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# Simulation and Genetic Algorithm-based approach for multi-objective optimization of production planning: A case study in industry

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**ABSTRACT**

To stay competitive on the constantly changing and demanding market, production systems need to optimize their performance daily. This is particularly challenging in labour-intensive industries, which is characterized by highly volatile customer demand and significant daily variability of available workers. The Uncertainty related to the key production parameters in the industry is causing disruptions in long-term production planning and optimization, which leads to the long lead production times, operational risks and accumulation of inventory. To address these challenges, production systems need to ensure adequate operational production planning and optimization of all variables that are influencing the productivity of their systems on a daily basis. To tackle the problem, this study elaborates the application of discrete event simulations and genetic algorithm, using the Tecnomatix Plant Simulation software, to support decision-making and operational production planning and optimization in the industry. The simulation model developed for this purpose considers: customers demand changes, variable production times, operationally available resources and production batch size, to provide an optimal production sequence with the highest number of produced pieces and the lowest total work in process (WIP) inventory per day. To demonstrate the efficiency of the methodology and prove the benefits of the selected optimization approach, a case study is conducted in the textile factory.

**ARTICLE INFO**

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## 1. Introduction

To address the constantly growing customer demands the retailers put great pressure on the textile industry requesting frequent delivery of small quantities of a large number of different products [1, 2]. Satisfying such a stochastic demand with a high level of efficiency and low level of inventory requires effective operational planning and optimization of a production system, using new technologies that can support not only strategical, but also real-time, operational decision-making [3].

Many researchers investigated different influencing parameters which influence the efficiency of a production system, such as production process organization [4], product type [5], lot size scheduling [4] and operator's skill level [2]. However, there has been little research and even less practical implementation related to the relationship between these parameters and their common joint influence on the daily operational planning and optimization of a production system in the textile industry.

In today's industrial practice decision-making and operational planning still heavily rely on the production planners and their experience (expert knowledge) and future projections based on the data from the past. In those circumstances, without a proper digital tool, it is not possible to anticipate the impact of each influencing parameter and ensure optimal operational production planning and decision-making [6].

Considering the number, stochasticity and complexity of the influencing parameters, many researchers have used computer simulation, particularly discrete event simulation, to investigate the performance of production systems and to perform their optimization [2, 7-15].

High complexity of the optimization problem in production systems is also the reason why researchers are using genetic algorithms to reduce the computational time and ensure the quality of the obtained solution [16-18].

According to [19, 20], optimization solutions for production planning which satisfy the demand for increased volumes with an increased number of styles and personalized products, are a very actual topic in the textile industry. More specifically, over the past decades, several business and market trends have emerged that have reshaped the way the garment and textile industry is organized. This means that the textile manufacturers must be able to respond to a significant number of small and irregular orders, which would only be possible in the case of a more efficient and agile production system.

This demonstrates the significant need for practical simulation models that would simultaneously consider the impacts of all the typical parameters relevant for the daily operational production planning, while supporting real-time decision-making with the minimal required computational time.

This study presents an application of the discrete event simulations and genetic algorithm, using the Tecnomatix Plant Simulation software, to support decision-making and production planning and optimization in textile industry. The discrete event simulations enable complex systems representations including all relevant parameters, while the GA provides variation and sequencing of all influencing parameters in a short computational time required for the efficient operational planning. Although the approach is demonstrated in the textile industry, it can be equally efficiently used in other industry sectors. Of special interest are the labour intensive industries with the high variability of demand. To show the benefits of the proposed approach, a case study was analysed based on the validated simulation model of a textile factory. The simulation model considers following factors: the changing customers demand (variable in terms of different product types and quantity); the production times in relation to the product type and quantity; the operationally available resources and their distribution within the production system; as well as the production batch size; in order to provide the optimal production sequence which will result in the highest number of produced pieces per day with the lowest total work in process (WIP) inventory. In contrast to the papers using similar approach [19] for the strategical and tactical planning, this study investigates the benefits of the dynamic daily operational production planning, simultaneously considering the influence of all relevant variables. To fulfil this objective and contribute new knowledge, the paper is structured as follows. The next chapter provides a brief introduction into the research approach and literature review within the chosen topic. Chapter 3 formulates the case study and outlines simulation models for the company under consideration. Chapter 4 details the benefits of using genetic algorithm (GA) optimization in daily production planning, while in the fifth chapter a final discussion is presented, offering an overall summary and key findings.

## 2. Materials and methods

### 2.1 Research method

In this study we used literature review not only to provide an overview of the use of optimization tools in operational production planning, but also to highlight a specific type of industry in which additional research is needed. The literature review is followed by a case study as the research method suitable to understand how and why some phenomenon takes place in specific situations [21]. This review has shown that the textile industry still lacks sufficient research related to operational production planning optimization. Moreover, our case study showed that the textile industry certainly represents a type of industry in which the application of simulation models in operational production planning can contribute significant impact. A detailed analysis of the case study method can be found in [22]. Credibility of the case study is based on the transparency of the applied research, processes, and procedures, which allows verification by other researchers [23].

### 2.2 Literature review

Simulation is becoming one of the most used technologies to understand and analyse the dynamics of manufacturing systems [24]. It can be used as a descriptive tool to: realistically represent real-world systems, increase understanding of the relationships between the various components of a system; predict the performance of the system under new operating conditions; support the decision-making etc., without disrupting the ongoing production activities [25]. Simply, simulation is a problem-identification and solving tool that is flexible and less costly than physical prototyping and experimentation [26].

