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Scheduling of a textile production line integrating PV generation using a genetic algorithm

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Abstract

Considering the technological advances of the industrial sector today, it appears that the management of energy resources has become increasingly prominent. Thus, to make this management more efficient, it is necessary to take into account the production planning and scheduling concept, since it allows influencing the scheduling of production at the level of cost and efficiency. Thus, the objective of this paper is to present a methodology that allows making the best possible scheduling of a textile production line to optimize it. This optimization is elaborated with the help of genetic algorithms, and, as it can be verified in this paper, it is possible to make an optimization of the production line at the level of energy cost or the level of energy consumption or optimization of both. Thus, the case study of this paper is based on a textile production line that produces a variety of products through three machines capable of performing numerous tasks, which can be done on more than one machine. Likewise, this production line enjoys photovoltaic production. This paper presents several case studies that allow for highlighting the impact of the methodology covered in the respective production line, where it is illustrated through different graphics.

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1. Introduction

Regardless of the type of industry, production planning and scheduling are seen as crucial tools to facilitate decision making, where scheduling is influenced by production planning, as this is precedent, as shown [1]. In general, they make it possible to optimize a given production line so that it can achieve the best possible efficiency,

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reducing the cost and the time of operation of that same line of operation, as shown [2,3]. So, considering this context, it is essential to emphasize that most of the problems in real life are complex and large problems. The job shop schedule (JSS) problem is one of them, where it belongs to the NP-hard problem class, as shown [4]. The complexity of this problem increases as the number of machines and tasks associated with the job shop increases. Thus, in order to solve this problem, different kinds of literature used heuristic algorithms such as Particle Swarm Optimization (PSO), Simulated Annealing (SA), Genetic Algorithm, among others, as shown in [5–7] respectively. However, according to [3,8], GA is the one that has the best performance regarding the JSS problem. Thus, considering what was said earlier, this paper has as main objective to optimize a job shop that takes advantage of renewable energy produced by photovoltaic (PV) panels, through GA. This optimization shows that there is a reduction in the production time of the job shop, where it also prevents the respective machines from being in an “idle” state. In the same way, this optimization shows that there is a better allocation of the energy resources of the respective job shop, which consequently leads to a reduction in the cost of operating the job shop.

Thus, this article is divided into five sections, where Section 1 is the introduction. Section 2 highlights the methodology used. In Section 3, the case study brings the different scenarios studied, wherein Section 4, the results obtained through these case studies, are discussed. Finally, Section 5 presents the conclusions.

