Mas et al., 2009). The option to favor diversity was supported by the physiologic pathways of musculoskeletal health stating that posture and load variation are beneficial (Mathiassen, 2006). One of the strengths and a novelty of this study is the fact that it included the calculation of diversity of force and MMH along with posture, which provides more risk factors being embedded by the GA, whereas, the majority of the algorithms presented in the literature relied on posture and movement, ergonomic score (from an evaluation method, e.g., OCRA, EAWS), learning skills, and others (Padula et al., 2017).

As far as exposure is concerned, it is one of the parameters contributing to the fitness function, but with less weight than diversity. In the literature, the cumulative exposure, with different criteria used between studies, is one of the key factors to evaluate the effectiveness of the job rotation schedule (Asensio-Cuesta et al., 2012a; Diego-Mas et al., 2009; Hochdörffer et al., 2018; Rajabalipour Cheshmehgaz et al., 2012; Xu et al., 2012). In this study, exposure did not change significantly because its weight was very low when compared to diversity. The choice to promote diversity over occupational exposure reflects the idea to promote an opportunity of relaxing overloaded motor units by having workstations that differ in all the risk factors considered (Mathiassen, 2006). Besides, the proposed formulation also considered homogeneity as a key feature, allowing workers to have a similar exposure during the shift. The team selected showed characteristics of versatility that were reflected on the matrix of the work team, where most of the workers were able to perform the majority of the workstations with autonomy. This is beneficial for workers since they have the possibility to improve their diversity and reduce exposure during the shift. A previous study has considered the balance between the workers as a contribution to the target function (Diego-Mas et al., 2009).

Even though there is no consensus in the literature about the effectiveness of this measure in the prevention of WRMSD’s (Comper and Padula, 2014), several approaches have been implemented, considering different criteria (Padula et al., 2017). The use of GA to generate job rotation plans in the industry is a common option due to its combinatorial nature and satisfactory results (Asensio-Cuesta et al., 2012a; Diego-Mas et al., 2009). The decision to use a GA to solve the combinatorial problem in designing the job rotation plan in this study was due to it already being proven to be successfully used in a similar context (Asensio-Cuesta et al., 2012a; Diego-Mas et al., 2009). The methods that were applied for selection, crossover, and mutation are well known and were used because these were found to be adequate for this problem (Moscato, 1989). The mutation rate, in this case, was higher than what is usually found in the literature, but better convergence results were reached with a higher mutation rate. The job rotation schedules generated by the GA provided better scores than the ones developed by the team leaders in homogeneity, diversity, and matrix quality.

Any tool developed to assist in work organization must be flexible and appropriate to the specific requirements of each production process. Nevertheless, the GA can be implemented in the rest of the assembly area, due to the similarity of processes. In the future, transfers to production areas can be made with the optimization of their specificities and characteristics. It’s also important to highlight that the work organization variables, such as the duration and number of working periods and the duration, and frequency of breaks during the shift, have not been changed. However, it will be interesting to compare the results of the fitness function of the two remaining shifts, late evening, and night, since the working periods have different durations. This comparison could give different perspectives to make a more suitable duration and distribution of working periods throughout the shift at the organization level. Also, recent publications suggest that motivational and preferential aspects within the job rotation could also be integrated (Asensio-Cuesta et al., 2019).

Despite presenting a case study with 12 workers with promising results, this formulation lacks a broader application and validation in an ecological context in order, to further understand its effectiveness in a larger scale sample and musculoskeletal symptom prevention. In an era of technological development, the use of direct quantitative assessment of risk factors in the working field, such as those acquired through motion sensors, would enable the proposed formulation to have more reliable risk scores than the ones globally provided by the EAWS.

4.6. Conclusion

The formulation developed in this study generated job rotation schedules considering constraints present in the assembly line of the automotive industry. This formulation has been proven to be a reliable solution to design job rotation plans, increasing diversity, decreasing exposure, and balancing homogeneity for the team. The solution presented in this study combined the information from workers in terms of qualification and the requirements of the workstations to generate and evaluate solutions looking for the best sequences. Moreover, this approach helped the team leaders, in a time-efficient manner, to decide which job rotation plan would be better suited when considering all the constraints, his experience and his knowledge about the workstations and his team.

From the company point of view, this approach could additionally be a relevant tool for data generation, which could be crucial for designing new production systems and to manage investments aimed at improving productivity and promote musculoskeletal health at work. Nonetheless, future research is warranted to analyze the effectiveness of the job rotation plans generated by this type of formulations with those provided by the team leaders, while considering a larger sample, how the plans impact the results of diversity, exposure, and homogeneity, and how they translate into the reduction of the prevalence of WRMSD.

Declarations

Author contributions statement:

Ana Assunção and João Rodrigues: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Nafiseh Mollaei and Carlos Fujão: Conceived and designed the experiments; Analyzed and interpreted the data.

Daniel Osório: Contributed reagents, materials, analysis tools or data.

António P. Veloso: Analyzed and interpreted the data.

Hugo Gamboa: Performed the experiments; Analyzed and interpreted the data.

Filomena Carnide: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

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Data availability statement

Data will be made available on request

Declaration of interests statement

The authors declare no competing interests

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2022.e09396 (Appendix 3)

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CHAPTER 5

A Job Rotation Plan for the Automotive Industry: A Comparison between a Plan Built Manually by The Team Leader and a Genetic Algorithm Formulation[3]

[3] **Submitted to:** Ana Assunção†, João Rodrigues†, Vera Moniz-Pereira, Nafiseh Mollai, Carlos Fujão, Daniel Osório, António P. Veloso, Hugo Gamboa, Filomena Carnide (2022) *Comparison of a job rotation plan built manually by the team leader and through a genetic algorithm formulation on quality criteria outcomes in the automotive industry*. International Journal of Environmental Research and Public Health

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Abstract

The aim of this study was to compare two processes for developing job rotation plans (performed by the team leader or through a genetic algorithm (GA) and how they perform in terms of diversity, homogeneity, exposure, matrix quality (MQ), and shift working sequence quality (SWSQ). The sample included 7 teams (89 workers) from an automotive industry. At a group-level analysis, values provided by the GA were not significantly different from the team leader for exposure, whereas differences were observed for diversity, SWSQ, homogeneity, and MQ. Weak correlation coefficients were observed for all outcomes, except for homogeneity and MQ. Individual results showed high limits of agreement for all outcomes, and a significant relationship between the difference and the mean of the methods for exposure and diversity. Overall, job rotation plans generated by the GA seems to be a promising tool to reduce the burden of team leaders when building job rotation plans.

Keywords: *assembly line, organizational measures, occupational exposure*

5.1. Introduction

Musculoskeletal disorders (MSDs) are one of the most common health problems in the workplace, with three out of five European workers reporting MSDs related to their working conditions (De Kok et al., 2019). In the automotive industry, MSDs are closely related to the risk factors that workers are exposed to, which can vary depending on the different conditions of the assembly line. These occupations are characterized by low level static muscle loads for long periods, highly repetitive work, short recovery periods, force exertions, and extreme postures, all of which, if maintained on the short-term (Assunção et al., 2021) or long term (Da Costa and Vieira, 2010; Hallman et al., 2019; Neupane et al., 2017) can lead to deleterious cumulative biomechanical loading and increased MSDs (Bernard and Putz-Anderson, 1997; Madeleine, 2010; Ohlander et al., 2019; Punnett, 1998).

Given the high economic and social impact of MSDs, automotive companies have changed their working conditions to improve workers' health and well-being. Approaches can vary, and include changes in tools, workplace conditions, and manufacturing processes, which can be made in the early or ongoing stages of product development to eliminate or mitigate the exposure to potential risk factors (Macdonald and Oakman, 2022). If these physical changes are not possible for technological, logistical, or financial reasons, companies tend to rely on more cost-effective solutions such as organizational measures, where the job rotation solution is often used (Kogi et al., 2003). The job rotation plans have been recommended as an organizational measure to reduce workplace exposure to multiple risk factors and, thus increase variability and reduce worker fatigue and monotony (Jorgensen et al., 2005; Rodriguez and Barrero, 2017; Yung et al., 2012). Numerous studies have been conducted on this topic, with job rotations relying on mathematical solutions such as genetic algorithms (GA) to improve working conditions and reduce MSDs (Asensio-Cuesta et al., 2012; Assunção et al., 2022; Diego-Mas et al., 2009). Each formulation has its own set of assumptions, criteria, and variables. Although there are other solutions to improve job rotation logistics, GA stands out from the remaining solutions, since it can solve complex combinatorial mathematical problems in situations where there are many possible outcomes and the environments are dynamic (Carnahan et al., 2000).

Despite recent literature suggesting a positive effect between job rotation plans and several psychological factors (e.g., job satisfaction, less stress), there is no consensus on how it may impact general physiological health outcomes (e.g., upper limb MSDs) when compared to not having any organizational measures (Mlekus and Maier, 2021). Moreover, additional information is also needed on the impact of how different solutions (i.e., mathematical vs manual job rotation plans) perform in reducing MSDs in the short and long term. This aspect is paramount, especially in the automotive industry, as job rotations are often performed manually by the team leaders, and where there are no studies comparing how they perform in terms of risk factor exposure with other mathematical solutions such as the GA.

Therefore, this study aimed to compare two processes for developing rotation plans: (1) through human intervention performed by the team leader; and (2) through a GA mathematical formulation. Specifically, this study aims to verify how each of the approaches perform in terms of diversity, homogeneity, exposure, matrix quality (MQ), and shift working sequence quality (SWSQ).

5.2. Methods

5.2.1. Sample

The sample was initially selected from a broader project aimed to determine the prospective associations between biomechanical risk factors and MSSs in different body regions in the automotive industry (Assunção et al., 2021), while also taking advantage of the mathematical formulation built to develop job rotation plans for this same production line (Assunção et al., 2022). In this secondary analysis, we used a sample of 302 workers (α = 5%, β = 0.20, d = 0.5, 20% of musculoskeletal symptoms prevalence in the automotive industry, and a 15% drop-out) (Charan and Biswas, 2013). The eligibility criteria included having a contract with the company, being allocated to the assembly line, having at least 3 months of seniority, not having any medical restrictions to perform the job assessed by the plant medical doctor, and not being a temporary worker. From the initial 16 teams, we used a convenience sample of 7 since they had complete information, that could be used and run on the GA. The study was carried out following the recommendations of the Declaration of Helsinki for Human Studies. The protocol was approved by the Ethics Committee of the Faculty of Human Kinetics, from the University of Lisbon (CEFMH Nº8/2019). All participants gave their written informed consent before they participated in the study.

5.2.2. Procedures

Job rotation Plan built manually by the team leader

In this automotive industry, team leaders from the assembly line were responsible for planning their team's job rotation plans every week using mostly their empirical knowledge about the biomechanical risk factors. Throughout the conception of the job rotation plans, they considered all the inherent constraints: absenteeism, versatility matrix (worker's qualification), medical restrictions, worker relationships, and production specifics. As support, they used an Excel file to plan the job rotation.

Job rotation plan formulated by a genetic algorithm

The GA used to generate the job rotation plans for the assembly line of an automotive industry is described in full detail elsewhere (Assunção et al., 2022). The proposed mechanism for building the fitness function consisted of three layers of analysis: (1) averaged total occupational exposure score, (2) diversity calculated for the sequence of workplaces considering the risk factors, and (3) a homogeneous rotation scheme, so that the scores allocated to the team were balanced among workers. Moreover, the job rotation plans were conceived considering the following variables: the versatility matrix, which comprehends the workers' qualifications, and an objective ergonomic risk assessment method implemented in the factory (i.e., European Assessment Worksheet (EAWS) (Schaub et al., 2013)). The EAWS data was used to characterize the biomechanical exposure. These scores quantify each workstation risk by providing an individual picture of each biomechanical risk factor (e.g., posture, force, and manual material handling).

Exposure, diversity, homogeneity, SWSQ, and MQ – quality criteria outcomes

Both job rotation sequences delivered by the team leader and generated by the GA were processed by a mathematical formulation (Assunção et al., 2022) built with the intention to provide quality criteria outcomes. The exposure, diversity, and SWSQ were calculated for each worker individually, whereas homogeneity and MQ values were calculated equally for each team of the assembly line.

Exposure

The first layer of assessment involved calculating the average occupational exposure score from the sequence of workstations assigned to each worker on the assembly line. The occupational exposure score of a workstation in each rotation period is obtained by multiplying the occupational exposure score by the percentage of time of that given period.

Diversity

Diversity is the amount of change in the exposure score between successive workstations for each one of the following risk factors: posture, force, and manual material handling. Generally, diversity was calculated through a score for the transitions between the presence of a risk factor between successive workstations. Since there were 4 working periods, there were 3 transitions evaluated. Independently of the risk factor, each transition can be categorized, based on the presence (1) or absence (0) of a risk factor.