Computer simulation has been successfully used by many authors for planning and optimization of particular production lines or entire production and logistics systems in the textile industry. Simulation has been used for the shirt manufacturing production line design [27], for balancing the trousers production line [28], for balancing a sweat-shirt sewing line [29], for balancing the garment production line, in the five different scenarios, based on the production process times collected through RFID [10]. Some other authors used simulation for monitoring of the garment production line, comparing the production times gathered through the manual time taking and through the installed sensing [9]. The model-driven decision support system that is fed by real-time data, using data simulation and communication technologies was developed to improve the productivity of the manufacturing process of a garment manufacturing line [30].

Discrete event simulation (DES) model was proposed as the first step towards sustainable production scheduling in the textile manufacturing industry [6]. As DES is widely used to analyse activities of planning, implementation and operation of manufacturing and logistics systems, the commercially available DES software tools are commonly used for decision-making in different manufacturing systems [19]. Some studies that compared the different DES software tools recognized the Tecnomatix Plant Simulation by Siemens as the one with good visual aspects and the ability to integrate with other software [31]. Other studies have proven that Plant Simulation is a useful tool for optimal resource utilization [32].

Optimization problems which require minimization or maximization of functions with several variables and constraints can be very complex and difficult to solve with the use of conventional optimization methods. This is why they are commonly solved using algorithms based on the principle of evolution [2]. Some of the best-known meta-heuristic techniques, such as simulated annealing, the genetic algorithm (GA), and tabu search, were reviewed by some authors [33, 34] who concluded that these methods are remarkably effective in solving many types of optimization problems, particularly in finding near-optimal solutions for problems in complex multi-dimensional search spaces. Modified steady state GA was used for batch sizing and production scheduling in a hybrid flow shop with a limited buffer [35]. The genetic algorithm GA has been increasingly used for production optimization and operational management in the textile industry, such as loading, facility layout design, line balancing and lot sizing [2]. A genetic algorithm (GA) was successfully applied by different authors for optimizing the assignment of operatives in an assembly line [36] and for balancing workers' walking along the assembly line [37]. The unrelated parallel machines scheduling problem, in the textile industry, with machine and sequence-dependent setup times and limited resources, was addressed by applying the genetic algorithm GA [38]. Some researchers proposed a multi-objective GA model to schedule multiple products to different assembling stages considering the total costs and manufacturing capacities. Based on the experimental results they concluded that the GA is more powerful than any existing methods for solving production planning and scheduling problems [39]. Other authors combined simulation with the GA for stochastic lot size scheduling problems to define sequencing and lot size rules, which maximize the expected profit per time unit, demonstrating that GA simulation is the right approach to be used in complex environments [40].

## 3. Case study

To demonstrate the GA-supported DES approach to daily operational production planning, with short computation time, the simulation model for a textile company was developed using the Tecnomatix Plant Simulation software.

The model is developed and implemented in the company that produces high-quality shirts. The company was established over 20 years ago as a private family business and today is recognized as one of the best shirts manufacturing companies in the Republic of North Macedonia. The company produces more than 300,000 shirts annually and exports over 95 % of its production. The company's production system includes following four departments: (1) Tailoring and cutting; (2) Preparation 1 (collars and cuffs); (3) Preparation 2 (front, back and sleeves); (4) Shirt assembly and final control. Each of these departments has a different number of workers and performs a different list of operations. The sequence of operations, as well as the process times, depend on the model of the shirt. The material flow within the departments is organized with the conveyors ensuring the first in first out (FIFO) principle. The material flows between the last operation in one department and the first operation in the next department are organized with the production carts which also play the role of the WIP inventory holders between the departments. Production is realized in batches whereas the batch size depends on the model of the shirt and the customer order quantity, however, the most common batch size contains 10 product pieces.

### 3.1 Previous reality

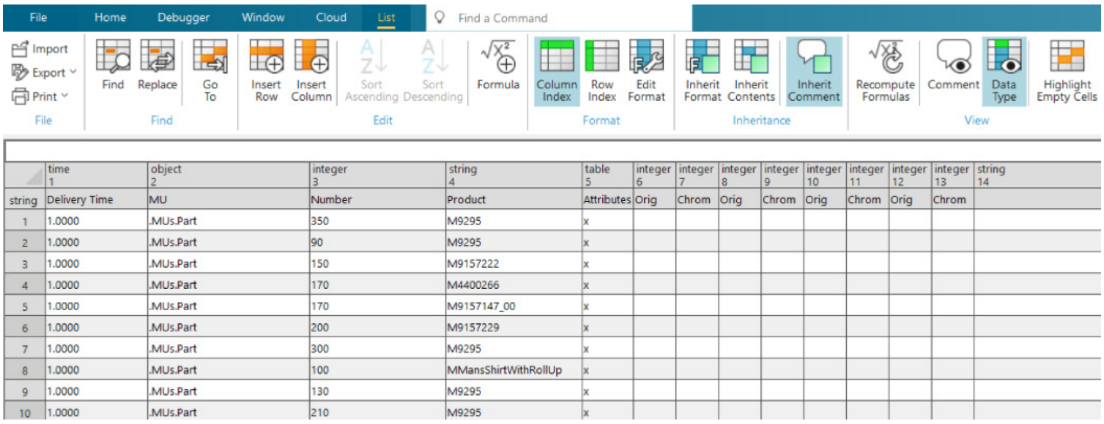
Before the simulation model was developed, production planning in the company was performed by the production manager, using Excel and the data on the customer orders from their Enterprise Resource System (ERP). Based on the customer orders and the operational lists for each model of the shirt, the production work orders were prepared and printed out to physically follow the material flows through the production system. The work orders include the data about the product (type, colour, size, etc.), batch size, list of operations that the product needs to go through, and process time for each of these operations. There is no real-time tracking of the products status or location through the system before the production is completed. The operational production scheduling in each department is performed by the department managers, based on their knowledge and experience. However, it is not coordinated among the departments, which slows the material flow and creates an uncontrolled WIP inventory accumulation.