2. Approach

The first stage of the method, Data Acquisition, consists of acquiring the different data associated with the production line, such as the consumption of machines and PV production in periods of 5 min. The task information is acquired, in relation to the beginning and end of each task, as well as the product information, namely the sequence of tasks to make the respective product. Regarding the functioning of GA, an initial random population is created. Considering the job shop’s work plan, it generates the list of necessary tasks to be carried out, where each of these tasks are randomly assigned to compatible machines (vertical permutation). In case a machine is full, and there is a task that can only be done on that machine, the creation is restarted. In order to reduce the rate of these deadlocks, the list of tasks in the work plan is ordered in ascending order of the number of compatible machines per task, that is, tasks that can only be done on one machine have priority over other tasks that can be made on two or more machines. Subsequently, after knowing the list of tasks associated with each machine, a rectangular static matrix is drawn up, which represents the work plan of the job shop, where each line represents the plan of a machine and the columns the periods. Then, a random permutation is applied to each plan of the machines (horizontal permutation), and it is verified that all restrictions are met. Otherwise, more permutations are carried out. After obtaining a population it will use it to run n defined generations. It should be noted that restrictions are validated at all stages of a generation. There are two types of restrictions, order, and collision. Regarding the first constraint, it consists of restricting that a given task X can only be executed if task Y is first executed. As for the second constraint, it is that two or three tasks cannot be performed at the same time. A generation begins with the crossover of the population of the previous generation. The crossover is a two-dimensional type, which will try to balance the tasks coming from each parent (individual), these being matrices. The crossover between two individuals (parents) begins with the formation of the list of tasks for the entire plan, ordered in decreasing order of makespan, and if they have equal times, it is ordered in ascending order of the number of machines compatible with the task. This, therefore, allows reducing the rate of invalid crosses between two individuals. At the end of the crossover it is checked whether all restrictions are being met. Then, from the population obtained from the crossover, the population is mutated. In this procedure, the algorithm takes each individual, and according to the percentage of mutation defined in the input data, it decides whether or not the mutation will be applied to a given individual. However, if the mutation is applied, it is based on exchanging two tasks in the plan. This exchange can be carried out between two tasks that have different times, as long as there is time available in front of the smaller task, which can compensate for the larger one. If the exchange is not possible, the algorithm tries to find other tasks to replace, and in the event of not being able to replace, it is passed to another individual. It is noteworthy that, in an individual chosen to mutate, only one task exchange operation is performed. Finally, in one generation, the selection phase is carried out, which allows building the population that will pass to the next generation. This phase begins with the union of the new and old population, that is, the crossed and mutated population with the initial population of the generation. Additionally, individuals who are repeated in the resulting population are filtered. Then, each individual, who represents a possible JSS, is evaluated. Then, the selection of the n best individuals, not repeated, between the old and the new population is made. The remaining individuals are obtained from non-elite tournaments. Each

tournament consists of two individuals chosen at random, where the individual with the lowest cost is the one most likely to be chosen. However, since this tournament is not elitist and to avoid directly choosing the individual with the lowest cost, a decimal number between 0 and 1 is generated randomly. If this value generated is less than or equal to the previously mentioned probability, then the individual with the lowest cost is chosen. Otherwise, the individual with the highest cost is chosen. At the end of the selection phase, the next generation begins with the population obtained from this selection, and all the procedures mentioned above are repeated. Finally, after all, generations are completed, the best individual is extracted from the last population, that is, the lowest cost JSS, generated by GA. Thus, in general, GA tries to minimize the energy cost of the elaborated JSS as much as possible. To give more consistency to the results, GA is run several times to have several solutions for further analysis and comparison, where this later facilitates the choice of the best solution.

3. Case study

The case study consists of a textile production line that can manufacture several products through a set of three machines that perform various tasks. In total, considering the week chosen, seven tasks are considered, where these are identified by the ID ranging from 1 to 7. The first machine can perform tasks 1 to 5, while the second machine can only perform tasks 1 to 4. The third machine can only perform tasks 1, 6, and 7. Task 1 can be done on any machine, while tasks 5, 6, and 7 can only be done on one machine. Likewise, tasks 2, 3, and 4 can be executed on either the first or second machine. Photovoltaic generation is available. Consumption and PV data are recorded in 5 min periods. The textile production line operates 16 h a day, which is equivalent to 192 periods. Table 1 highlights the cases study designed to test the approached methodology. The “Schedule optimization” column illustrates which components GA considers when preparing the schedule optimization of the production line. It is important to note that in case studies where the tariff is not considered in the “Schedule optimization” column, GA is unable to determine the cost of the solution generated directly, so it is necessary to evaluate these results in order to determine the cost. Thus, the column “Scenario” illustrates the components that are used to evaluate the solutions obtained. In the same way, this column allows us to emphasize that a given “Schedule optimization” can be evaluated in more than one way, as can be seen in the case of studies 1 and 2.

Table 1. Case study description.