Shift of working sequence quality

The SWSQ represents the quality of the job rotation sequence for each worker. This index is the weighted sum of both scores, 2 for diversity, and 1 for occupational exposure.

Homogeneity

This criterion guarantees the balance between the team, guiding the algorithm to avoid favouring workers differently.

Matrix Quality

The MQ is the parameter that should favour job rotation plans with reduced exposure and high diversity and high homogeneity.

This process allowed us to have the same metrics analysed for both job rotation plans (i.e., team leader vs. GA). Further insight on how each outcome was calculated is provided in full detail elsewhere (Assunção et al., 2022).

5.2.3. Statistical analysis

Descriptive characteristics of the sample were presented as mean ± SD. The paired *t*-test was performed to compare the mean outcome values of the manual method with that of the algorithm method for the normally distributed variables and the Wilcoxon signed-rank test for the non-normal distributed variables. Likewise, the relationship between the two methods was determined using the Pearson or Spearman correlation (*r*) for the normal and non-normal variables, respectively. The Bland and Altman analysis (Bland and Altman, 1986) was used to examine the limits of agreement (LOA) (mean difference ± 2 SD) between the different job rotation outcomes (exposure, diversity, SWSQ, homogeneity, and MQ) made by the GA and the team leader. The concordance correlation coefficient (CCC) (Lin, 1989) was also calculated to quantify the degree of agreement between the different job rotation outcomes given by the GA and the team leader with the line of identity. The CCC was interpreted according to McBride (2005) (McBride, 2005) recommendation: values less than 0.90 were poor, those between 0.90-0.95 were moderate, those between 0.95-0.99 were substantial, and values greater than 0.99 were excellent. A *p* value of < 0.05 was considered statistically significant. Statistical analysis was performed using IBM SPSS Statistics Version 25.0 (SPSS Inc., an IBM company, Chicago, IL, USA) and STATA version 13.1 (StataCorp, College Station, TX).

5.3. Results

A total of 89 workers from 7 teams from the assembly line were included in the analysis. The workers' mean age was 29.10±6.4 years, the seniority was 1.66±0.7 years and 38.8% were females. Looking at the composition of the teams, three had 11 workers, two had 15 workers, one had 17 workers and one had 9 workers.

Table 5.1 compares the job rotation plan criteria values determined by the team leader and the GA. For exposure, the mean output from the GA was similar to the one produced by the team leader (*p* value = 0.80), although the correlation was weak but close to be considered moderate (r = 0.44). The values for both the diversity and SWSQ from the GA and the team leader were weakly correlated (r = 0.29 and r = 0.44, respectively) and significantly different (p value < 0.001), with the GA generating higher scores compared to the team leader. Moreover, both SWSQ (CCC = 0.16) and diversity (CCC = 0.04) obtained low CCC values.

Table 5.1 - Comparison of exposure, diversity, and SWSQ between job rotation plans built manually by the team leader and through the GA. Values for exposure, diversity and SWSQ were considered distinctively for each worker.

	Job rotation by Genetic Algorithm	Job rotation by Team Leader	Mean difference[a]	p value[b]	r	CCC
Exposure	0.49±0.08*	0.49±0.11*	0.01±0.10	0.80[c]	0.44[¥]	0.57[¥]
Diversity	0.74±0.03	0.63±0.04	0.11±0.04	<0.001	0.29[¥]	0.04[¥]
SWSQ	1.98±0.11	1.76±1.33	0.23±0.13	<0.001	0.44[¥]	0.16

SWSQ Shift Working Sequence Quality, *CCC* Concordance Correlation Coefficient

[a] Mean difference between Job rotation by Genetic Algorithm and Job rotation by Team Leader

[b] p value based on paired sample t-test comparing Job rotation by genetic algorithm and job rotation by team leader

[c] p value based on Wilcoxon signed-rank test comparing Job rotation by genetic algorithm and job rotation by team leader

*Median and interquartile values were presented for non-normal variables

[¥] Significant at p value <0.001

The homogeneity and MQ scores given to each team by the GA were higher than those given by the team leader (Table 5.2). The values for homogeneity and MQ of the GA and the team leader were highly correlated (r = 1.00 and r = 0.93, respectively), and significantly different (p value < 0.001) for homogeneity, with the GA having higher scores compared to the team leader. Moreover, both homogeneity (CCC = 0.31) and MQ (CCC = 0.06) achieved low CCC values.

Table 5.2 - Comparison of homogeneity and matrix quality between job rotation plans built manually by the team leader and through the GA. Values for homogeneity and matrix quality were considered equal for the whole team.

	Job rotation by Genetic Algorithm	Job rotation by Team Leader	Mean difference[a]	p value[b]	r	CCC
Homogeneity	1.80±0.16*	1.63±0.27*	0.22±0.05	0.02	1.00	0.31[¥]
Matrix Quality	2.40±0.10*	2.16±0.08*	0.27±0.04	0.02	0.93[¥]	0.06

CCC Concordance Correlation Coefficient

[a] Mean difference between Job rotation by Genetic Algorithm and Job rotation by Team Leader

[b] p value based on Wilcoxon signed-rank test comparing Job rotation by genetic algorithm and job rotation by team leader

*Median and interquartile values were presented for non-normal variables

[¥] Significant at p value <0.001

Figures 5.1 displays the relationship between the job rotation plan criteria values determined by the team leader and the GA (Fig. 5.1a, c, e) as well as the results of the Bland and Altman analyses (Fig. 5.1b, d, f). For exposure and diversity, there was a significant association between the differences and the means of the values from the GA and team leader (exposure r = -0.39, $p < 0.001$; diversity r = -0.44, $p < 0.001$). On the contrary, for the SWSQ there was no association between the differences and the means of the values from the GA and team leader (r = - 0.20, p = 0.06). All the outcomes presented large LOA when comparing the values provided by the GA and the team leader, with the SWSQ also providing a large bias with a mean value of 0.23.

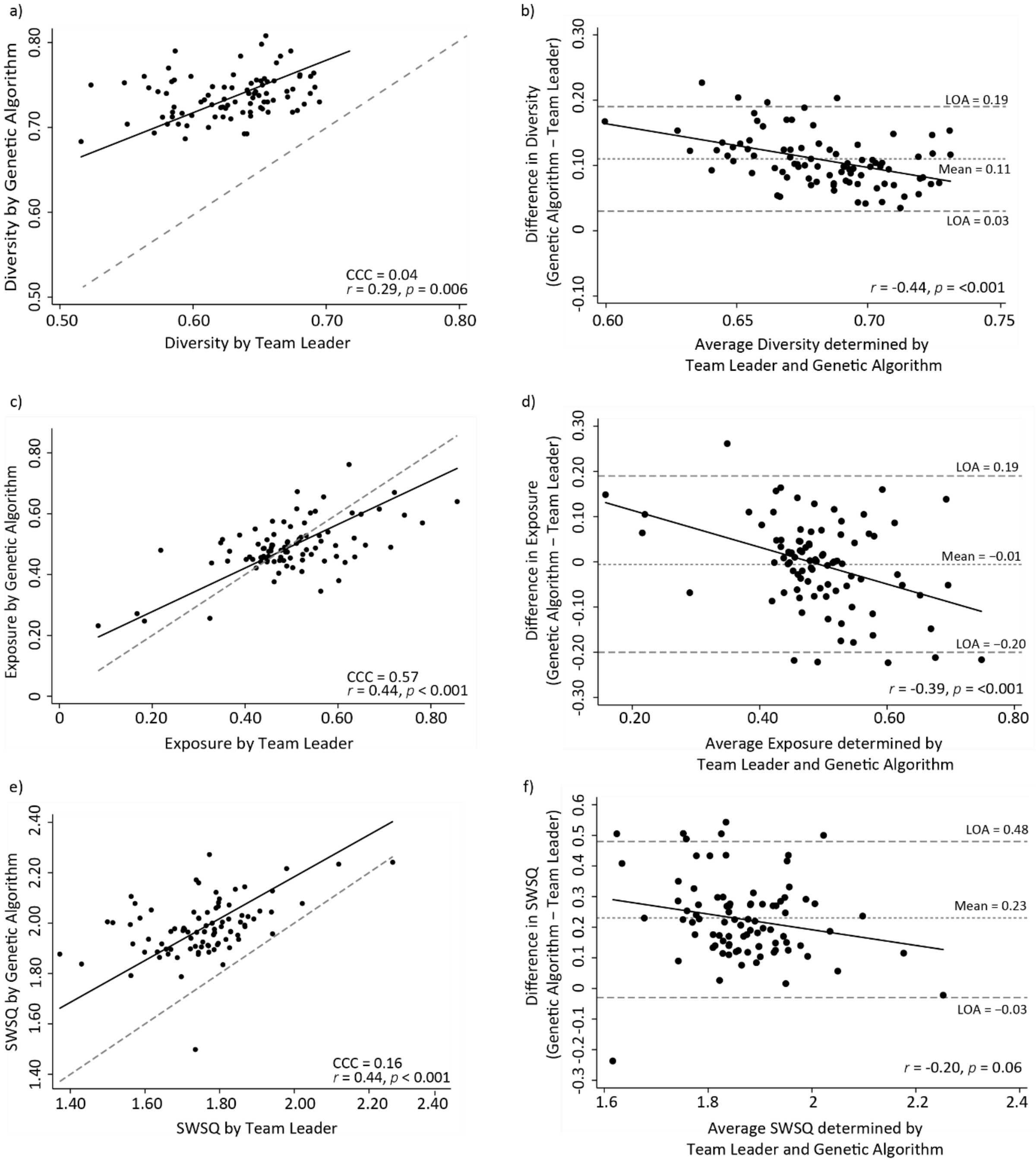

Figure 5.1 – Relationship between the output produced by the genetic algorithm and the team leader with regression line (solid line) and the line of identity (dashed line) for **a)** Diversity, **c)** Exposure, and **e)** SWSQ. The Bland and Altman plot of the difference between the output produced by the genetic algorithm and team leader with the regression line (solid black line), bias (short dashed line), and 95% LOA (long dashed line) for **b)** Diversity, **d)** Exposure, and **f)** SWSQ.

5.4. Discussion

The present investigation compared two methods to develop job rotation plans in the assembly lines of an automotive industry, regarding the outcomes of diversity, homogeneity, and exposure: (1) performed manually by the team leader; and (2) through a mathematical formulation using the GA approach. The main findings of this investigation indicate that the job rotation plan carried out by the GA differed from those obtained by the team leader for diversity, SWSQ, homogeneity, and MQ, both at the group and individual levels. On the other hand, for the exposure outcome, there were no mean differences between methods, although at the individual level wide LOAs were observed.

Over the past few years, there has been an increased focus in the ergonomics and engineering research fields to understand how job rotation plans could be used as an organizational measure to improve not only productivity in the workplace but also other psychological and physiological health outcomes (Mlekus and Maier, 2021; Posthuma et al., 2013). Moreover, there is also no evidence on how different methods used to build job rotation plans perform in terms of outcomes related to MSDs. As far as we know, this study provides for the first time a comparison between job rotation plans built manually by the team leader and those generated by a GA in a sample of workers in the automotive industry. Our results suggest that at the group level both the GA and the team leader job rotation plans produced similar results for the exposure outcome and had a moderate correlation. However, at the individual level, the job rotation plan provided by the team leader had a significant trend to overestimate the values provided by the GA, especially at higher values of exposure, while also having high LOA. These results highlight the ability and the empirical knowledge of team leader to build a job rotation that mitigates overall exposure, by managing through his experience the effort and difficulty related to each process in the workstation. These acquired skills may explain why there are no differences for exposure between the GA and the team leader at the group level results. In fact, the most recent meta-analysis investigating the effectiveness of job rotation plans concluded that having such organizational measure is associated with reduced musculoskeletal complaints and physical workload in workers performing high-intensity tasks, which is the case for those working in the assembly line of the automotive industry (Mlekus and Maier, 2021).