The deep dive analysis of the production system revealed the following: unbalanced production between the departments; long production lead times, high WIP inventory, efficiency highly dependent on qualified labour availability and its distribution between the departments, no evidence or analysis on the influence of the production batch size and the production sequencing. The mentioned challenges are greatly conditioned with the daily variation of: product types and therewith the required production operations, demand-quantity of each product that needs to be produced and therewith the required production times per product, number of available workers in each department. Therefore, the simulation model was developed, as a supporting tool for the operational daily production planning that will ensure the highest possible production effectiveness while at the same time considering the influence of all relevant influential parameters, in a short computation time.

### 3.2 Way forward: Using simulation model

Modelling and simulation start with the proper identification of the problem and specification of simulation objectives. Once the objectives are set, it is required to determine which fixed system parameters and variables are relevant for the observed system [22].

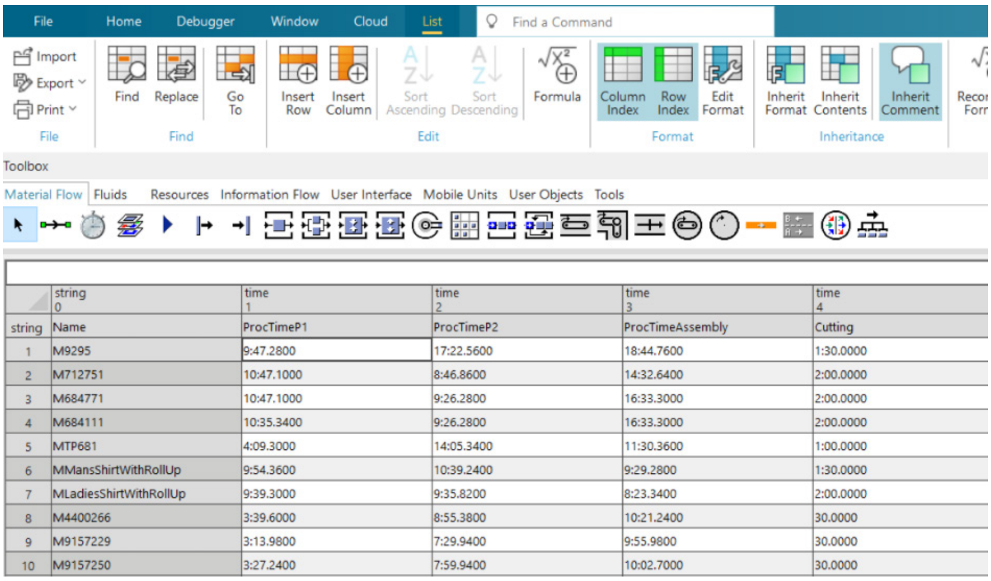
The customer demands (type and number of products, as well as the delivery times) represent the main input data for this simulation model. The data are gained from the real production system, for the period of ten weeks between June and August 2022. The company collects the customer orders on a weekly basis and sets the production plan based on the FIFO principle without the optimization of production sequencing according to the type or the quantity of the demanded products. The input of these data in the simulation was modelled through the delivery table called Production Plan (Fig. 1). In the table Production Plan, the first column defines the time when the products are entering the production system. Here, the times in all rows are set to one second, meaning that the products will enter the production system according to the PUSH principle and the FIFO sequencing. The customer demands, representing the number and the type of products that need to be produced, are defined in columns three and four, respectively. Special attributes of the products are defined in column five where the main attribute is the batch size of the product.



| | time 1 | object 2 | integer 3 | string 4 | table 5 | integer 6 | integer 7 | integer 8 | integer 9 | integer 10 | integer 11 | integer 12 | integer 13 | string 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| string | Delivery Time | MU | Number | Product | Attributes | Orig | Chrom | Orig | Chrom | Orig | Chrom | Orig | Chrom | |
| 1 | 1.0000 | .MUs.Part | 350 | M9295 | x | | | | | | | | | |
| 2 | 1.0000 | .MUs.Part | 90 | M9295 | x | | | | | | | | | |
| 3 | 1.0000 | .MUs.Part | 150 | M9157222 | x | | | | | | | | | |
| 4 | 1.0000 | .MUs.Part | 170 | M4400266 | x | | | | | | | | | |
| 5 | 1.0000 | .MUs.Part | 170 | M9157147_00 | x | | | | | | | | | |
| 6 | 1.0000 | .MUs.Part | 200 | M9157229 | x | | | | | | | | | |
| 7 | 1.0000 | .MUs.Part | 300 | M9295 | x | | | | | | | | | |
| 8 | 1.0000 | .MUs.Part | 100 | MMansShirtWithRollUp | x | | | | | | | | | |
| 9 | 1.0000 | .MUs.Part | 130 | M9295 | x | | | | | | | | | |
| 10 | 1.0000 | .MUs.Part | 210 | M9295 | x | | | | | | | | | |

**Fig. 1** Production plan representing weekly customer demands

The production operations, including the real system process times, for every potential product type in each department, are defined in the table Production Times (Fig. 2). The production times are defined based on the real system measurements considering the type of the product, operations that the product is going through during production and process times of each operation. These production times are further recalculated in the model, in each simulation run, relative to the currently available number of workers in each department.



