The Optimization of Production System Using Simulation Optimization Tools in Witness

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***Abstract*—**The paper highlights the problem of the use of computer simulation optimization aimed at increasing the efficient production of manufacturing and production systems. The paper presents the possibilities of making use of simulation optimization in the form of a simulation study that was performed within the framework of cooperative ventures between our workplace and an industrial partner. The aim was to use the Witness environment for the determination of the optimal number of machines for individual workstations or respectively, to establish the optimal number of production shifts for these workplaces in the production line of short-barrels for pistols in gun-maker company. The Witness Optimizer package was applied to this optimization problem. We used Hill Climb optimisation algorithm, which this package offers. The objective function includes the production quantity, and machine and staff costs. The optimization parameters and their range of variation were proposed on the basis of the predefined requirements of the entrepreneur.

***Keywords*—**Discrete event simulation, production system, simulation optimization, Witness.

I. Introduction

THE computer simulation of discrete events, so-called Discrete Event Simulation (DES), is becoming an essential support instrument in making the operation of production systems more effective. Among other things, this is due to its ability to simulate and follow up the stochastic and the dynamic properties of individual processes, and thus to predict their behaviour. Computer simulation is a widely used analytical tool which permits the study of complex systems that cannot be modelled by other mathematical and statistical methods. This simulation can be used to determine the state of certain controllable inputs to a system that will cause system outputs to be at their most favourable or optimal conditions. This is the principle of simulation optimization [1]. Simulation optimization is an extremely valuable technique for investigating the behaviour of many business processes ranging from manufacturing layouts to the operation of modern contact centres, from the handling of patient influx into emergency departments to the processing of internet enquiries on a web-site. Some common application areas of discrete event simulation are service stations such as airports, call centres and supermarkets; road and rail traffic; industrial production lines and logistical operations like warehousing and distribution [2]-[5]. With a simulation model, the creator simply sets up the correct real world rules at each stage where a real-world decision is made. The model then plays the scenario forward - taking each of these decisions in turn. This gives great insight into the performance of the described system in terms of throughput, services levels, resource utilization, profitability, etc. With a discrete event simulation model, it is possible to conduct experiments which show the ranges of current and projected outcomes without the need for costly pilot schemes that disrupt the on-going process.

Simulation optimization is the approach used when seeking a set of appropriate input values (decision variables) to produce the desired outputs and the problem setting thus contains the usual optimization components: decision variables, objective function and constraints [6]. A decision variable is an unknown in an optimization problem and the constraints are represented by these variables having to be contained in some feasible region. The objective function is a real valued function defined on these variables. For the DES there are several popular optimization approaches with different suitable areas - such as Ranking and Selection, Stochastic Approximation, and Ordinal Optimization etc. [7]. Various simulation optimization techniques can be classified based on the nature of the feasible region. If it is a continuous set, then it may be appropriate to use a gradient based search method such as stochastic approximation. If it is finite and fairly small, then it is possible to use ranking and selection methods, whereas if it is finite but with a wide range of combination possibilities then a meta-heuristic may be more appropriate. The works [8] and [9] provide a descriptive review of the main approaches for carrying out simulation optimization, and sample some recent algorithmic and theoretical developments in simulation optimization research. The most relevant approaches that have been developed for the purpose of optimizing simulated systems are also summarized in [10], where the authors concentrate on the meta-heuristic black-box approach that leads the field of practical applications.

II. Discrete Event Simulation Software

Currently, a wide range of commercial products are available on the market which are intended for the Windows and UNIX platforms, and which offer an extremely wide spectrum of possibilities for the modelling and simulation of

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manufacturing, logistical and other queuing systems [11], [12]. The results of a survey on the most widely used discrete event simulation software (conducted on 100 people working in the simulation field) are presented in [13]. The survey considers among other details some critical aspects like application domains (specifically, manufacturing and logistics), 3D and virtual reality potentialities, simulation languages, prices, etc. For each aspect and for each software product the survey reports a score between 0 and 10. These results help modellers in DES software selection.