Case study	Schedule optimization		Scenario		Constraints		#Working Days
	PV generation	Tariff	PV generation	Tariff	Order	Collision	
1.1	–	–	–	Flat	X	X	3
1.2	–	–	–	Dynamic	X	X	
1.3	–	–	X	Flat	X	X	
1.4	–	–	X	Dynamic	X	X	
2.1	X	–	X	Flat	X	X	
2.2	X	–	X	Dynamic	X	X	
3	X	Flat	X	Flat	X	X	
4	X	Dynamic	X	Dynamic	X	X	
5	–	Flat	X	Flat	X	X	
6	–	Dynamic	X	Dynamic	X	X	

The “restrictions” column indicates the types of restrictions that are considered in the elaborated GA, where these restrictions are “order” and “collision” restrictions already mentioned in Section 2. Finally, the last column refers to the number of working days of the production line to be carried out the schedule optimization. As for the first case study, it merely serves to test how GA behaves, considering only the restrictions imposed, where it is expected that in this scenario, the cost of solutions will be higher. In other words, in this scenario, there is no optimization of the production line schedule, thus serving this scenario as a basis to compare with the other scenarios. However, this case study is analyzed from 4 perspectives, as shown in this table. As for the second case study, this, in turn, only considers PV generation together with restrictions. Regarding the third and fourth case studies, these, in addition to the restrictions, also consider PV generation together with a tariff. In case of study 3, the objective of the fixed tariff is to force the GA to optimize the schedule of the production line according to the PV generation, leading to this schedule having the lowest possible consumption that consequently, taking into account the flat tariff, makes

the cost also as low as possible. So this case study aims to optimize the energy consumption of the production line. As for the fourth case study, it optimizes the schedule according to the PV generation and the dynamic tariff. As for the case studies 5 and 6, these, in turn, already consider a tariff along with the restrictions. Thus, it is intended that in these cases the GA draw up a schedule of the production line according to the tariff.

4. Results

After obtaining the Schedule optimization for each case study, each one is evaluated according to the information provided in the “Scenario” column of Table 1. Thus, Table 2 illustrates the results of the best and worst GA run for each case study, together with the standard deviation between them. In this table, in order to facilitate the distinction between the types of tariffs used, the costs obtained through the flat tariff, which is 0.10 €/kWh, are presented with a gray background, while the white corresponds to the costs obtained through of the dynamic tariff.

Table 2. Results of the best and worst run in GA for each case study.

Case study	Schedule optimization		Scenario		Best run	Worst run	Standard deviation
	PV generation	Tariff	PV generation	Tariff			
1.1	–	–	–	Flat	96,73 €	96,73 €	0
1.2	–	–	–	Dynamic	64,43 €	65,05 €	0,81
1.3	–	–	X	Flat	73,26 €	75,73 €	1,235
1.4	–	–	X	Dynamic	49,13 €	50,71 €	0,79
2.1	X	–	X	Flat	73,60 €	76,27 €	1,335
2.2	X	–	X	Dynamic	49,23 €	50,88 €	0,825
3	X	Flat	X	Flat	72,99 €	73,20 €	0,105
4	X	Dynamic	X	Dynamic	48,29 €	48,64 €	0,175
5	–	Flat	X	Flat	73,59 €	76,51 €	1,46
6	–	Dynamic	X	Dynamic	49,15 €	50,34 €	0,595

Concerning case study 1.1, it appears that the best and worst runs are the same, where this means that when schedule optimization only takes restrictions into account, the energy consumption of the production line is always the same. In the case of 1.2, this, concerning the previous case, considers a dynamic tariff, and it appears that even having the same schedule, the energy cost is lower than in case 1.1. Regarding the case studies 1.3 and 1.4, PV generation is applied to the energy consumption of the production line, in order to verify what would be the impact that PV generation would have on the energy cost obtained in a schedule optimization that did not consider the PV generation. Thus, for the best run, it is observed that from case 1.1 to 1.3 and from 1.2 to 1.4, there was a reduction of 23.47 € and 15.3 €, respectively. Regarding the study cases 2.1 and 2.2, in these, it is verified that when considering in the schedule optimization the restrictions together with PV generation, the obtained schedules have an energy cost similar to case 1.3 and 1.4. Regarding case studies 3 and 4, in these, energy costs are the lowest costs obtained in each tariff, where this happens since in both schedules’ optimizations, they consider PV generation together with the respective tariff. Finally, in case studies 5 and 6, the energy costs are slightly higher than cases 3 and 4. In these cases, GA makes the schedules only considering the respective tariff and restrictions. Thus, for the best run, the difference in costs between case studies 3 and 5 is 0.60 €, while the difference between cases 4 and 6 is 0.86 €. Fig. 1, demonstrates the different energy costs obtained in the best and worst run, for the 1000 generations generated by GA for the case study 4. At first glance, it appears that the energy cost of the solution either improves or remains unchanged. In the case of the best run, there are some moments where the cost of the solution has remained constant for some generations. However, after these moments, there are significant reductions in energy costs. Thus, for the best and worst race, the energy cost has reduced, respectively, by 0.77 € and 0.52 €. Fig. 2 highlights the best three-day schedules obtained in case studies 3, 4, and 6, represented by graphs (a), (b), and (c).