| | string 0 | time 1 | time 2 | time 3 | time 4 |
|---|---|---|---|---|---|
| string | Name | ProcTimeP1 | ProcTimeP2 | ProcTimeAssembly | Cutting |
| 1 | M9295 | 9:47.2800 | 17:22.5600 | 18:44.7600 | 1:30.0000 |
| 2 | M712751 | 10:47.1000 | 8:46.8600 | 14:32.6400 | 2:00.0000 |
| 3 | M684771 | 10:47.1000 | 9:26.2800 | 16:33.3000 | 2:00.0000 |
| 4 | M684111 | 10:35.3400 | 9:26.2800 | 16:33.3000 | 2:00.0000 |
| 5 | MTP681 | 4:09.3000 | 14:05.3400 | 11:30.3600 | 1:00.0000 |
| 6 | MMansShirtWithRollUp | 9:54.3600 | 10:39.2400 | 9:29.2800 | 1:30.0000 |
| 7 | MLadiesShirtWithRollUp | 9:39.3000 | 9:35.8200 | 8:23.3400 | 2:00.0000 |
| 8 | M4400266 | 3:39.6000 | 8:55.3800 | 10:21.2400 | 30.0000 |
| 9 | M9157229 | 3:13.9800 | 7:29.9400 | 9:55.9800 | 30.0000 |
| 10 | M9157250 | 3:27.2400 | 7:59.9400 | 10:02.7000 | 30.0000 |

**Fig. 2** Production times for each product in each department

The numbers of available operators in each department are defined as variables ($i$, $j$, $k$, $d$) which are replicated in the simulation model according to the real system, as well as the variable $s$ – representing the total number of available workers in all departments. The initial number of workers in the department preparation 1, was set to $I$ = 20, *the* number of workers in the department preparation 2, was set to $j$ = 40, *the* number of workers in the assembly and final control department was set to $k$ = 40, while the number of workers in the tailoring and cutting department was set to $d$ = 4. Consequently, $s$ was initially set to 104 and changed in some simulation runs according to the exact number of available workers on a particular day.

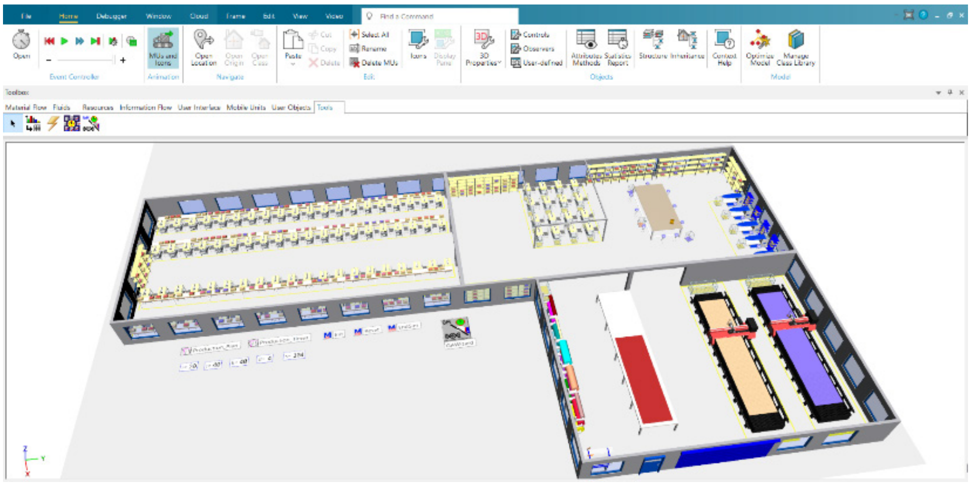


**Fig. 3** Simulation model of the case study textile factory

The simulation model developed for this case study (Fig. 3) is based on the steps proposed by [21] and followed by other researchers [6, 15]. This approach ensures that the simulation model has all the necessary characteristics which allow it to be used as a decision-making tool.

In the first step, to ensure that the simulation model can be used as a production planning and decision-making tool, it was important to verify the modelling logic and validate the model results with the real production data. Verification, in this case, considered the use of low-speed graphic animation within the Tecnomatix Plant Simulation software, ensuring that the simulation model has the same logic of movement as the real system. Validation was performed by comparing the simulation results of the selected production operating days (the first day in each of the ten observed weeks) with the existing analytical data of the real system performance in those exact operating days. The simulation results of all simulation runs were within the 95 % confidence interval of the real system performance (Table 1) thus validating the accuracy and reliability of the simulation approach.

In the second step, the genetic algorithm was introduced in the model to perform optimization and increase production efficiency with adequate daily operational production planning and sequencing in comparison to the FIFO principle used in the real system.

### 3.3 New reality: Operational production planning and optimization with the simulation model using GA

Once the verification and validation of the simulation model were performed, a GA Wizard was implemented in the model, to provide optimization of the system operational production planning.

Two opposite objectives were set for the GA optimization:

- Maximize the number of produced products per day, considering the customer weekly demand and currently available number of workers, and
- Minimize the total WIP inventory, in order to reduce the product lead-time and to reduce the operational risks of having high inventory levels.

The optimization with the GA Wizard considers:

- Production sequence of work orders generated according to the customer demand, considering the weekly demand and daily available production resources;
- Distribution of available workers between the departments, considering the distribution limits that are defined based on the worker's skills;
- Optimal batch size, considering the defined limits that are defined based on the literature and the company’s production planners’ experience;
- Total WIP inventory level, considering the capacity limits that are defined based on the targeted inventory levels, to achieve the highest production efficiency and throughput with the lowest possible WIP inventory. It is hereby anticipated that the increased throughput in the system with the low WIP inventory will positively influence the product lead-time.