A. Optimisation software packages

Historically, one of the main disadvantages of simulation was that it was not an optimization technique. An analyst would simulate a relatively small number of system configurations and select the one that appeared to provide the best performance. However, the availability of faster PCs and improved heuristic optimization search techniques (evolution strategies, simulated annealing, tabu search, etc.), are important pieces of evidence indicative of the new marriage between optimization and simulation in practice. At present, nearly every commercial discrete-event simulation software package contains a module that performs some sort of “optimization” rather than just pure statistical estimation. The goal of an “optimization” package is to orchestrate the simulation of a sequence of system configurations so that a system configuration is eventually obtained that provides an optimal or near optimal solution. Furthermore, it is hoped that this “optimal” solution can be reached by simulating only a small percentage of the potential configurations that would be required by exhaustive enumeration. Most of the optimization engines (packages) embedded in commercial simulation software are based on evolutionary approaches. The paper [9] surveys the most prominent simulation optimization software packages (either plug-ins or integrated) currently available, and their vendors and, the simulation software product that they support and the search techniques used.

B. Simulation studies in the Witness environment

Our workplace is equipped with a Witness environment, in which we have, in close cooperation with industrial partners, conducted a number of simulation studies that have led – at least in part, to increases in the productivity of manufacturing, queuing and logistical systems [14]-[16].

The Witness simulation environment is the product of the British Lanner Group [17], and is one of the most successful world-class environments for the simulation of manufacturing, queuing and logistics systems. The Witness simulation package is capable of modelling a variety of discrete (e.g., part-based) and continuous (e.g., fluids and high-volume fast-moving goods) elements. Depending on the type of element, each can be in any of a number of “states”. These states can be idle (waiting), busy (processing), blocked, in-setup, broken down, and waiting labour (cycle/setup/repair). Witness models are based on template elements. These may be customised and combined into module elements and templates for reuse. The most basic discrete modelling elements are Parts, Buffers, Machines, and Conveyors. Other discrete modelling elements include multiple types of tracks and vehicles, labour, carriers, shifts, variables and part attributes. The behaviour of each element is described on a tabbed detail form in the Witness user interface.

Simulation is not, in and of itself, an optimization procedure, but a means to model different scenarios and compare the results. Because the number of variable factors in a model can be very large, Lanner Group provides a plug-in module Witness Optimizer, which can intelligently test different combinations of changes within a model, and indicate the “best” model based on an objective function provided by the model builder [27]. This objective function quantifies the objective of the optimization. In addition, users provide information on any constraints within the system, i.e. factors within the model which can vary, and what their range of variation is. Model run-length, as well as number of replications, is also indicated by the user. More sophisticated users can choose from several different search methods to be used in arriving quickly at the optimum. The Witness Optimizer provides several optimization methods, ranging from simply running all possible combinations to more complex algorithms [18]. The Witness environment is used for the optimisation of manufacturing, logistics and queuing systems in a whole range of simulation studies. Process analysis using Witness has been conducted, for instance, in the lens manufacturing process flow of at firm in order to identify improvement-prone areas and improvement alternative solutions were proposed [19]. Other work illustrates the use of Witness computer simulation to design the production of a manufacturing company that produces snow-melting modules. The analysis presented here describes the production design process and compares the performance of the new design with the existing system’s performance [20]. The Witness environment was also used for the simulation of the ophthalmology service of the Regional Military and University Hospital of Oran in Algeria [21] or for analysis of the best layout for an industrial plant [22]. The results that were obtained from applying Witness Optimizer to a manufacturing example with seven decision variables are presented in [23]. Witness’s applications in simulation solution deployment have been illustrated in [24].

III. Formulation problem

The paper presents the possibilities of making use of simulation optimization in the form of a simulation study that was performed within the framework of cooperative ventures between our workplace and an industrial partner. To be exact, this was the use of the Witness environment for the determination of the optimal number of machines for individual work-stations or respectively, to establish the optimal number of production shifts for these workplaces in the production line of short-barrels for pistols in the Zbrojovka a.s. (gun-maker) company. The aim was to propose an optimal solution for increasing the productivity of the manufacturing system. The production process is described in Fig. 1. The machines used in the production process serve for the machining of the products in various production phases. These are, in particular, lathes, grinding and drilling machines. All these machines are used to machine only one product at a given moment. Thus, only one part enters the machine and a specific operation is carried out on it - and also, only one part leaves the machine. Individual machines are organised into groups. Each group forms a workplace intended to perform a certain operation. Every machine (except for one machine), is operated by one operator. For this reason, labour does not have to be considered in the model.