Another aspect to consider is the diversity and the homogeneity when looking at the conception of a job rotation plan. Our results suggest that the job rotation plan built manually by the team leader had a significantly lower score for diversity and homogeneity when compared to those of the GA, as well as on other surrogate quality indexes of the job rotation plan (SWSQ and MQ). For instance, the Bland and Altman for diversity showed a significant trend between the means and the differences of the methods, whereas SWSQ had high LOA and a significant bias between the GA and the team leader. Even though there is no gold standard to compare both these methods and how they perform when generating a job rotation plan, the fact that the GA provided higher scores on average for diversity, SWSQ, homogeneity, and MQ may be an indicator that the implementation of a GA solution may play a significant role in reducing MSDs. In that note, both job rotation sequences delivered by the team leader and generated by the GA were processed by a mathematical formulation (Assunção et al., 2022) allowed us to have the same metrics analyzed for both job rotation plans. In this regard, there is evidence supporting the importance of maximizing diversity in job rotation plans, since it is positively associated with satisfaction, learning and development, psychological and physiological health outcomes, and organizational performance outcomes (Mathiassen, 2006). In fact, by increasing workers' learning and development capacities through a more diverse job rotation plan, one can expect that the versatility matrix of the workers will be more flexible, which in the long run will improve the job rotation plans generated by the GA. It is also important to note that the GA solution obtained higher scores in the homogeneity outcome without compromising the overall exposure to known biomechanical risk factors, while also maximizing the diversity score. Homogeneity is an often under looked variable in the conception of a job rotation plan, but it is of key importance to maintain the balance between workers on the same team (Assunção et al., 2022).

Although this investigation used a novel approach by taking advantage of the mathematical formulation to run both the job rotation plans created by the team leader and the GA, which allowed for a direct comparison of both methods in several quality criteria outcomes, some limitations should be pointed. Our investigation design did not allow us to assess if the improvements observed in any of the outcomes related to the quality of the job rotation plan (i.e., exposure, diversity, homogeneity, SWSQ, and MQ) would in fact translate into the reduction of the incidence of MSDs. Nevertheless, outcomes such as diversity, exposure, homogeneity have established meanings in the literature (Mathiassen, 2006) which can be used to speculate and infer on the possibility of one method being a better fit for the medium to long term incidence reduction of MSDs. Additionally, this is an issue often observed in investigations related to the development of job rotation plans using mathematical formulations, where there is a lack of follow-up in the automotive industry to assess their effectiveness in reducing MSDs (Mlekus and Maier, 2021). Thus, in the future, it would be important to prospectively study MSDs prevention using the GA, according to the data presented in this study.

5.5. Conclusion

Job rotation plans generated by the GA differed from those provided by the team leader for the diversity, homogeneity, SWSQ, and MQ outcomes. Even though at the group level the values provided by the GA for exposure were like those of the team leader, none of the outcomes performed well at the individual level, with wide LOA being observed. Given that on average the values provided by the GA provided more favourable results for the diversity and homogeneity outcomes, the use of the GA method for developing job rotation plans in the automotive industry, maybe a potentially promising approach to not only reduce the burden of the team leader through the automation of this task but also to reduce MSDs in the assembly line of the automotive industry, considering the better results obtained by this process.

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CHAPTER 6

General Discussion

6.1. Introduction

Musculoskeletal disorders remain the leading cause of lost productivity in the workplace and have other well-known impacts on workers' well-being and health-related outcomes (De Kok et al., 2019; Sebbag et al., 2019). The recent report by the European Agency for Safety and Health at Work advocates that this problem needs to be tackled at multiple levels, starting at the individual level by adjusting the conditions under which workers perform their tasks (e.g., changing tools) and then progressing to a more macro level through implementing and revising multiple health policies to improve working conditions (De Kok et al., 2019). Looking across the entire spectrum of measures implemented by companies and sectors, there are several approaches to improving workplace conditions that need to be weighed in terms of their economic viability and feasibility (Tharmmaphornphilas & Norman, 2007). For instance, in the automotive industry, where the risk factors are known but difficult to improve, such as tasks performed overhead or inside the vehicle during assembly, most solutions to improve these working conditions are either too expensive or under unrealistic conditions (Hochdörffer et al., 2018). Moreover, for jobs where improvement methods are found, they may not be implemented due to time, financial or logistical constraints, e.g., related to assembly line synchronization or changes in working height conditions. In such scenarios, companies and industries tend to adopt organizational measures where job rotations are viewed as a simple strategy to mitigate exposure to known biomechanical risk factors and improve overall productivity by managing the time each worker spends on a given task (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012; Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Diego-Mas et al., 2009;Diego-Mas, 2020; Jonsson, 1988)

The aim of this dissertation was to provide new insight into the relationship between the biomechanical risk factors present in the automotive industry and the short-term effects of MSSs, as well as to develop a mathematical formulation to create job rotation plans and mitigate exposure to these known biomechanical risk factors. In Chapter 2, we provide a comprehensive summary of the current literature on WRMSD and its known biomechanical risk factors, while delving into detail the possible solutions to eliminate or reduce exposure to such factors, with a particular focus on job rotation plans. In Chapters 3 to 5 we present the original work of this dissertation, made in collaboration with the largest automotive industry in Portugal. A detailed discussion of each of the three studies is included in each chapter. The aim of this last section is to integrate and summarize the main research findings of each investigation and to provide a global overview of the implications for future research and their practical implications. Finally, we will also disclose and discuss some of the limitations of this research.

6.2. Summary of the main findings

6.2.1. Short-term exposure to risk factors and musculoskeletal symptoms

Looking at the current dissertation structure and how it is organized and linked between the different original investigations that comprise it, it was our intention that the first manuscript (Chapter 3) would analyse the topic of MSSs and its prospective relationship with biomechanical risk factors in an automotive production line during a typical working week (Assunção et al., 2021). The methodological approach involved a total of 228 workers divided into 16 randomly selected teams from the assembly and paint areas. These workers were followed throughout a work week, twice a day, and assessed for biomechanical risk factors through the EAWS methods and provided a self-reported score for the MSSs. This was the first study to provide observational evidence in which after just one week, the group of workers exposed to known biomechanical risk factors, such as force, posture, and percentage of time spent in a bent position and overall exposure, were at increased odds of reporting MSSs in the neck, shoulders and wrist body regions when compared to the low-risk group. The novelty of this investigation lies on the time frame of when the assessments took place, since most of the current body of literature covers investigations looking at associations of MSD and biomechanical risk factors at the medium and long term (Da Costa & Vieira, 2010; Guerreiro et al., 2020; Hallman et al., 2019; Punnett & Wegman, 2004) or in a cross-sectional approach (Coggon et al., 2013; Punnett, 1998). Moreover, we looked at the self-reported MSSs in the morning, before the shift started, and in the afternoon, after the shift ended, to understand how the MSSs were related to workers in the high vs low-risk groups. In this regard, a relationship between MSSs and the influence of known biomechanical risk factors was observed only for the models that accounted for the afternoon period, indicating that there is no carry over effect of self-reported pain to the next morning and that future investigations using the same method, should focus their assessments at the end of the working day. However, as previously mentioned, when looking at the entire workweek, there was a significant unfavourable trend for MSSs in the high-risk group. This information has practical implications for the automotive industry, since in the absence of a strategy to mitigate the exposure to which workers are subjected, there is a significant risk that cumulative biomechanical load may evolve to a MSD in a near future (Kennedy et al., 2006; Krebs et al., 2007).

6.2.2. Genetic algorithm development

With this problem in mind, the second manuscript of this dissertation (Chapter 4) aimed to develop a viable strategy to reduce exposure to biomechanical risk factors. Through a GA approach, a mathematical formulation was created to generate job rotation plans in the automotive industry that could minimize the risk of MSDs in the workplace by managing exposure to known biomechanical risk factors (Assunção et al., 2022). The key findings from this research were the conception of a viable algorithm that demonstrated a high diversity sequence during work hours and reduced overall exposure to risk factors, while maintaining homogeneity to balance the rotation between team members in the assembly line. In addition, the algorithm excelled in outperforming the team leader in the amount of time needed to create a job rotation plan for a week's work (i.e., 53 seconds for the GA vs. 3-4 hours for the team leader).

In a time of constant social and economic change, most companies and industries tend to adapt by optimizing their processes at both the human and manufacturing level. In the automotive industry, there are still processes that can be optimized, such as those related with job rotation plans. In this regard, the factory depended on team leaders to develop job rotation plans, which reduced the team leader's productivity in managing assembly area teams by shifting their focus to a task that was time consuming. Additionally, most of their knowledge used to create job rotation plans is empirical, with most plans being built considering each worker's ability to perform a set of workstations or the presence of an injury that precludes them from performing their job. Nonetheless, a job rotation plan, by definition, should be used to optimize an assembly line, but is also a tool to reduce MSDs (Diego-Mas, 2020; Jonsson, 1988; Song et al., 2016). The factory where this dissertation was conceived has implemented a risk assessment method, the EAWS (Schaub et al., 2013), which provides a risk score for each workstation that includes postures and movements and low additional physical efforts, action forces of the hand-finger system and/or the whole body, MMH, and repetitive load on the upper limbs. In this context, team leaders do not take into account the ergonomics risk assessment given by the EAWS in their job rotation plan, which reduces their ability to influence the exposure, diversity and homogeneity of their schedules and, above all, their ability to effectively prevent MSDs.

Due to the large number of criteria that must be taken into account when designing a job rotation plan (Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012), such as the multitude of restrictions, the high number of workstations in the assembly line and the risk assessment of each workstation, it is only logical that a mathematical formulation would be suitable to master such a task (Diego-Mas et al., 2009). Of all the different mathematical solutions, GA stands out from the remaining, since it can quickly handle complex mathematical problems in situations where there are a large number of variables and outcomes in a context of a dynamic environment (Carnahan et al., 2000). As mentioned in Chapter 4, a few successful GAs have been implemented in both the automotive industry (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012; Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Diego-Mas et al., 2009) and in other contexts (Boyd & Savory, 2001). These algorithms considered a diverse and distinct number of variables, mainly focused on increasing the diversity of job rotation plans, while overlooking other variables such as homogeneity (Assunção et al., 2022; Carnahan et al., 2000). On the other hand, most GAs (Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Diego-Mas et al., 2009) relied on changes in the overall intensity of the tasks performed to increase diversity, either using a specific or a generic risk assessment method. Nonetheless, these GAs did not account for the specific biomechanical risk factors that compose the overall score provided by the risk assessment method and how the GA can be best adjusted to create a more robust job rotation plan. For example, two workstations assessed as low-risk and high-risk could be placed back-to-back and still comply with the general diversity criterion. However, when looking at the individual risk factors identified for each workstation, it is possible that this approach could result in an overlapping exposure of a biomechanical risk factor (e.g., both workstations having tasks performed in an overhead position). Furthermore, most of these investigations developed GAs for the automotive parts supplier industry (Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012; Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Diego-Mas et al., 2009) with no information on the assembly lines of large automotive plants, where the specifics of the tasks performed at different workstations may differ.

Another important aspect of job rotation plans lies with the effectiveness of these strategies to decrease the incidence of MSDs and how job rotation plans generated by a GA approach compare to those performed by team leaders or other known experts. This issue will be addressed in the next sub-chapter.

6.2.3. Comparing genetic algorithm and team leader job rotation plans

Advances in modern technological achievements have been supported by key organizational strategies that have provided the means for the ongoing growth of multiple industries. On this note, the current body of knowledge suggests that job rotation plans may have a special role in improving overall working conditions and productivity by reducing the incidence of MSDs and other changes favouring psychological-related outcomes, such as job satisfaction, less stress, and greater labour flexibility (Mlekus & Maier, 2021). However, over the past decades much of the responsibility associated with the implementation of job rotation plans in the automotive industry has been handled by specialized workers, most of whom have leadership responsibilities to a specific team. Many of these team leaders rely on their empirical knowledge and workers' self-reported data to design their job rotation plans, which means sacrificing their own working time to perform a time-consuming task. As described in the previous chapter, the research in the field of ergonomics and industrial engineering has increased significantly to develop mathematical formulas that can optimize the process of generating job rotation plans (Asensio-Cuesta, Diego-Mas, Canós-Darós, et al., 2012; Asensio-Cuesta, Diego-Mas, Cremades-Oliver, et al., 2012; Diego-Mas, 2020; Diego-Mas et al., 2009). To our knowledge, there is currently no evidence comparing job rotation plans conceived by the team leader and those generated by a mathematical formula such as the GA in the context of the automotive industry. Therefore, in the third and last manuscript of this dissertation (Chapter 5), we compared these two methods in terms of: exposure, diversity, SWSQ, homogeneity and matrix quality.