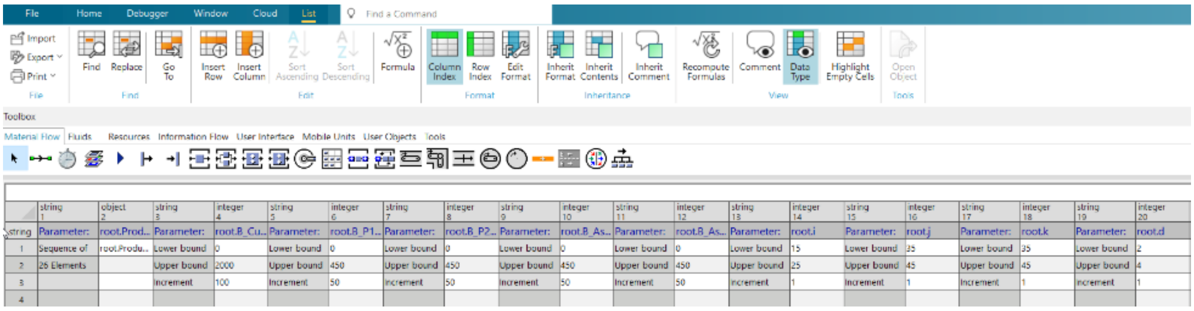



**Fig. 4** Defined limits for the distribution of available workers and for the buffer capacities in each department

The total number of available workers in the real system is 104, however, it varies daily. Therefore, the variable *s* was initially set to 104, and adjusted in each simulation run to the number of workers that came to work on that exact date. The limits for the distribution of the available workers in each of the departments (variables *i, j, k, d*) were set to: 15 < *i* < 25; 35 < *j* < 45; 35 < *k* < 45; 2 < *d* < 4; with an increment of one (Fig. 4).

The limit for the batch size was set 1 < batch < 10, with an increment of one. The limit for the buffer after the department of tailoring and cutting was set to 2000 with an increment of 100, while for all other buffers between the other departments was set to 450, with an increment of 50 (Fig. 4).

The GA Wizard performed work orders (representing customer demands) sequencing while varying the number of workers in each department and varying the capacity of the available buffers, within the defined limits, to find the right sequence which will ensure the best fitness value considering the defined weightings of each of the defined objectives.

To model the opposing objectives, a variable called MinWIP was introduced and defined in an EndSim Method (Fig. 5). In the method, the MinWIP is calculated as the deviation between 10.000 and total WIP inventory between all production departments.

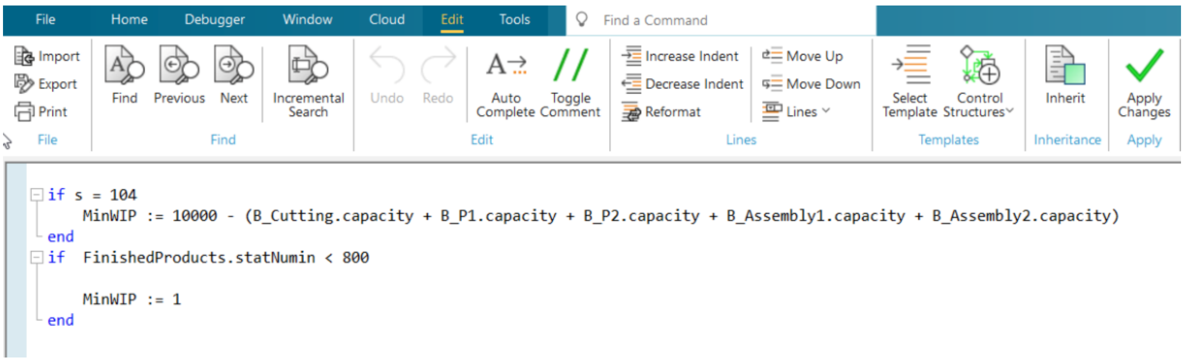



**Fig. 5** EndSim Method, calculating the MinWIP and penalizing solutions that are not good enough to be considered

This formulation enables the minimization of the total WIP inventory to be reformulated into the maximization of the MinWIP variable (the higher the deviation, the lower the total WIP inventory) which enables the search for the optimal solution by maximizing both variables (the number of finished products and MinWIP) in the GA Wizard (Fig. 6). Additionally, the EndSim method is penalizing the solutions in which the number of produced products per day is less than 800, by simply setting the value of the MinWIP variable to one. In that way, the search for the optimal solution from the point of both objectives is facilitated.

The parameters used during the Tecnomatix GA Wizard optimization were: (i) one hundred generations; (ii) the size of generation is ten individuals; (iii) the elitist system was used for the selection, where the best solutions were used to generate offspring for the next generation; (iv) multi-objective optimization, and (v) weighting of the optimization objectives (Fig. 6).

The best optimization solution was searched as the best fines value expressed through the weighting of the two defined objectives, where the weights of the first and second objectives were based on the preferences of the company's production manager and were set to 0.7 and 0.3, respectively (Fig. 6).

Fig. 7 shows the evolution of optimized solutions against the number of generations, confirming that one hundred generations are sufficient for obtaining the optimization convergence in these simulation runs.

The developed model was tested for the daily operation of the first working day in each of the ten weeks. The main output of each simulation run consisted of the sequence of the production work orders (Fig. 8), distribution of workers to the production departments (Table 2) and the optimal batch size (Table 3).

Fig. 8 shows the GA optimization results (of the 5. simulation run): production buffers' required capacity, workers' distribution, batch size and production sequence.