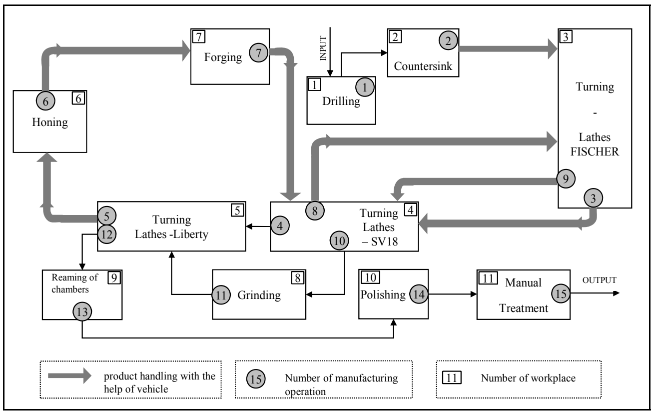

Fig. 1: Scheme of the operation of the production plant [16]

Table I shows the actual quantities of machines in individual workplaces which are used in the current system for machining the products, together with the number of shifts during which the workplace is in operation.

TABLE I: NUMBER OF MACHINES (SHIFTS) IN INDIVIDUAL WORKPLACES OF THE CURRENT SYSTEM

Workplace No.	Description of workplace	Number of machines	Number of shifts
1	Drilling of the short barrel of the gun	3	2
2	Drilling –countersinking	1	2
3	Turning-Lathe – Fischer	3	2
4	Turning-Lathe - SV 18	7	2
5	Turning-Lathe - Liberty	6	2
6	Honing	5	2
7	Forging	2	3
8	Grinding	6	2
9	Turning-Lathe – chambers	3	2
10	Polishing - chambers	2	2
11	Manual treatment	9	1

Each workplace performs a certain operation. The product comes through some workplaces repeatedly; therefore one workplace carries out a variety of different operations. The time values of individual operations were provided by the plant operator from their planning system, where the data for all machines is stored. Data collection has been carried out in that workplace for a long time, hence we can consider this data to be very correct. So any further measurement directly in operation would just be a waste of time. The manufacturing plant works in a three-shift operation. Most workplaces are in two-shift operation, though.

In operation, maintenance of the machine is done on a regular basis. Thanks to this maintenance, faults on individual machines are only exceptional occurrences. Maintenance time, together with the elimination of faults, takes up 3 % of machine time.

IV. MODELLING AND SIMULATION OF THE CURRENT PRODUCTION LINE

Every operating workplace of the production line is modelled in the Witness environment with the help of the Machine of Single type element. The quantity of machines in a particular workplace and their cycle-time are set up according to Table I and data provided by the operator. If a workplace carries out a few operations with a different cycle-time, this parameter is considered as a variable. The value of this variable is then set up in the output rule of the buffer in front of the workplace concerned. Product handling in the production process is performed by vehicles. These are modelled with the help of the Vehicle element. To create the process model of maintenance and faults in individual workplaces, the auxiliary Machine type element is used, which takes care of fault generation (i.e. maintenance on individual machines of the particular workplace). Thus, each workplace has its own fault generator. In the model, working shifts are created with the help of the Shift element. For simulation purposes, three one-week shifts were created. The shifts were then assigned to the individual workplaces as per the number of shifts in which the particular workplace is in operation every day.

