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► **To cite this version:**

João Rodrigues, Hugo Gamboa, Nafiseh Mollaei, Daniel Osório, Ana Assunção, et al.. A Genetic Algorithm to Design Job Rotation Schedules with Low Risk Exposure. 11th Doctoral Conference on Computing, Electrical and Industrial Systems (DoCEIS), Jul 2020, Costa de Caparica, Portugal. pp.395-402, 10.1007/978-3-030-45124-0\_38 . hal-03741572

**HAL Id: hal-03741572**

**<https://inria.hal.science/hal-03741572v1>**

Submitted on 1 Aug 2022

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# A Genetic Algorithm to Design Job Rotation Schedules with Low Risk Exposure

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**Abstract.** In automotive industries, the manufacturing processes are characterized by repetitive tasks and physically demanding work, with possible long-term implications on the musculoskeletal health of the workers. One key organizational strategy that provides an improvement in the prevention of musculoskeletal disorders are job rotation schedules. These are usually designed manually, being (1) time demanding and (2) a subjective evaluation of the schedule's risk. In this work, a genetic algorithm is presented, to generate automatically a daily job rotation schedule. The quality of the schedule is based on objective scores assigned to workstations by the European Assembly Worksheet (EAWS) risk screening tool, guiding the algorithm in reaching a final solution that promotes schedules with lower exposure to the sequence of workstations assigned to each worker of the team. The schedules generated by the algorithm were compared to schedules designed by the team leaders and presented a better overall result.

**Keywords:** genetic algorithm · job rotation · occupational exposure.

## 1 Introduction

Job rotation schedules are usually the responsibility of team leaders, who must assign each worker to the set of workstations the worker has to perform over the working day. Considering this, (1) team leaders spend a considerable amount of time to design these plans correctly, and (2) do not have into consideration an objective measure of the occupational risk of each workstation.

In this work, a method based on a genetic algorithm for the automatic design of a job rotation schedule to support the task of team leaders is proposed. The algorithm considers the qualification of workers and the occupational exposure score of each workstation evaluated by the European assembly worksheet (EAWS) [10]. The proposed method will search for solutions that have low exposure scores for each worker and a balanced plan for the team.

## 2 Contribution to Life Improvement

In this work we focus on the benefits of automatic generation of job rotation schedules, which have several advantages: (1) by generating solutions automatically, team leaders can focus more of their time on their main tasks; (2) as the algorithm is designed with the consideration of objective scores of each workstation, the result will promote a more balanced exposure over the working day of each worker. These factors contribute to maximize the mentioned advantages, improving the welfare of both workers and team leaders.

## 3 Literature Revision

The design of job rotation plans follows a specific purpose. Several strategies have been developed depending on the context and application of these tools. For instance, in Asensio-Cuesta et.al (2012), a model has been designed to prevent work related musculoskeletal disorders in environments with high repeatability of movements, considering mechanical (using the Occupational Repetitive Actions (OCRA)), environmental and organizational factors [1]. Another study presents a job rotation schedule that uses the workers' qualifications, the workstation's exposure (based on EAWS) and the most recent allocation of each worker applying a linear programming-based heuristic [7]. Finally, other works are found in which both reduction of exposure and increase of productivity are the focus [9][2]. In these cases, the authors used a mixed integer programming model, considering organizational and mechanical variables.

Beyond reported studies, others were found in which the risk assessment was made to reduce the cumulative effect of sequential working tasks on the same body region by using the Rapid Entire Body Assessment (REBA) tool [11]. In[4] the proposed model adds posture diversity to reduce the accumulated risk of body postures. Additionally, a study (2014) with the purpose to reduce repetitive task sequences based on ergonomic, environmental, competence and skill factors was found [8].

Other works were found to include permanent and temporary disabilities of the workers as well as their preferences [6]. In Boenzi et. al. (2013) an integer programming model was used to find not only the optimal job rotation schedule, but also the optimal break schedule, in order to minimize the workload on teams of the assembly lines of an automotive industry. Finally, literature has also been found where the age of workers is included in the model, given the importance of the associations between the ageing process and work-related musculoskeletal disorders [3]. Several of the reviewed approaches used genetic algorithms [2][8][4][6], demonstrating to be reliable in reaching the desired solutions.

## 4 Research Contributions

This section outlines (1) the variables used to define the mathematical model used to design the function that guides the genetic algorithm in reaching a solution (2) the mathematical model, (3) the structure of the genetic algorithm and (4) the results.

### 4.1 Problem Definition, Variables and Mathematical Formulation

The problem in demand is combinatorial. For this case, a specific team (URQ) with 12 workers, of the assembly line of an automotive industry, was selected. The working shift considered was the early shift, divided in 4 working periods with the following distribution: (1) 22.6%; (2) 30.7%; (3) 27.0%; (4) 19.7%. The problem will be illustrated as a matrix (job rotation plan) that has the workstations assigned to each worker (rows) during each rotation period (columns) (e.g. Figure 2a).