This case study does not belong to computationally complex ones. Therefore, an average computation time of the ten simulation runs, for the defined parameters and limits, was 25 seconds. The computation time increases significantly with the problem complexity (in relation to the number and type of variables analysed in the system, their range and increment, as well as in relation to the number and size of generations of the GA). However, it can be expected that this approach can perform production optimisation and operational production planning of medium complex problems in just a few minutes.

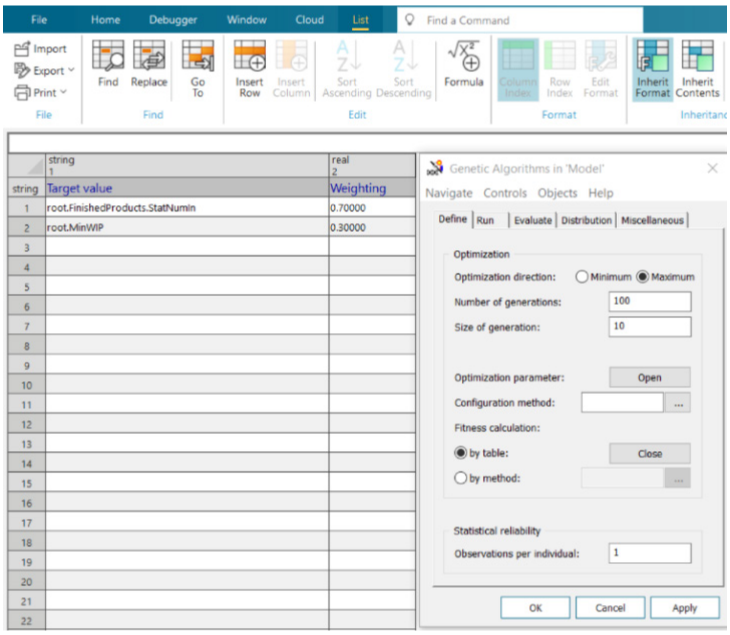



**Fig. 6** Optimization parameters set in the GA Wizard of the Tecnomatix Plant Simulation

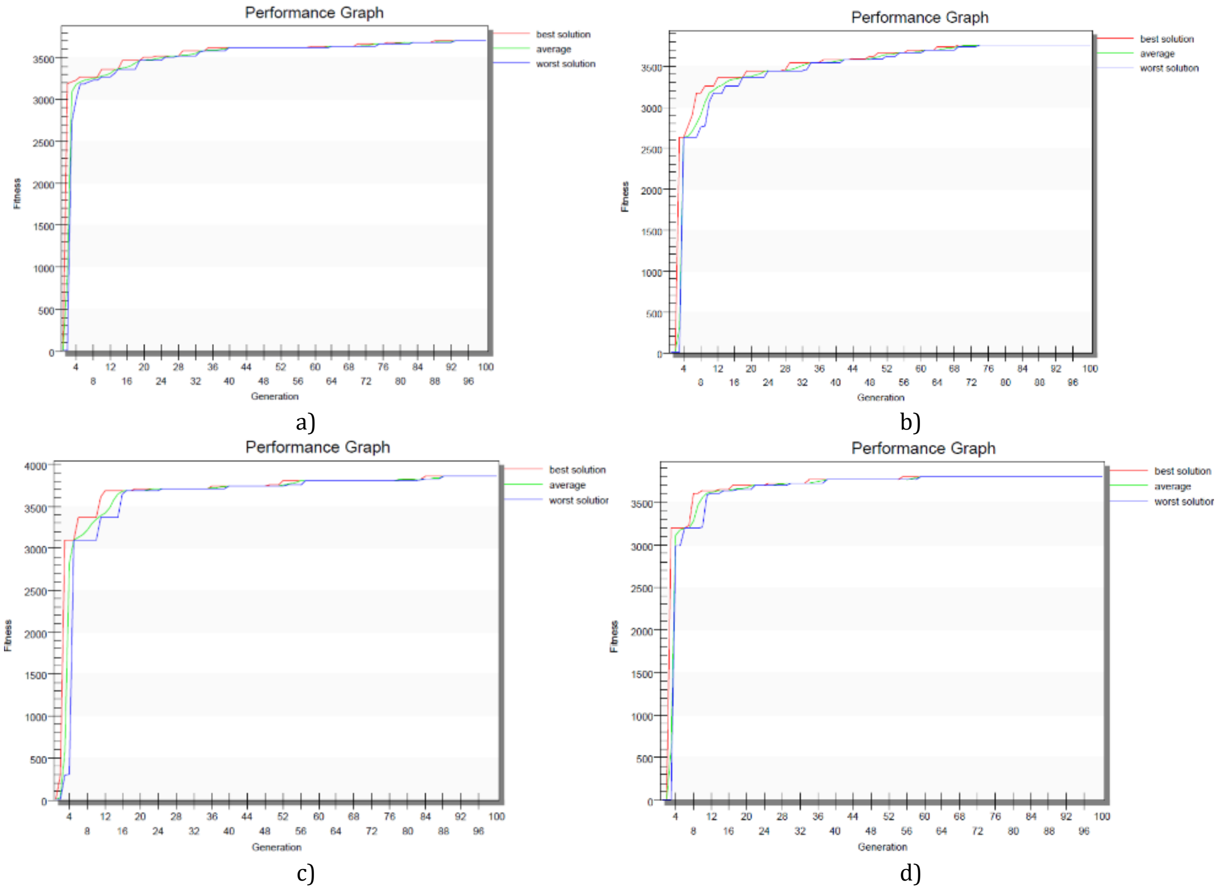



**Fig. 7** Typical performance graphs of the ten performed simulation runs (a: 1, b: 5, c: 7, d: 10)

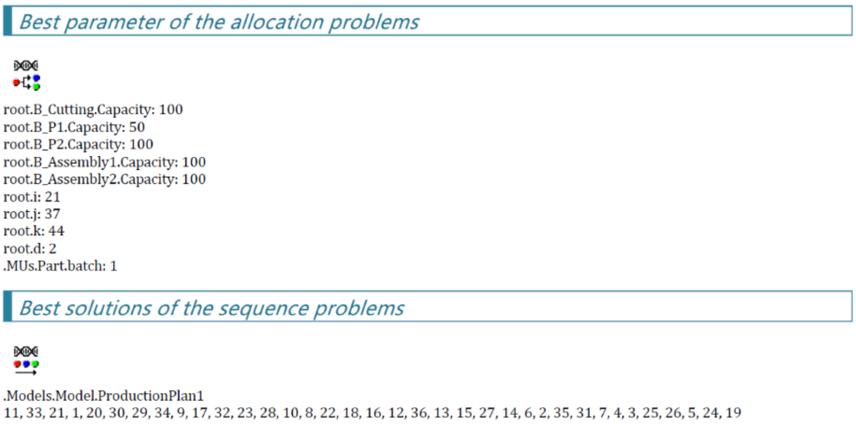



**Fig. 8** GA optimization results, workers distribution, production buffers' capacity and production sequencing

## 4. Discussion

The simulation results of both developed models are presented in Table 1, where the basic one was used for the verification and validation of the simulation approach, while the second was integrated with the GA.

Comparison of the real system data and the simulation results without GA, undoubtedly verify the relevance and accuracy of the simulation model.

Comparison of the real system and the simulation results with the GA demonstrate great optimization potential of simulation and genetic algorithm for the operational production planning and sequencing (Fig. 9).

**Table 1** Real system vs. simulation results – daily production and WIP in the selected days, in number of pieces

| | Real system | | Simulation | | Simulation with GA | |