After building the model of the production line, the proposed model must first be verified. The verified model will subsequently be used for simulation experiments and optimization. As the system in view works in continuous operation, the model would first have to be filled with products (reach equilibrium) in order to verify the model with the real system. This can be done in the Witness environment due to the parameter warm-up period. The value of this parameter determines the time when the followed-up statistics and variables are zeroed. Determination of the warm-up period for the output of a discrete-event simulation model is very difficult for the optimization of a solution. If the length of the warm-up period is underestimated, there will be some bias in the simulation results. If overestimated, output data is wasted and the number of experiments that can be performed in a period of time is reduced. A wide variety of methods for estimating the warm-up period have been proposed over the past 40 years. These can be categorised under five headings, briefly outlined in [25]: graphical methods, heuristic approaches, statistical methods, initialisation bias tests and hybrid methods. It is apparent, that no one single method can be recommended above any of the others. We use a very simple graphical method. This approach relies upon the visual inspection of the time-series of the simulation output - in our case the daily production.

Because the current system is unsteady and it gets saturated after 15 days, the steady model No.3 published in [14] is used for warm-up determination. The daily production time series is presented in Fig. 2. The zero values represent no production at the weekend. On the basis of this, the value warm-up period is set to 259200 seconds, which corresponds to a time period of 3 days. This time is sufficient for filling the whole model with products and to reach the steady-state behaviour of a system. Total simulation time is 2 weeks (i.e. 3 days Warm Up, 11 days testing period)..

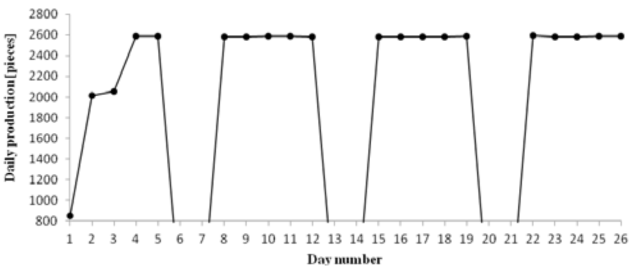

Fig. 2: The course of daily production over 26 days

Table II shows the results of the simulation of the current production line. Only informal and static techniques [26] were used for verification, validation and testing.

TABLE II: REPORT ON CURRENT PRODUCTION LINE RESULTS

Workpl. No.	Description	No. of machines	No. of shifts	Busy Time [%]	Blocked Time [%]
1	Drilling	3	2	35.00	61.97
2	Countersinking	1	2	47.07	49.77
3	Turning-Lathe – Fischer	3	2	37.34	58.72
4	Turning-Lathe - SV 18	7	2	50.69	46.31
5	Turning-Lathe - Liberty	6	2	35.03	61.97
6	Honing	2	2	96.95	0.00
7	Forging	2	3	74.28	6.33
8	Grinding	6	2	27.29	1.11
9	Turning-Lathe – chambers	3	2	50.42	0.00
10	Polishing - chambers	2	2	23.38	0.00
11	Manual treatment	9	1	0.55	0.00
TOTAL		44	22	43.45	26.02

During the verification process, the percentage capacity utilization of individual workplaces and total production of the production line were especially monitored. The values of the monitored characteristics are in close proximity to those of the real system and verify our model.Table II also shows how ineffective operation of this manufacturing system is. More than half of the workplaces are blocked. This is caused due to filling the buffers between individual workplaces (buffer capacity is 5000). The busy time of most workplaces is less than 50%. The Honing Workplace of is the bottleneck of the system (busy time is practically 100%, 3% maintenance). Total production is 5531 pieces during the monitored time (11 days) and 81 labourers work in this process. Due to this poor result, optimization of this inefficient system was performed and the results are presented in the next section. The Witness Optimizer package is applied to this optimization problem.

V. OPTIMISATION OF PRODUCTION SYSTEM

This section focuses on experimentation with the model of current system to find the best solution. The Witness Optimizer package was applied to this optimization problem. We used Hill Climb optimisation algorithm, which this package offers. The results are presented in the form of many tables and graphs.

Finding the best solution can mean many different things, highest throughput levels, lowest costs, highest production, etc. Usually, it means a specific combination of these types of factors. Within optimization, the key is to define what the best solution looks like. This is encapsulated in an objective function which can be as simple or as complex as required. In Witness the objective function is set inside the simulation model as a standard user-defined function. In our case, the objective function calculates the marginal profit by subtracting the operational costs and staff costs from the marginal revenue received from selling the products. We consider the marginal revenue to be €15 per unit and worker costs €10 per hour. Other variables are denoted in Table III. Then the objective function called *profit* is defined in form (2), where variable *lab_cost* is expressed in form (1).