In this case, the generation of a job rotation schedule has to comply with several conditions and requirements, namely: (1) Each worker has to be assigned to 4 workstations during the working day; (2) On each rotation period, each workstation can only be performed once; (3) On each rotation period, one worker can perform the task of a single workstation; (4) Workers can repeat the same workstation during the working day, depending on their qualification; (5) Each workstation assigned to a worker has to be part of their qualification;

In order to design a job rotation plan and its quality assessment, the set of variables considered must be clearly exposed and described. Overall, there are two kinds of variables that were used to design a job rotation plan:

**Mechanical Exposure Variables (EAWS)** The main variable involved in defining the quality assessment of a job rotation schedule is the overall score that quantifies the physical workload of a workstation. This variable is extracted from the EAWS screening tool and is estimated by the scores assigned to individual risk factors of the workstation. The score is presented by a traffic light scheme and is the variable that has the highest relevance on the fitness function.

**Organizational Variables** The organizational variables contemplate (1) the qualification of workers in a specific URQ to guarantee valid sequences, as well as (2) the duration of each rotation period.

As aforementioned, the assessment involves calculating an averaged score of the occupational exposure associated with the sequence of workstations assigned over the rotation periods to a worker and how deviated are the exposure scores of the team.

The *occupational exposure* score given to a workstation on the rotation period  $rot$  is calculated by multiplying the workstation's mechanical risk score ( $EAWS_{ws}$ ) with the percentage of time  $\Delta t\%_{rot}$  of the rotation period in which the workstation is scheduled. The value of time is fixed depending on the rotation period in which the station has been allocated. Finally, the resulting score for a sequence of workstations ( $OE_w$ ) is given by the sum of the occupational exposure scores over the set of rotation periods ( $n_{rot} = 4$ ):

$$OE_w = \sum_{rot=1}^{n_{rot}} EAWS_{ws} \times \Delta t\%_{rot} \quad (1)$$

In order to have a value between 0 and 1 as an output, the  $OE_w$  has to be normalized, such that if a worker has a score of 0, it means that he/she is exposed to the best possible sequence of workstations from the set of workstations the selected worker can do. On the other hand, a score of 1 means that he/she is exposed to the worst possible sequence of workstations. These scores are calculated for each worker based on the workstations they can do. The exposure score for the highest value ( $max_w$ ) is associated to 1, while the lowest value ( $min_w$ ) to 0. The calculation of the worst and best reference exposure sequences for each worker is not made in each step of the algorithm, but rather once before the algorithm is applied. The normalization is then made based on the reference scores ( $max_w$  and  $min_w$ ):

$$\overline{NOE} = \sum_{w=1}^W \frac{OE_w - min_w}{max_w - min_w} = \sum_{w=1}^W \frac{NOE_w}{W} \quad (2)$$

,being  $NOE_w$  the normalized occupational exposure score for a worker's sequence,  $W$  the number of workers on the team and  $w$  the iterator over the number of workers,  $OE_w$  the occupational exposure score for a worker's ( $w$ ) sequence,  $min_w$  and  $max_w$  the minimum and maximum occupational exposure scores of a valid worker's sequence, respectively.

The final variable that is used in the *fitness function* is the standard deviation of the occupational exposure scores of the team. This variable has the purpose to guide the algorithm finding solutions that balance the exposure scores of the team, not favoring one worker in regard to the other:

$$Dev = 1 - \sqrt{\frac{1}{W} \sum_{w=1}^W (NOE_w - \overline{NOE})^2} = 1 - \sigma_{oe} \quad (3)$$

,being  $\sigma_{oe}$  the standard deviation of the occupational exposure,  $W$  the number of workers on the team,  $w$  the iterator over the number of workers,  $NOE_w$  the occupational exposure score for a worker,  $\overline{NOE}$  the mean occupational exposure score of the team and  $Dev$  the deviation score. The higher the value of  $\sigma_{oe}$ , the worst is the exposure balance of the rotation plan. In order to have a value that has a positive trend (*the higher the better*), the deviation score ( $Dev$ ) is a result of an inverse sum of the standard deviation. The *fitness function* is now the combination of the previously explained variables. For a team there is the normalized occupational exposure score and the deviation score. The combination is made by adding these two variables with different weights:

$$MQ = M_{oe} \overline{NOE} + M_{dev} Dev \quad (4)$$

,being  $MQ$  the matrix quality score,  $M_{oe}$  the weight factor of the occupational exposure score and  $M_{dev}$  the weight of the deviation score. In this work,  $M_{oe} = 1$  and  $M_{dev} = \frac{1}{3}$ , The algorithm has the task of maximizing Equation 4.