|---|---|---|---|---|---|---|
| Days | Production | WIP | Production | WIP | Production | WIP |
| 1 | 1098 | 6654 | 1110 | 6588 | 1212 | 499 |
| 2 | 1000 | 4889 | 980 | 4958 | 1073 | 300 |
| 3 | 1153 | 8185 | 1130 | 8243 | 1310 | 391 |
| 4 | 1104 | 5154 | 1110 | 5128 | 1195 | 315 |
| 5 | 1245 | 5048 | 1260 | 4988 | 1268 | 434 |
| 6 | 1137 | 6253 | 1120 | 6348 | 1164 | 541 |
| 7 | 1117 | 5899 | 1100 | 5989 | 1160 | 409 |
| 8 | 1202 | 7742 | 1188 | 7758 | 1283 | 350 |
| 9 | 1031 | 6553 | 1020 | 6566 | 1204 | 537 |
| 10 | 1135 | 9235 | 1150 | 9099 | 1300 | 360 |

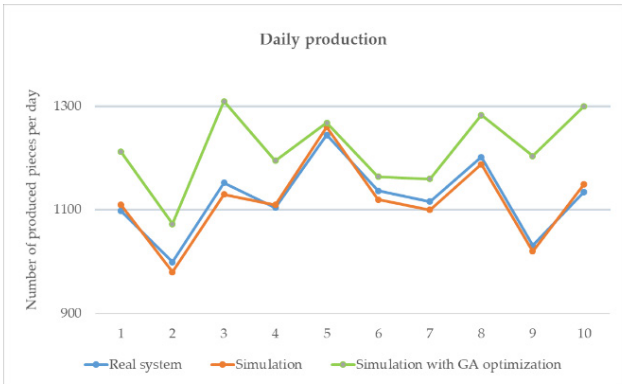



**Fig. 9** Daily production – comparison of the real system analytics and simulation results

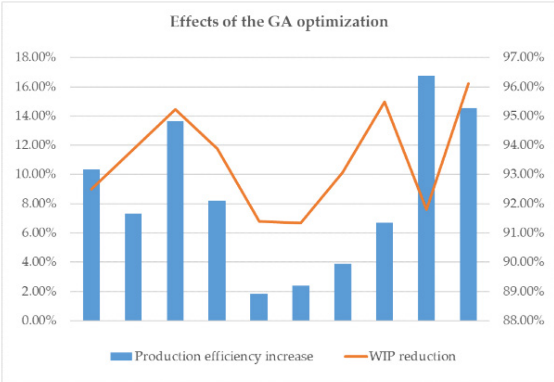



**Fig. 10** Effects of the GA optimization

As shown in Fig. 10, the use of GA for the production sequencing can lead to an average increase in productivity between 8.5 % and 17 %. However, even more significant savings can be achieved through the reduction of WIP (Fig. 11).

According to the simulation results for the selected days, the operational production planning and sequencing with the use of GA and limitations of the WIP inventory, can lead to an average reduction of the total WIP between 93 % and 96 % (Fig. 10). This reduction is the result of the adequate production sequencing as well as the optimal distribution of the available workers between the departments and the optimization of batch size.

In the real system, the available workers were always distributed in the same way. Contrastingly, in the simulation model, the GA optimization proposed different workers' distribution between the departments in each simulation run (Table 2).