By using our previously built mathematical formula, that enabled not only the development of a job rotation plan but also the assessment of scores for diversity, exposure, SWSQ, homogeneity, and matrix quality (Assunção et al., 2022), we were able to run information from job rotation plans of 7 teams (89 workers) created by the team leader and compared them with the results of the GA. Both methods were compared in relation to several quality criteria, including the average occupational exposure from the sequence of workstations assigned to each worker, how different the magnitude of the change in exposure is between workstations, how balanced a team is in terms of exposure (i.e., homogeneity) and finally two other outcomes related with quality of the sequence of workstations and a matrix parameter providing the best combination of these three outcomes: exposure, diversity and homogeneity. The key findings of this investigation showed that the job rotation plan generated by the GA differed from those created by the team leaders in terms of diversity, SWSQ, homogeneity and matrix quality. No differences were observed for the exposure outcome. Nevertheless, all the outcomes had broad LOAs, indicating large differences at the individual level. As pointed out in Chapter 5, these results may be of importance for the automotive industry, especially when it comes to diversity, homogeneity, SWSQ and matrix quality. While there is no gold standard to compare these two methods and their performance in creating a job rotation plan, the fact that the GA yielded higher scores for diversity, SWSQ, homogeneity, and matrix quality can be indicative that implementing such a solution may play a role in reducing MSDs in the medium to long term. On this note, the diversity outcome has been gaining a significant relevance in the conception of the job rotation plans, since accounting only for exposure may compromise the effectiveness of this organizational strategy. This assumption is based on the importance of giving muscles adequate recovery time to avoid higher levels of fatigue and to reduce mechanical load and, thus the risk of MSDs (Mathiassen, 2006). Therefore, the idea of designing a more diverse job rotation plan is to allow for a job sequencing between workstations that encourages load variation, even though average exposure is kept constant (Mathiassen, 1993). All these aspects were considered in the development of our GA (Assunção et al., 2022), where diverse exposure to posture, force and manual material handling were maximized. Looking at our GA's fitness function, each worker had a score calculated based on occupational exposure and diversity, with the latest having a higher weight in this formulation. These considerations may explain the differences between the team leaders' scores on diversity and those on GA.

Following the same trend, the homogeneity scores achieved by the GA were also superior when compared to those provided by the team leader, which may indicate that the GA job rotation plans may be more balanced in terms of exposure and diversity for each team. Putting this information into perspective, one can speculate that over time in the eventual situation where a team leader provides a similar job rotation plan, with low diversity and low homogeneity, this may contribute to the phenomenon observed in Chapter 3, where workers in high-risk group are exposed to risk factors week after week, and hence at risk for cumulative fatigue and the onset of MSDs. On the other hand, if the job rotation plans are generated by the GA, considering the homogeneity in the fitness function, the difference between the high-risk group and the low-risk group may be reduced, with possible implications for future incidence of MSDs.

6.3. Methodological considerations

This dissertation was part of a specific group of grants awarded by the Portuguese Foundation for Science and Technology in which the main goal was to bridge the gap between industries/companies and academia. This specific grant revealed to be an excellent opportunity to work in a close partnership with the largest automotive company operating in Portugal, which allowed us to have access to a significant proportion of their assets in an ecological industrial setting. This industry is organized according to a series production model, consisting of four production areas, which had a single assembly line, with an imposed cadence. The production was of the semi-continuous type, developed in three shifts, with a fixed crew, of eight hours of work each, with three breaks planned for each work shift: one of longer duration (30 minutes) reserved for the period of meals and others two shorter intervals (7 minutes), for rest. The factory operates on the four levels of the production process (Press, Body, Paint, and Assembly).

Since the main goal of the dissertation was to understand the short-term relationships of biomechanical risk factors and MSS on an automotive assembly line, while conceiving a job rotation plan tool to mitigate exposure to these known risk factors, this dissertation also allowed for an excellent opportunity to make a difference on how the factory runs and operates its human resources. Despite all these major benefits, this collaboration also faced significant challenges such as: recruitment and how to achieve a meaningful sample size; and how to implement other physiological outcomes without compromising the operations conducted in the assembly line.

In the first study of this dissertation (Chapter 3), we recruited a representative sample of the assembly and paint areas, which was followed over the course of one week to assess the relationship between self-reported symptoms and biomechanical risk factors. When looking at the results, one could argue that a possible limitation is the lack of an additional week of assessments to understand the impact of the days off and how it would affect the self-reported symptoms in the following week. Given that we had daily assessments with self-reported questionnaires, both in the morning and in the afternoon periods, we chose not to overload the workers with an additional week of assessments that could lead to a potential disruption of the operations in the assembly line. In fact, due to the progressive drop-out observed throughout the work week, we ended up having to remove the fifth day to preserve our sample power.

In Chapter 4, we presented the manuscript where we developed a job rotation plan that used a GA approach focused on parameters such as diversity, homogeneity, and exposure. Because the results of the first manuscript provided important information about which biomechanical risk factors were associated with MSS, it was only logical to use this information as part of the exposure parameters for the design of the GA. However, regarding other known risk factors (e.g., MMH, vibrations), no associations were found for short-term symptoms in the upper-limbs and low back symptoms, even though such relationships may be relevant when looking at medium and long-term symptoms self-reports. In fact, other observational research (Punnett, 1998) has observed that these risk factors were associated with complaints in other body regions. Therefore, through a more holistic approach, it was our intent to take advantage of the already implemented ergonomic risk assessment method (EAWS) by including it in the GA in order to provide a major source of decisions onto diversity and exposure.

Finally, in Chapter 5, we provided a much-needed comparison between job rotation plans generated by the GA and those made by the team leaders in terms of diversity, homogeneity, exposure, SWSQ and matrix quality. Despite these results, there is still a literature gap on how job rotation plans are perceived by workers in terms of satisfaction when built by the GA vs. the team leaders, and on what will be the long-term impact of implementing such a tool. One of the main goals of this dissertation was to create a job rotation that would reduce the impact of exposure to MSDs. Nonetheless, accessing the impact of the created mathematical formulation on the MSD incidence presented to be a significant challenge, since there were several confounding factors in the ecological industrial setting. For example, alongside the job rotation plans, the automotive industry is constantly updating the workplace with new assembly lines, tools, workers, and other organizational measures such as shifts, making it quite difficult to pinpoint the exact contribution of the job rotation plan to the MSD milieu. In fact, this might be one of the major underlying reasons for the inconclusive/inconsistent results provided by other job rotation plan investigations (Leider et al., 2015; Mlekus & Maier, 2021). Nonetheless, when using a holistic ergonomic approach, it is important to consider that the job rotation plan is just one strategy among others, and it is only through the cumulative stacking effect of the different ergonomic solutions that we can make a significant impact on the problem related with MSDs.

6.4. Future research

To overcome the aforementioned shortcomings, it is important that future research focuses on the true medium and long-term effects of job rotation plans in MSSs and MSDs, and how they are perceived by workers and team leaders in terms of job satisfaction and time management. To do so, data collection on MSSs and MSDs would have to be collected in a cohort study and compared to our data before the implementation of the job rotation plans conceived by the GA. However, one should consider that such a study would require a long-term follow-up (e.g., with 6 months follow-up) to allow enough time to observe the development of MSS/MSD. On the other hand, the algorithm was developed considering the specific characteristics of the assembly line, which may limit its applicability in other production areas, such as the painting area. Future research should analyse the capacity of the GA to be optimized through its mathematical formulation and hence, meet the needs of other areas/industries to improve their job rotation plans.

In an era of technological development, the use of a direct quantitative assessment of risk factors in the workplace, such as those acquired by motion sensors, would allow the proposed formulation to have more reliable risk assessments than those provided by the EAWS.

Therefore, research is needed to assess whether the introduction of these new assessment methods would improve the GA's ability to provide better job rotation plans

6.5. Practical implications

Based on the key findings of this dissertation, some important recommendations can be made to the automotive field and other related industries. Through the implementation of the GA, one can expect improvements in the management of human resources and possibly in the incidence of MSDs among the industry workers, all of which will directly or indirectly impact the overall quality of life at work. By introducing the GA into the daily planning routine of the different teams, the company will provide team leaders with an opportunity to better manage their schedules and be more available to perform other tasks on the assembly lines, as they will be spending less time planning (e.g., the different job rotations).

In addition, our finding that one week of work had implications on the self-reported symptoms depending on the exposure to known biomechanical risk factors, raises awareness on how automotive industries should manage their working teams, and highlights the importance of having organization tools (e.g., job rotation plans) to balance overall exposure, increase diversity and optimize homogeneity.

Finally, using the algorithm could be seen as a tool for planning possible changes in the production line (e.g., line balancing, changing processes, and introducing a new process or product) and to understand or even predict the impact of these changes in terms of industrial engineering and risk assessment.

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Thesis related outcomes

First author papers in scientific journals

Published

Assunção, Ana; Mollai, Nafiseh; Rodrigues, João; Fujão, Carlos; Osório, Daniel; Veloso, António P.; Gamboa, Hugo; Carnide, Filomena. 2022. A GENETIC ALGORITHM APPROACH TO DESIGN JOB ROTATION SCHEDULES ENSURING HOMOGENEITY AND DIVERSITY OF EXPOSURE IN THE AUTOMOTIVE INDUSTRY. Heliyon. 8, e09396. https://doi.org/10.1016/j.heliyon.2022.e09396

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Publications related to the subject (co-authorship)

Bernardes, Sarah; **Assunção, Ana**; Fujão, Carlos; Carnide, Filomena. 2022. THE ROLE OF WORK CONDITIONS ON THE FUNCTIONAL DECLINE IN SENIOR WORKERS IN THE AUTOMOTIVE INDUSTRY. Work no. 2, pp. 753-763. DOI: 10.3233/WOR-213638

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Book chapters

Bernardes, Sarah, **Assunção, Ana**; Fujão, Carlos, Carnide, Filomena. 2022. FUNCTIONAL CAPACITY PROFILES ADJUSTED TO THE AGE AND WORK CONDITIONS IN AUTOMOTIVE INDUSTRY. In:, et al. Occupational and Environmental Safety and Health III. Studies in Systems, Decision and Control, vol 406. Springer, Cham. https://doi.org/10.1007/978-3-030-89617-1_49

Conference papers

Rodrigues, João; Gamboa, Hugo; Mollai, Nafiseh; Osório, Daniel; **Assunção, Ana**; Fujão, Carlos, Carnide Filomea. 2020. A GENETIC ALGORITHM TO DESIGN JOB ROTATION SCHEDULES WITH LOW RISK EXPOSURE. In: Camarinha-Matos, L., Farhadi, N., Lopes, F., Pereira, H. (eds) Technological Innovation for Life Improvement. DoCEIS 2020. IFIP Advances in Information and Communication Technology, vol 577. Springer, Cham. https://doi.org/10.1007/978-3-030-45124-0_38

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Oral presentations in International Conferences

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Appendix A

European Assembly Worksheet (EAWS)

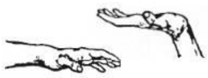
European Assessment Worksheet v1.3.6 ESO

Plant	Gender of operator m ☐ f ☐	Body height
Line	MTM Analysis	Analyst
Task / Workplace	Task duration [s]	Observation ☐ Planning ☐ / Date

Result of overall evaluation: *Calculate the total score of whole body and compare it to the UL score.The overall result is determined by the higher value and the appropriate traffic light is checked. Anyway, interpretation should take into account both values.*

☐ Green ☐ Yellow ☐ Red	Whole Body	=	Postures	+	Forces	+	Loads	+	Extra	Upper Limbs
		=		+		+		+		

EAWS evaluation			
0-25 Points	Green	Low risk: recommended; no action is needed
>25-50 Points	Yellow	Possible risk: not recommended; redesign if possible, otherwise take other measures to control the risk
>50 Points	Red	High risk: to be avoided; action to lower the risk is necessary

Extra points "Whole body" (per minute / shift)								Extra points
0a	Adverse effects by working on moving objects	0 none	3 middle	8 strong	15 very strong			Intensity
0b	Accessibility (e.g. entering motor or passenger compartment)	0 good	2 complicated	5 poor	10 very poor			Status
0c	Countershocks, impulses, vibrations 	0 light	1 visible	2 heavy	5 very heavy			Intensity × frequency
		0 [n]	1 1 - 2	2,5 4 - 5	4 8 - 10	6 18 - 20	8 > 20	
0d	Joint position (especially wrist) 	0 neutral	1 ~ 1/3 max	3 ~ 2/3 max	5 maximal			Intensity × duration or frequency
		0	2	2,5	4	6	8	
		[s]	3	10	20	40	60	
		[n]	1	8	11	16	20	
		[%]	5	17	33	67	100	
0e	Other physical work load (please describe in detail)	0 none	5 middle	10 strong	15 very strong			Intensity
	Extra = ∑ lines 0a – 0e	note: Max. score = 40 (line 0c, 0d); Max. score = 15 (line 0a, 0e); Max. score = 10 (line 0b)			note: correct evaluation, if duration of evaluation ≠ 60 s			=

Lines 0a-b mainly relate to the Automotive Industry, for other sectors additional elements may be necessary. For details see the EAWS manual.