## 4.2 Genetic Algorithm and Results

Genetic algorithms are based on the theory of evolution, being structured with the following steps: (1) generation of the initial population; (2) evaluate the fitness of each chromosome of the population; (3) the selection of a set of chromosomes from the population pool; (4) apply crossover and mutation of the selected chromosomes to generate offspring for a new population and (5) evaluate final conditions to stop or continue to generate new populations. The proposed algorithm follows the same architecture. In this work, population means a set of job rotation plans; *chromosome* means a valid job rotation plan and gene means a workstation of a job rotation plan.

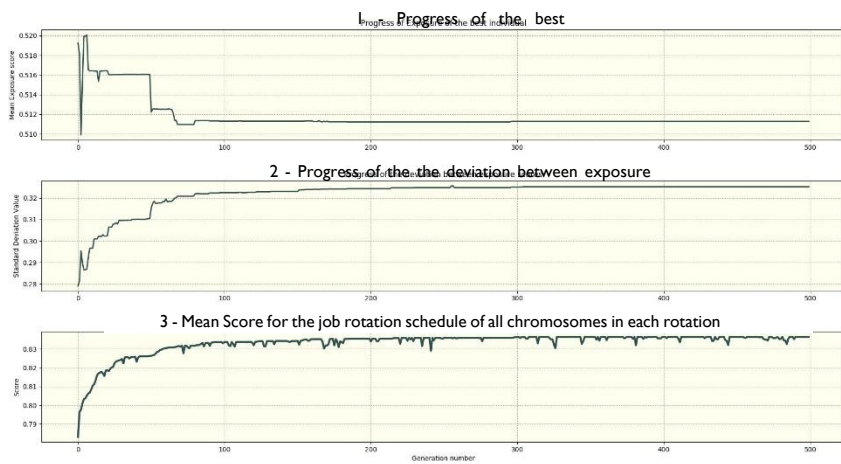
As presented in the Section 3, the methods used in genetic algorithms vary, depending on the type of problem itself and the restrictions that the problem implies. In the proposed algorithm: (1) the population has a size of 25 chromosomes; (2) the selection methods are elite selection (2%) and a method that merges the roulette-wheel and rank based selection (30%); (3) the crossover method is a permutation-based method called ordered crossover (OX) and generates 90% of the new population; (4) the mutation method is the bit-string mutation and generates 10% of the new population; (5) the closing conditions are met when the iteration number is higher than 500 and the best chromosome's score of the current population is higher than the mean value of scores for the weekly plan of the team leader, which is **0.78**.

Fig. 1 shows how each variable of the equation 4 vary over the iterative process. The third subplot demonstrates that the algorithm is able to reach a solution that complies with the requirements of the mentioned equation, maximizing the overall matrix quality score. The first and second subplot show how the algorithm varied the variables over time to reach better solutions.

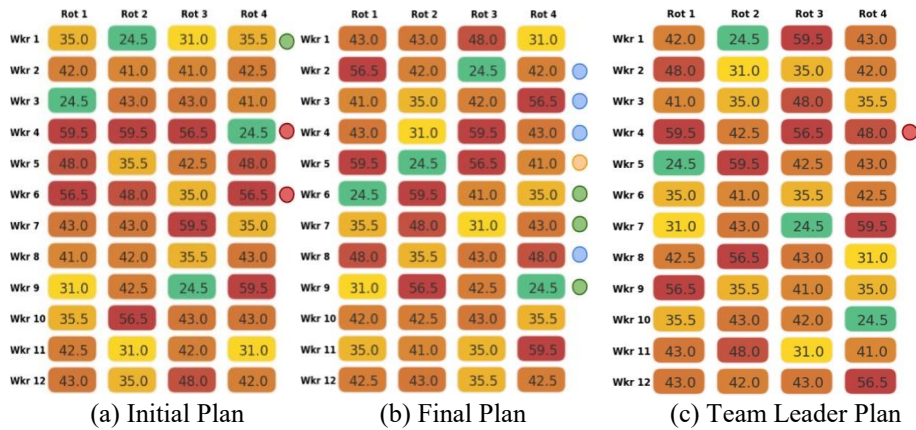
In Fig. 2a and 2b are presented a randomly selected job rotation plan from the first population, and the final outputted plan of the algorithm, respectively. The score of the initial and random job rotation plan is **0.76**, while the score of the final job rotation plan is **0.84**. In both cases, relevant sequences are highlighted. On the initial matrix, the sequences with higher and lower risk are showed with red and green circles, respectively. On the final matrix, sequences where red labelled workstations are outside the rotation with the longest period (*Rot 2*) are labelled blue, the sequences where red labelled workstations are located on the longest rotation period are labelled green and the sequence with the workstation with lowest risk is located on the longest rotation period is labelled orange. The result can also be compared with the job rotation plan designed by the team leader, which has a score of **0.78**. The table with the scores of the job rotation plans designed by the team leader for a week plan are presented in Table 1. The algorithm was able to give a solution in a mean value of 7.8 seconds.