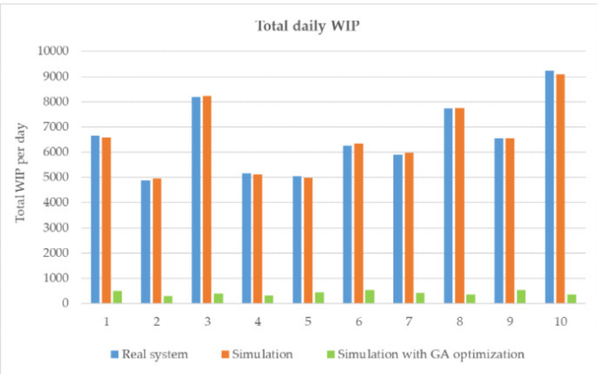



**Fig. 11** Total WIP – comparison of the real system analytics and simulation results

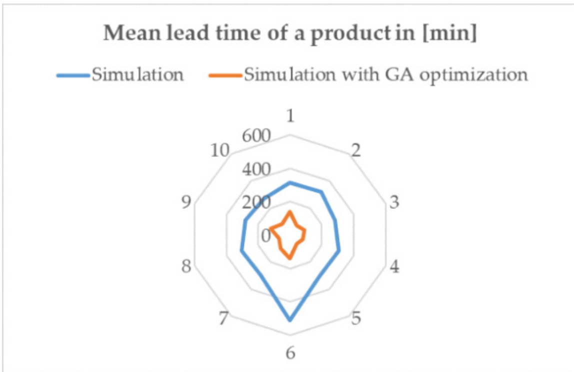



**Fig. 12** Comparison of the mean production lead times for the simulated products (min)

**Table 2** Distribution of available workers between the departments in real system and in each simulation run

| | Real system | | | | | Simulation with GA | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *s* | *i* | *j* | *k* | *d* | *i* | *j* | *k* | *d* |
| 1 | 104 | 20 | 40 | 40 | 4 | 22 | 37 | 43 | 2 |
| 2 | 96 | 18 | 36 | 40 | 2 | 20 | 37 | 36 | 3 |
| 3 | 104 | 20 | 40 | 40 | 4 | 22 | 39 | 39 | 4 |
| 4 | 104 | 20 | 40 | 40 | 4 | 25 | 40 | 36 | 3 |
| 5 | 104 | 20 | 40 | 40 | 4 | 21 | 37 | 44 | 2 |
| 6 | 99 | 20 | 38 | 37 | 4 | 21 | 37 | 39 | 2 |
| 7 | 95 | 17 | 39 | 35 | 4 | 22 | 35 | 36 | 2 |
| 8 | 104 | 20 | 40 | 40 | 4 | 24 | 38 | 39 | 3 |
| 9 | 104 | 20 | 40 | 40 | 4 | 24 | 38 | 39 | 3 |
| 10 | 104 | 20 | 40 | 40 | 4 | 25 | 35 | 41 | 3 |

**Table 3** GA optimization of batch size and its influence on assortment size

| | Real system | | GA optimization | |
|---|---|---|---|---|
| Day | Batch size | Assortment size | Batch size | Assortment size |
| 1 | 10 | 5 | 1 | 6 |
| 2 | 10 | 3 | 1 | 6 |
| 3 | 10 | 5 | 6 | 4 |
| 4 | 10 | 5 | 5 | 6 |
| 5 | 10 | 7 | 1 | 7 |
| 6 | 10 | 7 | 1 | 6 |
| 7 | 10 | 1 | 1 | 4 |
| 8 | 10 | 4 | 1 | 6 |
| 9 | 10 | 5 | 3 | 5 |
| 10 | 10 | 3 | 10 | 4 |

Table 3 shows GA optimization of production batch size in comparison to the constant batch size that is determined in the real system. The simulation results of the assortment size (Table 3) prove that the increase of productivity through the GA optimization is not due to the assortment size reduction, as one might suppose, but a consequence of the optimal sequencing, as well as the resource and material flow distribution.

Furthermore, the simulation results proved that such an extreme reduction of the WIP and optimization of the batch size, as expected, positively influenced the product lead time. Based on the simulation results, the reduction of product lead time was more than 3 times (from average 318 min to average 95 min). The mean value of the lead time reduction, per day for all products, was between 70 % and 78 % (Fig. 12).

These results prove and verify the effectiveness of the DES and GA approach for operational production planning and optimization in the case study.

## 5. Conclusions

The textile industry is challenged by highly stochastic and unpredictable demand, as well as specifically stochastic production performance caused by the predominantly manual operation and low level of digitalization, which are resulting in high levels of WIP inventory and long product lead-time. At the same time, the production planning and resource utilization optimization is based on outdated data and the experience of the production planners. This is not specific to just the textile industry, but is common in other industries as well, particularly the labour intensive ones with the low level of automation and digitalization. The approach proposed within this case study investigates the possibility to improve production performance in industry by improving operational production planning and optimization. The approach considers the application of discrete event simulation and genetic algorithm, to perform the operational production sequencing of the customer orders, distribute the available workers to the work departments, and determine the optimal batch size, in a way to maximize productivity and minimize the WIP inventory and product lead time. The proposed approach was tested using the Tecnomatix Plant Simulation software to eliminate the weaknesses of the manual scheduling procedures based on the judgment and experience of the production planners. Although it was applied to the case study of the shirts production company, the proposed approach is not limited to the textile industry but could be efficiently applied in other industry sectors. The results of this case study validated the ascendency of the simulation approach in operational planning and optimization, as well as the high efficiency of the genetic algorithm. Future steps in the research and practice should consider integration of the simulation software with the existing ERP system to ensure real-time data consideration, as well as with the potential MES (Manufacturing Execution System) which would transform the simulation model into the production system digital shadow. In that way, the simulation model would become a real-time dynamic operational planning tool with the capacity to perform not only the daily but also the real-time production scheduling and optimization.

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