Shift Duration and Tasks:		
Description	Formula	Result
Real shift duration [min]		
Lunch break [min]	-	
Other official pauses [min]	-	
Non repetitive tasks (i.e. cleaning, supplies, etc) [min]	-	
Net duration of repetitive task/s (a) [min]	=	
No. of real units (or cycles) (b)		
Net cycle time [s]	(a/b × 60) =	
Idle Time [s]		

Comments / proposals for improvements

EAWS form v1.3.6 © AMI 2019 1/4

European Assessment Worksheet v1.3.6 ESO

Basic Postures / Postures and movements of trunk and arms — Postures

(incl. loads of <3 kg, forces onto fingers of <30 N and whole body forces of <40 N)

Static postures: ≥ 4 s

High frequency movements:
Trunk bendings (> 60°) ≥ 2/min
Kneeling/crouching ≥ 2/min
Arm liftings (> 60°) ≥ 10/min

Symmetric: Evaluation of static postures and/or high frequency movements of trunk/arms/legs

$$\text{Duration [s/min]} = \frac{\text{duration of posture [s]} \times 60}{\text{Task duration [s]}}$$

Asymmetric: Trunk Rotation 1) | Lateral Bending 1) | Far Reach 2)

													Sum of lines	Trunk Rotation 1) int	dur	Lateral Bending 1) int	dur	Far Reach 2) int	dur
		[%]	5	7,5	10	15	20	27	33	50	67	≥ 83		0-5	0-3	0-5	0-3	0-5	0-2
		[s/min]	3	4,5	6	9	12	16	20	30	40	≥ 50		Intensity × Duration		Intensity × Duration		Intensity × Duration	
		[min/8h]	24	36	48	72	96	130	160	240	320	≥400							
Standing (and walking)																			
1		Standing & walking in alteration, standing with support	0	0	0	0	0,5	1	1	1	1,5	2							
2		Standing, Confined space	0,7	1	1,5	2	3	4	6	8	11	13							
3	a	Bent forward (20-60°)	2	3	5	7	9,5	12	18	23	32	40							
	b	with suitable support	1,3	2	3,5	5	6,5	8	12	15	20	25							
4	a	Strongly bent forward (>60°)	3,3	5	8,5	12	17	21	30	38	51	63							
	b	with suitable support	2	3	5	7	9,5	12	18	23	31	38							
5	a	Elbow at/above shoulder level	3,3	5	8,5	12	17	21	30	38	51	63							
	b	With S01 exoskeleton	2,5	3,8	6,4	9,0	13,1	16,2	23,1	29,0	39,0	48,0							
6	a	Hands above head level	5,3	8	14	19	26	33	47	60	80	100							
	b	With S01 exoskeleton	4,1	6,2	11,0	14,8	20,0	25,5	36,5	46,5	62,0	77,5							
Sitting																			
7		Upright with back support slightly bent forward or backward	0	0	0	0	0	0	0,5	1	1,5	2							
8		Upright no back support (for other restriction see Extra Points)	0	0	0,5	1	1,5	2	3	4	5,5	7							
9		Bent forward	0,7	1	1,5	2	3	4	6	8	11	13							
10	a	Elbow at / above shoulder level	2,7	4	7	10	13	16	23	30	40	50							
	b	With S01 exoskeleton	1,9	2,8	4,9	7,0	9,1	11,2	16,1	21,0	28,0	35,0							
11	a	Hands above head level	4	6	10	14	20	25	35	45	60	75							
	b	With S01 exoskeleton	2,8	4,2	7,0	9,8	14,0	17,5	24,5	31,5	42,0	52,5							
Kneeling or crouching																			
12		Upright	3,3	5	7	9	12	15	21	27	36	45							
13		Bent forward	4	6	10	14	20	25	35	45	60	75							
14	a	Elbow at / above shoulder level	6	9	16	23	33	43	62	80	108	135							
	b	With S01 exoskeleton	5,2	7,8	13,9	20,0	29,1	38,2	55,1	71,0	96,0	120,0							
Lying or climbing																			
15		Lying (on back, breast or side) w/ arms above head	6	9	15	21	29	37	53	68	91	113							
16		Climbing	6,7	10	22	33	50	66											
													∑ (a)	∑ (max.=15)		∑ (max.=15)		∑ (max.=10)	
														∑ (max. = 40) (b)					

1) Trunk

	0	1	3	5
int	slightly ≤10°	medium 15°	strongly 25°	extreme ≥30°
	0	1,5	2,5	3
dur	never 0%	4 s 6%	10 s 15%	≥ 13 s ≥ 20%

2) Far Reach

	0	1 (0,75)	3 (2,25)	5 (3,75)
int	close	60%	80%	arm stretched
	0	1	1,5	2
dur	never 0%	4 s 6%	10 s 15%	≥ 13 s ≥ 20%

note: Max. duration of evaluation = duration of task or 100%!

note: correct evaluation, if task duration ≠ 60 s

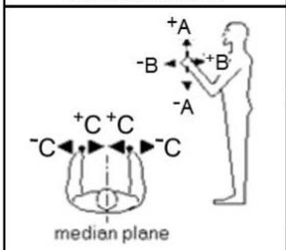
Postures = ∑ lines 1 - 16	(a)	+	(b)	=	

European Assessment Worksheet v1.3.6 ESO

Action forces (per minute) — Forces

No.	Description									Evaluation
17	Forces onto fingers (e.g. clips, plugs)	Int	0		7	15		25	50	Intensity × Duration
			16,7% F_{max}		33,3% F_{max}	50,0% F_{max}		66,7% F_{max}	F_{max}	
		Duration stat	0	1	1	1,5	2	3,5	7	
		[s]		3	6	9	12	20	≥ 30	
		[%]		5	10	15	20	33	≥ 50	
		Duration dyn	0		1,5	2		2,5	3	
		[n]			4	10		15	≥ 20	
18	Forces onto arms / whole body forces	Int	0		6	15		25	50	Intensity × Duration
			16,7% F_{max}		33,3% F_{max}	50,0% F_{max}		66,7% F_{max}	F_{max}	
		Duration stat	0	1	1	1,5	2	4	8,5	
		[s]		3	6	9	12	20	≥ 30	
		[%]		5	10	15	20	33	≥ 50	
		Duration dyn	0	1	2	3	4,5	6,5	10	
		[n]		1	3	6	8	10	≥ 12	

Forces Fmax onto arms / whole body forces
M for males & F for females



Data based on the "Assembly specific force atlas" (Wakula, Berg, Schaub, Glitsch, Ellegast 2009)

Direction	ST Upright M	ST Upright F	ST Bent M	ST Bent F	ST Above head M	ST Above head F
+A	480	315	435	285	430	280
-A	500	325	370	240	495	320
+B	320	210	400	260	305	200
-B	485	315	605	390	480	310
+C	290	185	310	200	210	140
-C	255	165	205	135	210	140

Direction	KN Upright M	KN Upright F	KN Bent M	KN Bent F	KN Above head M	KN Above head F
+A	420	270	380	245	425	275
-A	430	280	345	225	495	320
+B	445	290	495	320	410	270
-B	495	325	445	290	425	275
+C	300	195	290	190	275	180
-C	245	160	205	135	280	180

Direction	SI Upright M	SI Upright F	SI Bent M	SI Bent F	SI Above head M	SI Above head F
+A	405	265	385	250	395	255
-A	440	285	375	245	455	295
+B	405	260	455	295	365	240
-B	380	250	425	275	370	240
+C	250	165	270	175	200	130
-C	235	155	205	135	210	135

Finger forces Fmax (F=Female M=Male)

Posture	F_{max} M	F_{max} F
Posture A1 (power grip, pliers)	315	205
Posture A2 (ball of the thumb)	235	155
Posture B1 (thumb or thumb to 4 fingers)	110	70
Posture B2 (index or wide pinch)	75	50
Posture C (hook, palmar, strong pinch)	85	55

Action forces = ∑ lines 17 - 18 — note: correct evaluation, if task duration ≠ 60s — =

Manual Material Handling (per shift) — Loads

Weights of loads [kg] for repositioning (lifting / lowering), carrying and holding as well as pushing and pulling

+ Reposition, carrying & holding									
Male (kg)	3	10	15	20	25	30	35	≥40
Load points	1	1,5	2	3	4	10	17	25
Female (kg)	2	5	7	10	12	15	20	≥25
Load points	1	1,5	2	3	4	5,5	7	25

Pushing and pulling	Means of transport										
M1	Wheelbarrows and Dollies	Male (kg)	50	75	100	150	200	≥ 250			
		Female (kg)	40	60	80	115	155	≥ 195			
M2	Carriage, trolleys. No fixed rollers	Male (kg)	50	75	100	150	250	350	≥ 550		
		Female (kg)	40	60	80	115	195	270	≥ 425		
M3	Carts, roller conveyors, pallet truck	Male (kg)	50	75	150	250	350	500	600	800	≥ 1250
		Female (kg)	40	60	115	195	270	385	460	615	≥ 960
Load points			0,5	1	1,5	2	3	4	5	6	8

Posture, position of load (select characteristic posture)

+	trunk upright and / or not twisted load at the body	little trunk bending or twisting; load at or close to the body	bending trunk deep or far forward; little trunk bending forward and trunk twisting simultaneously; load far from body or above shoulder level	Asymmetric postures (bending trunk far forward and twisting; load far from the body; limited postural stability while standing or crouching) or kneeling
Posture points	1	2	4	8

Working Conditions (pushing and pulling only)

(+)	very low rolling resistance	trolley pushing / pulling on (very) slick floor	rough floor and above small gaps / edges	on structured sheet metal, into / out of a track	trolleys have to be teared off when starting, strongly damaged floor	very high rolling resistance
Conditions points	0	1	3	5	6	8

Frequency of load manipulations [frequecy/shift], holding time [min/shift] or travel distance [meter/shift]

×										
Frequency (#) of repositionings / pushing & pulling short	5	25	120	350	750	1000	1500	2000	2500	≥ 3000
Duration (holding time) [min]	2,5	10	37	90	180	≥ 240				
Distance (carrying, pushing & pulling long) [m]	300	650	2500	6000	12000	≥16000				
Duration points	1	2	4	6	8	10	11	13	14	15

Manual Material Handling (result)

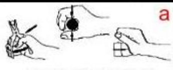
19	(Load + posture + (condition points)) × duration points	Repositioning 1)	(+) × =	Holding 1)	(+) × =	Carrying 1)	(+) × =	Pushing & Pulling short 1)	(+ +) × =	Pushing & Pulling long 1)	(+ +) × =

Handling = ∑ line 19 — 1) Maximal cumulative duration points for all tasks of repositioning, holding, carrying as well as pushing & pulling all together = 15 — =

European Assessment Worksheet v1.3.6 ESO

Upper limb load in repetitive tasks — Upper Limbs

Force & Frequency & Grip (FFG) — Basis: number of real actions per minute or percent static actions (analyze only the most loaded limb)



a — power grip/contact grip

b — finger or moderate pinch (thumb to >2 fingers, finger)

c — strong pinch (thumb to 1 or 2 fingers)

Legend

%SA = Percentage of Static Actions	%DA = 100% - %SA
FDS = Force-Duration Static	FFD = Force-Frequency Dynamic
GS' = Modified Grip Points Static (Grip x %SA)	GD = Grip Points Dynamic
%FLS = Percentage of Static Actions at force level	%FLD = Percentage of Dynamic Actions at force level
SC = Static Contribution	DC = Dynamic Contribution
FDGS = Sum of Static Contributions	FFGD = Sum of Dynamic Contributions

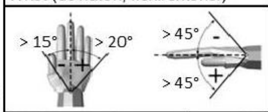
Force [N]	Calc Stat				Static actions (s/min)						Grip			Dynamic actions (real actions/min)								Calc Dyn			
	FDS	GS'	%FLS	SC	≥45	30	20	10	5	3	0	2	4	2	10	15	20	25	30	35	≥40	FFD	GD	%FLD	DC
0 – 5					1	1	0	0	0	0	abc			0	0	0	1	2	3	4	7				
> 5 – 20					4	2	1	1	0	0	ab	bc		0	0	1	2	3	4	6	9				
> 20 – 35					7	5	3	2	1	1	ab	b	c	0	1	2	3	4	6	8	12				
> 35 – 90					11	8	5	3	2	1	a	b	b	1	2	3	5	7	9	12	18				
> 90 – 135					16	11	7	4	3	2	a	ab	b	2	3	5	7	9	12	15	***24***				
> 135 – 225					***21***	14	10	6	4	3	a	a	b	4	5	6	8	11	14	***20***	***32***				
> 225 – 300					***28***	18	12	8	5	4	a	a	b	5	6	7	9	12	16	***26***	***40***				

20a	FDGS = ∑ SC_i	100%	FFG = FDGS + FFGD	FFG	%DA = ΣFLDj	FFGD = ∑ DC_j	%DA

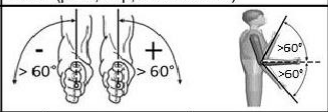
Hand / arm / shoulder postures (use duration for worst case of wrist / elbow / shoulder)

20b

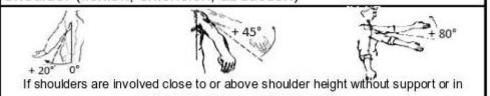
Wrist (deviaton, flex./extens.)