## 5 Discussion

On Fig. 1 is seen that Dev score increases over each iteration, which means that the exposure score of each sequence of the matrix will be more similar between each other, balancing the occupational exposure of the team. It can also be noted that this balance is accomplished by no significant change from the mean exposure scores.



**Fig. 1.** Progress of the scores over the iterative process of the algorithm for the mean exposure (1), the deviation of the team’s exposure (2), and the matrix quality score (3)



**Fig. 2.** a) Initial job rotation plan (score: 0.76). (b) Final job rotation plan (score: 0.84). (c) Job rotation plan designed by the team leader (score: 0.78).



In this case, there was a peak of the mean exposure score in the beginning, however this peak tends to decrease over the iterative process. The initial plan, from Fig. 2a showed flaws in the sequences, namely for workers (*Wkr*) 4 and 6, which have 3 red labelled workstations on their sequences, resulting in very high-risk exposure levels. Conversely, *Wkr* 1 had a very low risk exposure level, unbalancing the plan.

**Table 1.** Scores for the normalized occupational exposure (*NOE*), deviation (*Dev*) and the quality of the job rotation schedule (*MQ*) for the team leader's plans of the week and the algorithm's output.

| Plan       | 1    | 2    | 3    | 4    | 5    | 6    | Initial | Final |
|------------|------|------|------|------|------|------|---------|-------|
| <i>NOE</i> | 0.51 | 0.51 | 0.52 | 0.51 | 0.50 | 0.51 | 0.51    | 0.51  |
| <i>Dev</i> | 0.83 | 0.81 | 0.79 | 0.82 | 0.79 | 0.80 | 0.75    | 0.97  |
| <i>MQ</i>  | 0.78 | 0.77 | 0.78 | 0.78 | 0.77 | 0.78 | 0.76    | 0.84  |

The job rotation plan that resulted from the algorithm, on Figure 2b, shows that the main purpose of the algorithm in balancing the scores for all workers and keep the exposure as low as possible was achieved. The longest periods for the early shift are the second and third rotation periods (*Rot 2 and Rot 3*). These have an increased contribution on the exposure risk. In the final plan, when red labelled workstations are on the longest rotation period (*Rot 2*), such as on sequences of *Wkr* 6, 7 and 9, the risk is balanced with green and yellow labelled workstations. In the case of having red labelled workstations on the sequence, but not on the longest rotation period, such as in the sequences of *Wkr* 2, 3, 4, 5 and 8, lower risk exposure workstations balance the risk of the sequence with green and/or yellow on the longest rotation period. In the case of *Wkr* 5, having multiple red labelled workstations implies the need of the workstation with lower risk on the longest rotation period.

Comparing Figures 2b and 2c and looking at Table 1, there are similarities in how the sequences are balanced. Nevertheless, the deviation between sequences scores is much higher in the case of the team leader's plan.

This model brings a new methodology in integrating EAWS variables as the main guiding factor to reach solutions for job rotation schedules. Compared to the work of Hochdörffer *et. al.*, where partial scores were used, the information is less, but can be used to easily adapt the model in any environment that uses occupational scores and qualifications of workers in their protocols.

## 6 Conclusion and Future Work

The main purpose of this work was to guarantee that the results are reliable and realistic to support team leader's decisions and to reduce the burden imposed to them since it is a time-consuming process, and this was achieved.

In the industrial context, the implementation of such measures can have a great impact in reducing management and health related costs, by means of preventing work related injuries and complains. Additionally, such work is a tool for team supervisors and workers to evaluate the risk of the schedules and what can be improved on the team.

For instance, simulations of schedules can be performed to identify problems such as the lack of versatility of workers, and how this versatility could be improved to ameliorate the quality of the schedule.

Improvements can be made on the current method. The use of the overall score only evaluates the workstation globally, while other aspects of the workstation, described on the EAWS tool are not used, namely posture, manual material handling and force scores. In a future approach, other organizational variables should also be considered, namely the skill level of workers and the diversity in the sequence.

**Acknowledgments.** This work was partly supported by Fundação para a Ciência e Tecnologia, under Grant UID/DTP/UI447/2019 to CIPER–Centro Interdisciplinar para o Estudo da Performance Humana (unit 447), Ph.D. grant SFRH/BDE/102750/2014, Ph.D. grant PD/BDE/142973/2018 and Ph.D. grant PD/BDE/142816/2018.

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