It is important to note that the total number of tasks performed is the same in all, and these are shown in green. Each of these graphs also highlights, in blue, the respective energy consumption of the production line when performing the respective tasks. Regarding the third case study, the schedule elaborated considers the two restrictions, together with the flat rate and PV generation. In this case, it is observed that the schedule was modeled according to the generation of the PV, where there is a higher concentration of tasks during the moments when

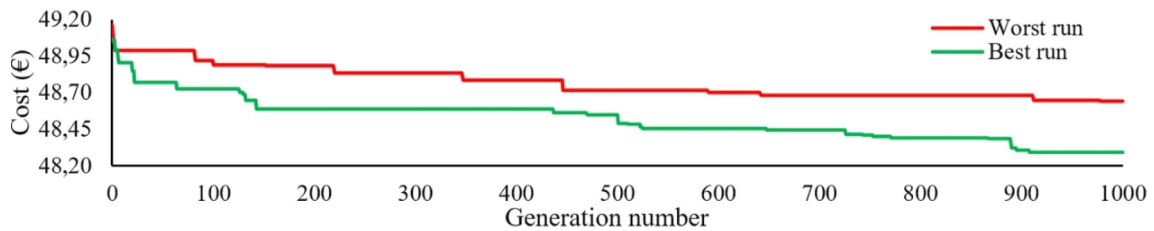


Fig. 1. Solutions obtained in the best and worst run, for the 1000 generations for the case study 4.