Elbow (pron, sup, flex./extens.)



Shoulder (flexion, extension, abduction)



If shoulders are involved close to or above shoulder height without support or in awkward postures, multiply score ×3

Posture points	10%	25%	33%	50%	65%	85%	PP
Wrist/Elbow	0	0,5	1	2	3	4	
Shoulder	0	1,5	3	6	9	12	
Shoulder w/exosk	0	1,1	2,3	4,5	6,8	9	

Additional factors

20c			
	Gloves inadequate (which interfere with the handling ability required) are used for over half the time	2	☐
	Working gestures required imply a countershock. Frequency of 2 time per minute or more (i.e.: hammering over hard surface)	2	☐
	Working gestures imply a countershock (using the hand as a tool) with freq. of 10 time per hour or more	2	☐
	Exposure to cold or refrigeration (less than 0 degree) for over half the time	2	☐
	Vibrating tools are used for 1/3 of the time or more	2	☐
	Tools with a very high level of vibrations	4	☐
	Tools employed cause compressions of the skin (rednesses, callosities, blebs, etc.)	2	☐
	Precision tasks are carried out for over half the time (tasks over areas smaller than 2-3 mm)	2	☐
	During almost the whole time one or more additional factor/s is/are present	3	☐
	Additional points (choose the highest value)	=	AF

Repetitive tasks duration

20d

Net Duration [min/shift]	60	90	180	300	420	480	+
Shift Points (1 hour = 1 point)	1	1,5	3	5	7	8	

Work Organization	Breaks are possible at every time (Cycle time longer than 10 minutes)	Breaks are possible at given conditions (Cycle time between 1 and 10 minutes)	Breaks lead to a stop of the process (Cycle time shorter than 1 minute)	+
Work Organization Points	0	1	2	

Breaks (≥ 8 min) [#/shift]		0	1	2	3	4	5	6	≥7	+
Break points	*cycle time ≤ 30 s*	3	2	1	0	-1	-2	-3	-4	
	cycle time > 30 s	0		-0,5		-1		-1,5	-2	

Duration Points = DP

Upper limb load in repetitive tasks

20	(a) Force & Frequency & Grip		(b) Postures		(c) Additional factors		(d) Duration		Upper Limbs
	(FFG	+	PP	+	AF)	×	DP	=	

Appendix B

Ethics Committee Approval

FACULDADE DE MOTRICIDADE HUMANA

Conselho de Ética
para a Investigação

Para:

Drª Ana Assunção
Faculdade de Motricidade Humana

Data: 1 de março de 2019

Projeto: "Eficácia de um plano de rotação na prevenção de sintomatologia músculo-esquelética na indústria automóvel: desenvolvimento de uma plataforma digital"

Estado CEIFMH: Positivo, com Recomendações (em anexo)
Parecer CEIFMH N.º: 8/2019

Este Conselho analisou o projeto em epígrafe. Confirma-se que o mesmo está em conformidade com as diretrizes nacionais e internacionais para a investigação científica que envolve seres humanos, incluindo a Declaração de Helsínquia sobre os Princípios Éticos para a Investigação Médica em Seres Humanos (2013) e a Convenção sobre os Direitos do Homem e a Biomedicina ("Convenção de Oviedo", 1997). As recomendações não envolvem alto risco e são deixadas ao critério do investigador.

O Presidente do Conselho de Ética para a Investigação da FMH

Paulo A. S. Armada da Silva

Conselho de Ética da Faculdade de Motricidade Humana, Universidade de Lisboa
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FACULDADE DE MOTRICIDADE HUMANA

Conselho de Ética para a Investigação

Projeto: "Eficácia de um plano de rotação na prevenção de sintomatologia músculo-esquelética na indústria automóvel: desenvolvimento de uma plataforma digital"

Estado CEIFMH: Positivo, com Recomendações
Parecer CEIFMH N.º: 8/2019

Anexo

1. **Consentimento Informado Livre e Esclarecido (CILE)**: No texto introdutório recomenda-se a substituição do termo "exposição biomecânica" por outro equivalente. Questiona-se se o entendimento deste termo por parte dos participantes é coincidente com o dos investigadores;

2. **Objetivos e Relevância**: Num contexto industrial dinâmico (no plano tecnológico, produtivo, organizacional e humano) e em permanente evolução, a construção de um instrumento, que gera planos de rotação de pessoal em função de determinados critérios, deve permitir acompanhar essas mutações, sob pena de rapidamente (e nestes contextos, por vezes, são alguns meses) estar obsoleto. No projeto não está espelhada essa preocupação, de deixar um legado que pode fazer evoluir. Transparece a ideia de construção de um instrumento fechado que responde à necessidade de um dado estado do processo produtivo num determinado momento (o momento de coleta de dados). E se a produção mudar? E se a tecnologia de suporte à produção mudar? E se a organização dos layouts e tempos de trabalho mudar? E se os recursos humanos forem diferentes, por exemplo em número? O projeto não faz referência às potencialidades do instrumento proposto para acomodar estas ou outras alterações do processo produtivo. Recomenda-se, assim, atenção a este aspeto na fundamentação da relevância do projeto;

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Conselho de Ética
para a Investigação

3. **Metodologia:** O projeto propõe-se avaliar o efeito da implementação de um plano de rotação na redução da sintomatologia músculo-esquelética. Para que este objetivo seja alcançado julgamos que poderia ser contemplado um terceiro momento de recolha de dados de sintomatologia músculo-esquelética, suficientemente distanciado no tempo, do momento de implementação do modelo de rotação;

4. **Benefícios para os participantes.** Recomenda-se considerar a possibilidade de os participantes terem acesso a todos ou a parte dos dados referentes à sintomatologia músculo-esquelética auto-reportada assim como aos resultados finais ou parciais do projeto.

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Appendix C

A genetic algorithm approach to design job rotation schedules ensuring homogeneity and diversity of exposure in the automotive industry[2]

(Supplementary Material)

[2]**Based on:** Ana Assunção, Nafiseh Mollai, João Rodrigues, Carlos Fujão, Daniel Osório, António P. Veloso, Hugo Gamboa, Filomena Carnide (2022) *A genetic algorithm approach to design job rotation schedules ensuring homogeneity and diversity of exposure in the automotive industry*. Heliyon. 8, e09396. https://doi.org/10.1016/j.heliyon.2022.e09396

Supplementary Material

1. Example

A demonstration of how to apply the concepts will be described in the following section. In this example, the number of workers (W) is 6, the number of workstations (WS) is also 6, and the number of rotation periods (rot) is 4. In this hypothetical scenario, the workers considered have a qualification matrix presented in Figure 1. The workstations were scored based on the EAWS as presented in Table C.1**.**

Table C.1 - Risk factor scores for all categories of the EAWS. The colours on the Action Forces section represent the type of force exerted: black - dynamic and static forces; dark grey - dynamic forces; light grey - the risk factor is not present. The unit %t indicates the percentage of time spent in that risk factor during 1 cycle time, and n represents the number of times these risk factors appear in 1 cycle time.

	Posture (%t)							MMH (points)				Force (%t or n)												
	NS		T		E							WB						HAF						
	ASL	AHL	B	SB	GA6	GA8	GA10	R	C	H	P	1	2	3	4	5	6	1	2	3	4	5	6	S
Ws 1	0		19	0	39	18	9	0	0	0	0													60
Ws 2	0		15	0	53	11	9	0	0	0	0													42
Ws 3	0		31	0	18	16	3	0	0	0	0													48
Ws 4	0		4	0	33	8	1	0	0	0	0													36
Ws 5	9	24	0	0	13	1	2	0	0	0	0													57
Ws 6	0		22	0	29	23	5	11	0	0	0													43

Abbreviations: Ws – Workstation; NS – Neck and shoulder; ASL – At/Above shoulder level; AHL – Above head level; T- Trunk; B-Bent; SB-Strongly bent; GA6 – Arm reach at 60%; GA8 – Arm reach at 80%; GA10 – Arm reach at 100%; MMH – Manual material handling; R – Repositioning; C – Carrying; H – Holding; P – Pushing and Pulling; WB – Whole body force; HAF – Hand Arm Finger force; S – Score.

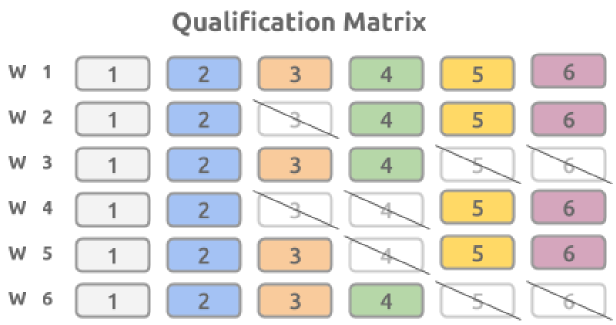

Figure C.1 - Example of a qualification matrix for 6 workers and 6 workstations.

Abbreviations: w – worker.

The way exposure, diversity, and homogeneity scores were calculated are demonstrated in the following section. For this example, consider the randomly generated job rotation schedule, presented in Figure C.2.

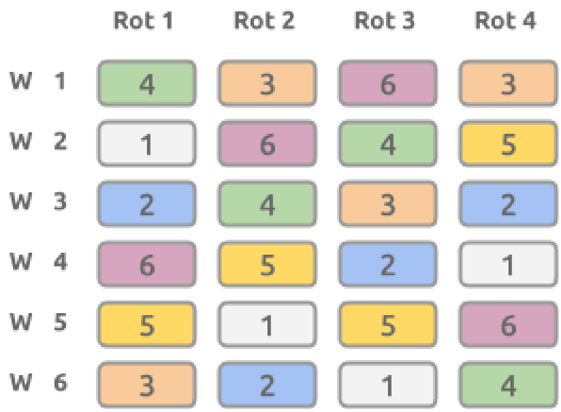

Figure C.2 - Randomly generated job rotation plan for the example.

Abbreviations: w – worker; Rot – rotation period.

1.1. Example of Exposure

For the calculation of exposure and diversity, take into consideration the sequence of workstations given to $w2$.

The exposure is calculated using Eq. (2) and computed in Eq.(17):

$$OE_2 = (0.23) * 60 + (0.30) * 43 + (0.27) * 36 + (0.20) * 57 \tag{17}$$

The OE_2 score (47.71) is then normalized using Eq. (3), which uses the maximum and minimum possible occupational score for a specific worker. In this case, looking at Table 3, $ws1$ is $w2$ most demanding workstation. Repeating this workstation over the 4 rotation periods gives the worst working sequence: 1 → 1 → 1 → 1 (max_2 = 60). The workstation with lower score for $w2$ is $ws4$. Repeating this workstation over the 4 rotation periods gives the best working sequence: 4 → 4 → 4 → 4 (min_2 = 36). The normalized score is (based on Eq. (3)):

$$NOE_2 = \frac{47.71 - 36}{60 - 36} = 0.33 \tag{18}$$

The closer the OE_2 score is to the max_2, the closer to 1 would be NOE_2 score, indicating a worse exposure score.

1.2. Example of diversity in Posture and MMH

The calculation of diversity score for posture and MMH was made, and process was the same. In Figure C.3 the presence/absence of the risk factor for each body region category of posture, for $w2$ is depicted.

Regarding posture and MMH, the process was the same. In Figure C.3. was depicted the presence/absence of the risk factor for each body region category of posture, for $w2$.

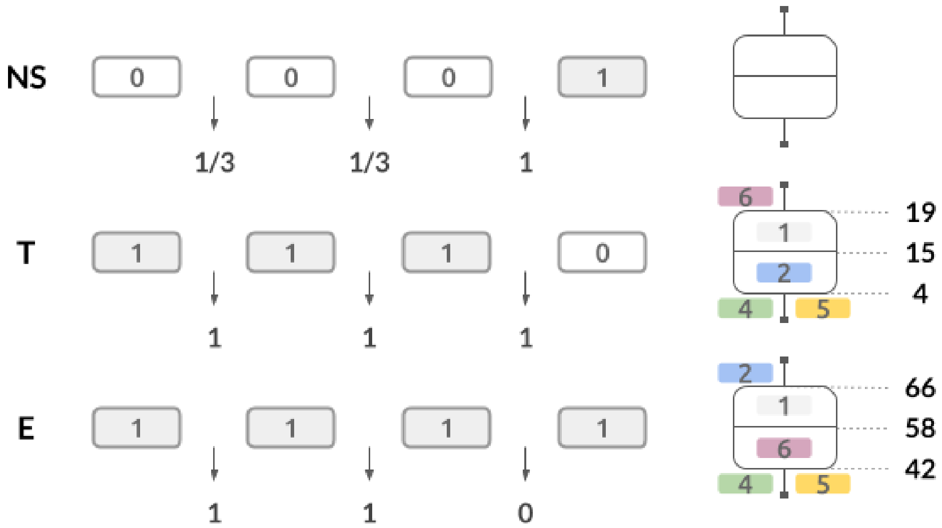

Figure C.3 - Presence and absence of each risk factor category (NS- Neck and Shoulders; T-Trunk; E-Elbow) of posture for the working sequence of worker 2. On the right side of the Figure, the distribution of the risk factors scores is presented for each risk factor category in quartiles. The workstations are located on the quartiles where they belong. The distribution for NS is omitted because it did not reach that step.

The Neck and Shoulders (NS) body region was only present on workstation 5, with a transition score for the first and second shift of 1/3 (transition type 2), while for the last shift, the transition was scored as 1 (transition type 1). Trunk and Elbow were present in more workstations. When two back-to-back workstations had the same posture or MMH risk factor present, the transition score was calculated by inspecting the change in quartiles. The distribution of scores for each worker and each risk factor of Posture and MMH was calculated and divided into quartiles. In Figure C.3, each body region had its distribution. Therefore, each workstation fits in one of the quartiles, for instance, $w6$ had a score of 22 for the trunk and fits in the upper quartile, indicating that out of all the workstations, it is the one with a higher risk for the trunk. After making this evaluation, the transition scores were now based on the inter-quartile transitions on shifts. For instance, for the trunk, the transition of the first shift was scored as 1, because there was an inter-quartile transition between $ws1$ and $ws6$ For elbow, the last shift was scored as 0, because there was no inter-quartile transition between $ws4$ and $ws5$. The transition scores for NS, Trunk, and Elbow were, respectively, for each transition:

$$tsA_{t,p}1 = \frac{\frac{1}{3} + 1 + 1}{3} = 0.78 \quad (19)$$

$$tsA_{t,p}2 = \frac{\frac{1}{3} + 1 + 1}{3} = 0.78 \quad (20)$$

$$tsA_{t,p}3 = \frac{1 + 1 + 0}{3} = 0.67 \quad (21)$$

The final transition score for posture was the average (Eq. (22)):

$$tsA_{t,p} = \frac{0.78 + 0.78 + 0.67}{3} = 0.74 \quad (22)$$

To calculate the transition scores for MMH, the process was the same. In this case, the values for all were almost 0, therefore the risk factor was majorly absent, except for the repositioning category of $ws6$. Therefore, the transition scores for each shift of $w2$, for repositioning are (1) 1, (2) 1, and (3) 1/3. The transition scores for each shift were:

$$tsA_{t,mmh}1 = \frac{1 + \frac{1}{3} + \frac{1}{3} + \frac{1}{3}}{4} = 0.50 \quad (23)$$

$$tsA_{t,mmh}2 = \frac{1 + \frac{1}{3} + \frac{1}{3} + \frac{1}{3}}{4} = 0.50 \quad (24)$$

$$tsA_{t,mmh}3 = \frac{\frac{1}{3} + \frac{1}{3} + \frac{1}{3} + \frac{1}{3}}{4} = 0.33 \quad (25)$$

The final transition score for MMH was the average (Eq. (26)):

$$tsA_{t,mmh} = \frac{0.50 + 0.50 + 0.33}{3} = 0.44 \quad (26)$$

1.3. Example of diversity for force

The process to calculate the transition score for force was presented in Figure C.4.

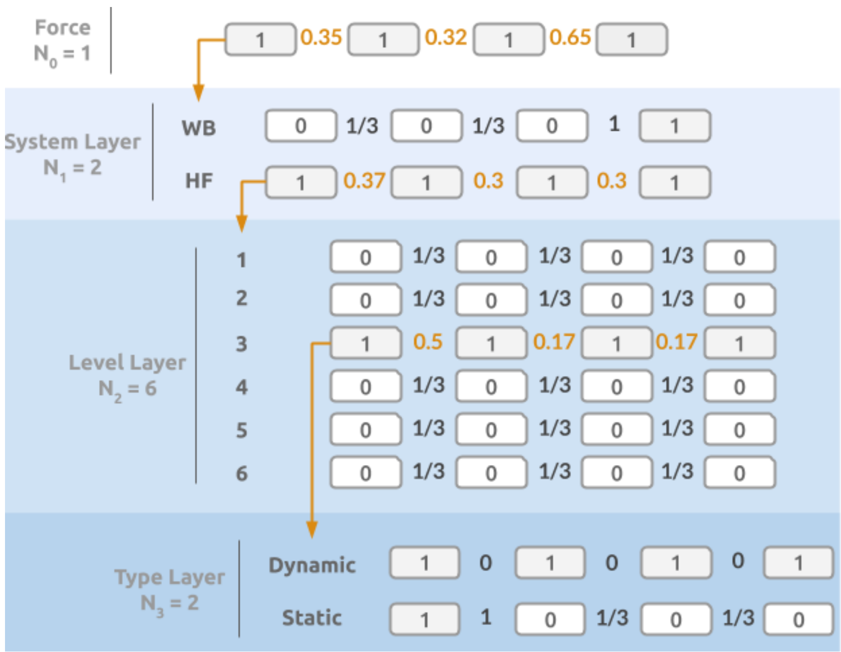

Figure C.4 - Calculation of transitions score in force in each layer.

Abbreviations: WB – Whole body forces; HF - Hand Arm Finger Forces

As in posture and MMH, the first layer (Force) inspects the presence and absence of the risk factor in each workstation. In the case of $w2$, the factor was always present. Therefore, the transition score for each shift was calculated on the transition scores of the next layer (System Layer). In this layer, the evaluation was made for both *Whole Body* and *Hand Arm Finger* forces. For the *Whole Body*, the scores followed transition types 1 and 2. Regarding *Hand Arm Fingers*, the risk factor was always present, therefore the transition score was calculated by the next layer (Level Layer). For each force level (1 to 6), the transition score was calculated. For *Hand and Fingers* system of worker 2, the only force level with risk factor presence was level 3. As the risk factor was present in all rotation periods, the score was calculated on the last layer (Type Layer). In the sequence of $w2$, the only workstation with static forces was $ws1$, while the remaining workstations were absent of the risk factor. On the other hand, dynamic forces were present in all workstations, which means that no diversity was achieved. The score, in the last layer, was 0. Using all the previous information, we were able to calculate the scores for the previous layers. For Level Layer 3:

$$tsB_{t,f}2_1 = \frac{0+1}{2} = 0.50 \tag{27}$$

$$tsB_{t,f}2_2 = \frac{0+\frac{1}{3}}{2} = 0.17 \tag{28}$$

$$tsB_{t,f}2_3 = \frac{0+\frac{1}{3}}{2} = 0.17 \tag{29}$$

For the System Layer HF:

$$tsB_{t,f}1_1 = \frac{\frac{1}{3}+\frac{1}{3}+0+\frac{1}{3}+\frac{1}{3}+\frac{1}{3}}{6} = 0.37 \tag{30}$$

$$tsB_{t,f}1_2 = \frac{\frac{1}{3}+\frac{1}{3}+0.17+\frac{1}{3}+\frac{1}{3}+\frac{1}{3}}{6} = 0.30 \tag{31}$$

$$tsB_{t,f}1_3 = \frac{\frac{1}{3}+\frac{1}{3}+0.17+\frac{1}{3}+\frac{1}{3}+\frac{1}{3}}{6} == 0.30 \tag{32}$$

Finally, the transition score for the force risk factor was:

$$tsB_{t,f}1 = \frac{\frac{1}{3}+0.37}{2} = 0.35 \tag{33}$$

$$tsB_{t,f}2 = \frac{\frac{1}{3}+0.3}{2} = 0.32 \tag{34}$$

$$tsB_{t,f}3 = \frac{1+0.3}{2} = 0.65 \tag{35}$$

$$tsB_{t,f} = \frac{0.35+0.32+0.65}{3} = 0.44 \tag{36}$$

1.4. Diversity Score

The final diversity score for $w2$ was calculated following Eq. (7):

$$Ts_2 = \frac{3 * tsA_{t,p} + 2 * tsB_{t,f} + 1 * tsA_{t,mmh}}{6}$$

$$Ts_2 = \frac{3 * 0.74 + 2 * 0.44 + 1 * 0.44}{6} \tag{37}$$

$$Ts_2 = 0.59$$

1.5. Example of homogeneity and the job rotation schedule quality

The results of exposure and diversity for the rotation schedule are presented in Table C.2.

Table C.2 - Scores for the normalized occupational exposure (NOE), diversity (T_s), homogeneity (Hom), shift working sequence quality ($SWSQ$) and the quality of the job rotation schedule (MQ) presented in Figure C.2.

Worker	NOE	T_s	$SWSQ$
1	0.33	0.48	1.63
2	0.49	0.59	1.69
3	0.25	0.63	2.01
4	0.46	0.70	1.94
5	0.73	0.79	1.85
6	0.28	0.57	1.86
	Hom		$\overline{SWSQ}$
	1.74		1.83
MQ		2.27	

The calculation of the homogeneity score was obtained using Eq. (12) calculating the standard deviation of the NOE and T_s scores. The score that evaluates the quality of a working sequence, on average, was made applying Eq. (14).

The final quality score of the entire job rotation schedule, including the evaluation of the working sequences, as well as the overall homogeneity of the plan, was made with Eq. (15), being the result 2.15.

Appendix D

The role of the industrial work transformation on the exposure patterns

[2]**<u>Accepted for presentation on the International Symposium on Occupational Safety and Hygiene</u>:** Ana Assunção, Sarah Bernardes, Carlos Fujão, Jacqueline Gaspar, Filomena Carnide (2019) *The role of the industrial work transformation on the exposure patterns*. In Proceedings of the International Symposium on Occupational Safety and Hygiene.

The role of the industrial work transformation on the exposure patterns

Assunção, Ana[1]; Bernardes, Sarah[1]; Fujão, Carlos[2]; Gaspar, Jacqueline[2]; Carnide, Filomena[1]

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The recent trends in the labour market are bringing new challenges to employers and employees, with the increase of adverse psychosocial conditions having a significant impact on musculoskeletal health. The main goal of this study is to estimate the association between biomechanical and psychosocial factors and musculoskeletal symptoms in the neck, shoulder, elbow, wrist/hand and low back. Cross-sectional data from assembly workers, in an automotive industry were collected (n=352). The Copenhagen Psychosocial Questionnaire was used to characterize the psychosocial factors and the Nordic Musculoskeletal Questionnaire was used to collected musculoskeletal data. Biomechanical risk factors were extract from ergonomics assessments. Odds ratio with 95% confidence intervals were computed using logistic regression and all estimates were adjusted for sex and age. Out of the 352 workers, 36.6% reported discomfort in at least one segment. Out of this, 20.9% reported multisite pain. Biomechanical factors did not show an association with musculoskeletal symptoms. Several psychosocial dimensions were significantly associated with the occurrence of musculoskeletal symptoms, however, from all dimensions' quantitative demands, emotional demands and work pace were the only ones associated with in all body segments. The major findings from this study suggest no associations between biomechanical risk factors with musculoskeletal symptoms, whereas psychosocial factors may play a key role on the onset of musculoskeletal health.

Keywords: musculoskeletal symptoms; psychosocial factors, biomechanical factors, automotive industry.

1. INTRODUCTION

The main goal of industries and task design to lower the potential development of work-related musculoskeletal disorders (WRMDs) remains a challenge. The etiology of WRMDs is complex, with occupational factors assuming an important role on the onset of these disorders.

Biomechanical factors related with work environment and the way the work is performed are among the risk factors responsible for the increase of musculoskeletal complaints (Punnett & Wegman, 2004). Moreover, WRMDs complaints can be observed as the early stages of the professional life (Nahit, Macfarlane, Pritchard, Cherry, & Silman, 2001).

Beside the physical dimension, psychosocial constructs also play an important role on the onset of musculoskeletal symptoms (Lang, Ochsmann, Kraus, & Lang, 2012), For instance, an organizational workplace intervention might contribute to the mitigation of exposure to physical demands (Stock et al., 2018). The impact of psychosocial factors on musculoskeletal disorders is particularly relevant under the current change of the labor market (Roquelaure et al., 2012). Recent trends toward more sedentary, automated and stereotyped work tasks have resulted in higher workloads, less exposure variation, fewer breaks and prolonged low-level exertions.