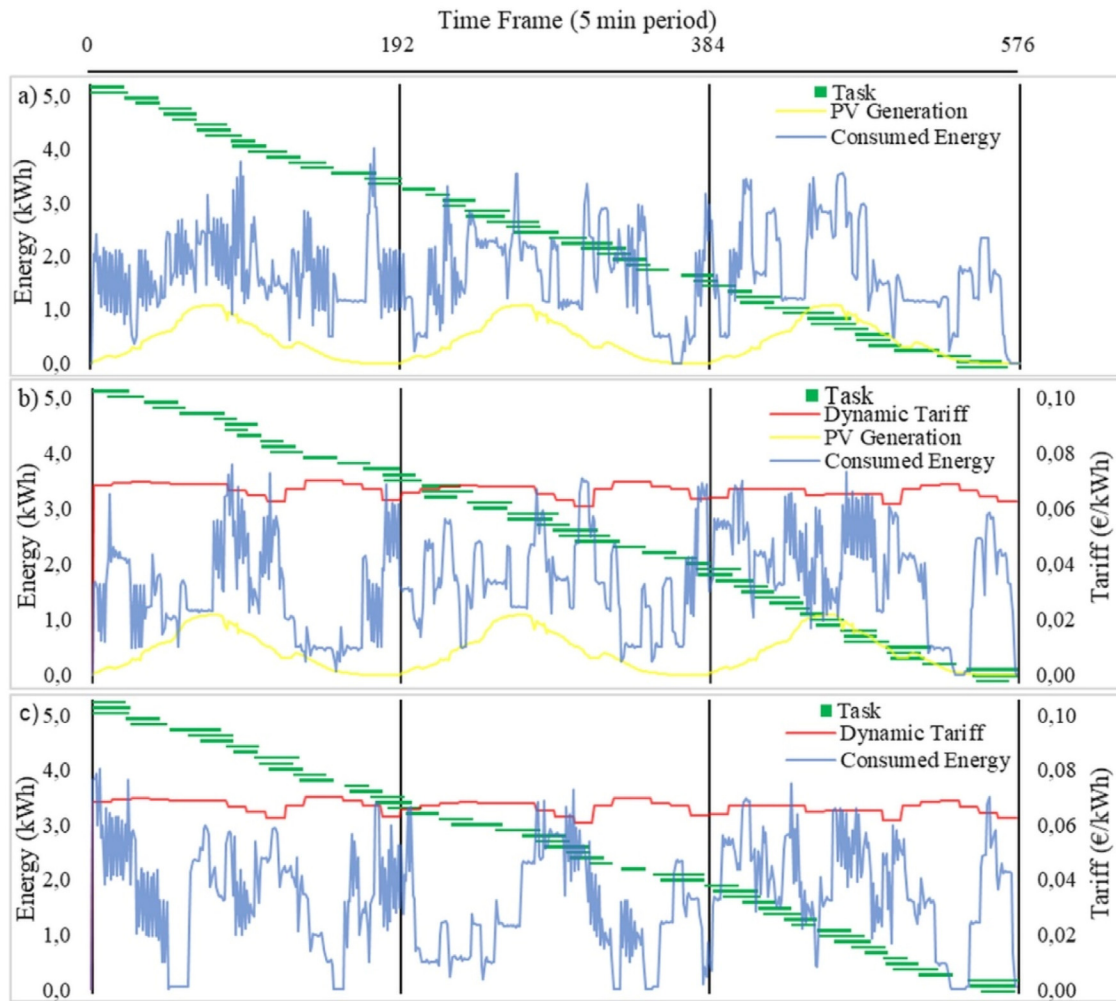


Fig. 2. The best production line schedules for case study 3, 4, and 6.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

there is PV generation. Thus, the times when there is the highest energy consumption of the production line, are the times when there is the greatest PV generation. An energy peak appeared at the end of the first day of work, where it appeared since the respective tasks performed at that moment could not be delayed. If they were delayed, the remaining tasks on the production line would not be performed on time, jeopardizing the delivery of the products. As for the case study 4, this, concerning the previous one, considers a dynamic tariff. In this case, on the one hand, it appears that in the moments where the tariff is higher, the energy consumption of the textile production line is

lower. On the other hand, it is also observed that in the time intervals where there is PV production together with low tariffs, energy consumption is higher. In other words, this schedule shows an optimization in terms of energy consumption and cost. Regarding the case study 6, in addition to the restrictions, it also considers the dynamic tariff. In this case, it is verified that the elaborated schedule has a higher energy consumption in the moments when the tariff is lower and, in the time intervals where the tariff is higher, it has a consumption that, in certain moments, is almost zero or even null. Thus, in this case, the generated schedule represents an optimization of the energy cost of the production line.

5. Conclusion

The developed methodology draws up a schedule for the textile production line that represents an optimization of this in terms of energy consumption or, in terms of energy cost or even optimization of both. Thus, this paper highlights the energy costs resulting from different case studies to highlight the different optimizations mentioned. As future implementations, it would be to apply a new restriction in GA to control the energy peaks, where if a given limit is exceeded, another tariff is applied, which is higher.

CRedit authorship contribution statement

Carlos Ramos: Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing - review & editing. **Rúben Barreto:** Data curation, Formal analysis, Investigation, Validation, Visualization, Writing - original draft, Writing - review & editing. **Bruno Mota:** Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Luís Gomes:** Investigation, Methodology, Software, Validation, Writing - review & editing. **Pedro Faria:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Zita Vale:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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