Industrial companies show a tendency to eliminate operational leeway, particularly following implementation of the lean principle.

A trend in the automotive industry suggests an increase of work standardization, best practice (performing the tasks in the same way) and limiting operational leeway (coping strategy) (Koukoulaki, 2014).

The aim of this study is to estimate the associations between biomechanical factors, psychosocial work environment and musculoskeletal outcomes.

2. MATERIALS AND METHODS

2.1. Participants

A cross-sectional study was conducted in an assembly area in an automotive industry.

All direct workers in assembly area were invited to participate in the study (n=989). Team Leaders were excluded. Written informed consent was obtained from all participants.

2.2. Data collection

Questionnaires. The questionnaire contained questions for: demographic factors, lifestyle habits, musculoskeletal symptoms and pain intensity, psychosocial factors and capacity for work.

Demographic factors. The demographic factors included date of birth, gender, height, weight, date of admission in the company.

Musculoskeletal symptoms. The Nordic Musculoskeletal questionnaire adapted to the Portuguese language (Mesquita, Ribeiro, & Moreira, 2010) was used to assess the occurrence of musculoskeletal symptoms (pain, tingling or numbness) in the last 12 months and in the past 7 days, as well as the preclusion for doing daily activities related with the presence of pain (last 12 months). If a participant reported pain in the past 7 days, the intensity of that pain was selected using a visual analogue scale, with 10 points where 0 means "no pain" and 10 means "worst possible pain".

Psychosocial factors. Psychosocial factors at work were assessed using the Copenhagen Psychosocial Questionnaire (COPSOQ) Portuguese version (Silva et al., 2010). In the present study, 13 scales with a total of 19 questions were used. The scales represent 4 main domains: Demands at work (4 scales), Work organization and job content (2 scales), Interpersonal relations and leadership (6 scales) and Work-individual interface (1 scale). Questions in six scales (influence at work, variation, commitment to the workplace, social support from colleagues, social support from supervisors, and social community at work) were answered using a five-step response ranging from "always" to "never/hardly ever." In seven scales (possibilities for development, meaning of work, predictability, recognition, role clarity, role conflicts, and quality of leadership) questions were answered in five steps from "to a large extent" to "to a very small extent."

Biomechanical risk factors. The biomechanical risk factors were assessed using the EAWS (Schaub, Caragnano, Britzke, & Bruder, 2012), by certified ergonomists working within company. This method is often used in the automotive industry. The matrix of versatility of the participants was collected, providing information of each workplace that they were able to perform. Only the workplaces that workers could perform independently were considered.

2.3. Statistical analysis

For data analysis, a descriptive analysis was carried out to determine the parameters of central tendency (mean, standard deviation and median) and frequencies (absolute and relative).

To analyze the associations between demographic, biomechanical and psychosocial risk factors with the prevalence symptoms in different body segments, we used bivariate logistic regression analysis (Enter method) for each estimators of the risk factors, and a multifactorial logistic regression analysis (backward conditional method), including as factors, the variables that had statistically significant associations in previous models. We calculated significance tests and confidence intervals from the maximum likelihood estimation of the coefficients and their standard errors. Statistical analyses were performed using IBM SPSS Statistics version 25.0 (SPSS Inc., an IBM Company, Chicago, Illinois, USA). For all tests, statistical significance was set at $p<0.05$.

3. RESULTS

In total, 372 workers replied to the questionnaire. Out of these, 20 were excluded (15 Team Leaders and 5 without written informed consent). Total sample was 352 subjects.

Descriptive characteristics of the workers are presented in Table 1, stratified by gender and total sample. Results are presented by gender and for the entire sample. Out of the 352 employees assessed, 24.4% were woman and 15.1% had more than 45 years. Weight, height and body mass index were statically different between genders ($p<0.05$).

***Table 1** – Descriptive characteristics of sample*

	Woman mean±SD (n)	*Man mean±SD (n)*	*All Sample mean±SD (n)*
Age (yrs)	33.6±9.1 (86)	33.9±9.5 (266)	33.8±9.4 (352)
Seniority (yrs)	3.5±5.7 (86)	7.0±8.8 (266)	6.2±8.3 (352)
Weight (kg) *	64.6±10.1 (77)	77.7±12.9 (258)	74.7±13.5 (335)
Height (cm) *	163.1±0.1 (83)	175.8±0.1 (260)	172.7±0.1 (343)
BMI (kg/m²) *	22.3±7.7 (76)	24.8±4.6 (257)	24.2±5.6 (333)

*Differences between group values ($p<0.05$)
Abbreviations: Body Mass Index (BMI)

Table 2 includes the prevalence of the musculoskeletal symptoms in the last 12 months for lower back, neck and upper limb (shoulders, elbow and wrist/hand). Out of the 352 workers, 36.6% reported discomfort in at least one segment. Out of this, 20.9% reported multisite pain. Women presented a higher prevalence of discomfort/pain when compared to men in every segment. Writs/hands were the segment that had higher prevalence values in both genders.

***Table 2** – Prevalence of musculoskeletal symptoms in the last 12 months in the neck, upper limbs and low back*

	Woman n (%)	*Man n (%)*	*All sample n (%)*
Neck	29 (35.4)	65 (26.4)	94 (28.7)
Shoulders	29 (34.9)	76 (30.0)	105 (31.3)
Elbow	22 (25.9)	42 (16.9)	64 (19.2)
Writs/hand	39 (45.3)	105 (40.5)	144 (41.7)
Low back	30 (35.7)	86 (34.5)	116 (34.8)

Figure 1 depicts the logistic associations between psychosocial dimensions from COPSOQ questionnaire with the symptoms reported in the last 12 months in the neck, shoulder, elbow, wrist/hand and low back. Cognitive demands, influence and social support from the supervisor did not yield any statistical association, whereas the role clarity showed to be a protective factor only for wrist/hand (OR=0.642 95% CI: 0.424-0.972).

For all 5 segments, there were 5 psychosocial dimensions that showed to be a protective factor: predictability, recognition, social community at work, quality of leadership and job satisfaction. Possibilities for development did not show any associations with symptoms in the elbow and wrist/hand site, for the remaining segments it showed to be protective.

Quantitative demands, emotional demands and work pace are associated with the occurrence of musculoskeletal symptoms in all segments.

Table 3 presents the average score evaluation for all workstations and the associations between the biomechanical factors and musculoskeletal symptoms in the different body regions. We observed no associations between all biomechanical factors and musculoskeletal symptoms.

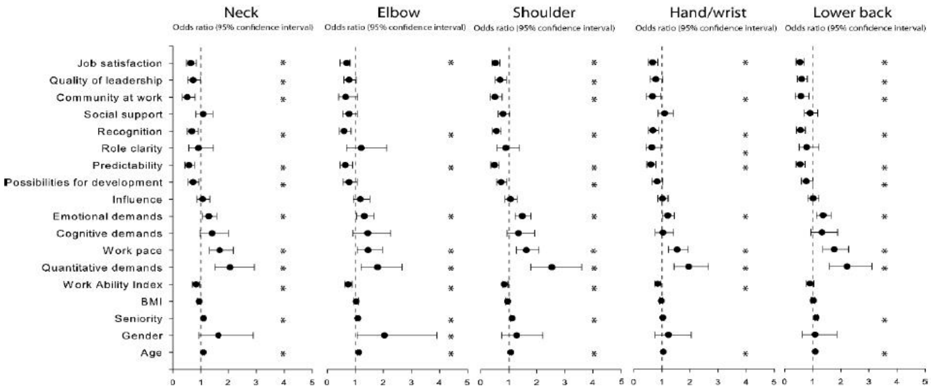

Figure 1 - Associations between psychosocial risk factors and musculoskeletal symptoms (neck, shoulders, elbow, wrist/hand and low back); odds ratio is adjusted for sex and age and are presented for the total sample.

Table 3 *– Associations between biomechanical risk factors and musculoskeletal symptoms; odds ratio are adjusted for sex and age and are presented for the total sample.*

	mean±SD	**OR**	**CI (95%) for OR**
Neck			
Score total	24.68±9,6	1.011	0.985-1.037
Score posture	14.78±5.9	1.006	0.979-1.033
Score force	5.27±4.7	1.035	0.984-1.088
Score tool	7.84±4.3	1.102	0.871-1.394
Score MMH	7.49±3.8	0.964	0.867-1.071
Shoulders			
Score total	24.68±9,6	1.000	0.975-1.026
Score posture	14.78±5.9	1.003	0.977-1.029
Score force	5.27±4.7	1.033	0.985-1.084
Score tool	7.84±4.3	1.025	0.818-1.284
Score MMH	7.49±3.8	0.961	0.870-1.063
Elbows			
Score total	24.68±9,6	0.986	0.957-1.016
Score posture	14.78±5.9	0.990	0.959-1.022
Score force	5.27±4.7	1.023	0.967-1.082
Score tool	7.84±4.3	1.000	0.763-1.310
Score MMH	7.49±3.8	0.926	0.810-1.058
Wrists/hands			
Score total	24.68±9,6	1.009	0.986-1.033
Score posture	14.78±5.9	1.009	0.985-1.033
Score force	5.27±4.7	1.037	0.992-1.085
Score tool	7.84±4.3	0.958	0.777-1.181
Score MMH	7.49±3.8	0.970	0.886-1.061
Low back			
Score total	24.68±9,6	0.990	0.966-1.015
Score posture	14.78±5.9	0.994	0.969-1.020
Score force	5.27±4.7	1.003	0.956-1.052
Score tool	7.84±4.3	1.029	0.823-1.288
Score MMH	7.49±3.8	0.915	0.826-1.013

Abbreviations: Manual Material Handling (MMH)

4. DISCUSSION

The aim of this study was to estimate the associations between biomechanical factors, psychosocial work environment and musculoskeletal outcomes.

The results from our study suggests, that in this specific sample, dimensions of psychosocial factors were statistically associated with musculoskeletal complaints in the 12 months' previews to the questionnaire in the neck, low back and upper limbs. Their effects were generally common across all 5 body regions. On the other hand, the biomechanical risk factors reported in the ergonomics risk assessment were not statistically associated with musculoskeletal symptoms in none of the segments.

Although, significant differences were found for the exposure of force and manual material handling among symptomatic and asymptomatic workers in the multifactorial model, these determinants were not relevant to explain the prevalence of musculoskeletal symptoms in the last 12 months, regardless of the segment under analysis.

In the industrial field, psychosocial factors have been shown to have a significant impact on musculoskeletal outcomes, either partially or completely, regardless of other physical risk factors (Bernard, 1997).

The findings from our study follow the results from the change of labor market (Roquelaure et al., 2012; Rugulies, Aust, Burr, & Bultmann, 2008), where jobs that became more flexible (precarious and temporary), informal (home-based, unregulated) and insecure (Eurofound, 2013) led workers to feel higher psychosocial demands.

The higher prevalence of musculoskeletal symptoms were reported at neck, upper limbs and low back, which is in agreement with the results reported in other studies (Colombini & Occhipinti, 2006; Van Eerd et al., 2016).

It is important that more studies address not only the role of psychosocial factors in the occurrence of these symptoms, but also discuss the role of these factors in prognosis and the recovery process following the onset of these disorders. In addition, these factors may impact other outcomes such as functional limitation or the ability to sustain a full day work.

Some methodological issues need nevertheless to be addressed. Both psychosocial work environment and musculoskeletal symptoms may be influenced by several of individual, social and confounders such as sex, age and seniority. In line with this, the presence of a chronic health conditions among workers is also likely to influence both the perception of psychosocial work environment and the report of musculoskeletal symptoms.

The assessment of the risk factors in the workplace is a complex and problematical field of research. Observational methods are among the most common used, with some having limitations in the accuracy of the measurements.

The use of direct measurement systems to perform the ergonomic analysis can provide large quantities of highly accurate data on biomechanical load. The accuracy of this data would allow to differentiate the risks associated to each body regions, allowing more precisely associate the self-reported symptoms to work conditions.

As exposures and outcomes were collected cross-sectionally, it is not possible to discern the temporal sequence between the exposure to adverse work-related psychosocial factors and the occurrence of musculoskeletal symptoms.

5. CONCLUSIONS

In conclusion, the psychosocial risk factors played a relevant role on the occurrence of musculoskeletal complaints in an automotive industry. Notwithstanding, it is important to make a detailed analysis on the possible factors that integrate each of the psychosocial dimensions that were significant in the analysis performed, in order to better understand the context. With an ever-changing automotive industry, where work standardization leads to a more sedentary working environment, it seems that psychosocial factors may be involved in explaining the occurrence of musculoskeletal symptoms in workers despite the characteristic biomechanical demands of this field.

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