TABLE III: LIST OF VARIABLES USED FOR OBJECTIVE FUNCTION DEFINITION

Variable name	Description
n_prod	the total number of products produced over the monitored period
m_cost	operational costs of machines mainly energy costs
lab_cost	total cost of staff over the monitored period
n(wpl)	the number of machines in the specific workplace
lab_time(wpl)	busy time of a worker at a machine in the specific workplace

$$lab\_cost = €10 \cdot \sum_{wpl=1}^{11} \left(n(wpl) \cdot lab\_time(wpl) \right) \qquad (1)$$

$$profit = n\_prod \cdot €15 - m\_cost - lab\_cost \qquad (2)$$

Now that the objective function of the optimization has been established, the next step is to define what can vary. This means setting the values of decision variables (also called optimisation parameters). The main task of our optimization problem is to determine an adequate number of machines in an individual workplace, or possibly, to set up an appropriate number of working shifts for these workplaces. Therefore, in our case the decision variables are simply the number of machines in individual workplaces and number of shifts operating these workplaces. The values (range of variation) of these parameters are defined on the basis of the predefined requirements of the user and according to the simulation results of the current system and conclusions in [14]. The entrepreneur did not allow an increase in the number of machines in a workplace (reduction of machine number is possible). Further, it is possible to change the number of working shifts of individual workplaces and the overall staff requirement must be below 81 workers.

The decision variables are defined in Table IV. The variable denoted as *n_workplace* represents the number of machines in a specific workplace and the variable denoted as *shift_workplace* represent the number of working shifts of specific workplace. The suggested values and constraints shown in Table IV are set according to conclusions in [14]. The suggested values are used among other things for the analysis of the objective function variation. The constraints are defined for some couple of variables and for overall staff requirement in the form (3).

$$\sum_{wpl=1}^{11} \left(n\_workplace \cdot shift\_workplace \right) \leq 81 \qquad (3)$$

TABLE IV. LIST OF DECISION VARIABLES WITH CONSTRAINTS

Workpl. No.	Variable name	Values	Suggested value	Constraint
1	n_drill	1,2,3	2	
	shift_drill	1,2	1	n_drill*shift_drill<4
2	n_countersink	1	1	
	shift_countersink	1,2	1	
3	n_fischer	2,3	3	
	shift_fischer	2,3	2	
4	n_SV18	5,6,7	7	
	shift_SV18	2,3	3	n_SV18*shift_SV18>13
5	n_liberty	3,4,5,6	5	
	shift_liberty	2,3	2	8<n_liberty*shift_liberty<13
6	n_honing	2	2	
	shift_honing	3	3	
7	n_forging	2	2	
	shift_forging	3	3	
8	n_grind	3,4,5,6	5	
	shift_grind	2,3	2	8<n_grind*shift_grind<13
9	n_chamber	2,3	3	
	shift_chamber	2,3	3	n_chamber*shift_chamber>5
10	n_polish	1,2	1	
	shift_polish	2,3	3	2<n_polish*shift_polish<5
11	n_treatment	1	1	
	shift_treatment	1	1	

Due to these constraints, the total combinations of decision variables 294912 are decreased to 12288. Some variables are constant. For example, the Honing workplace is potentially the bottleneck. Therefore, we can heuristically argue that the Honing workplace should be used maximised. It also follows that the Forging workplace has to be high-usage. Both workplaces have to operate in three shifts and have to use 2 machines. In contrast, the Manual Treatment workplace can operate only with a single shift, with one manual treatment station.

How many replications of each set of decision parameters, is question that also need to be answered in order to establish an optimization experiment. The analysis of the objective function variation can help us to determine the number of replications. We used the Analyze option from the Model Optimization dialog of the Witness environment for this purpose. There is some variation of the objective function in results for the suggested values. Therefore, it is appropriate to run the optimization algorithm with 5 replications for each set of decision variables. After setting the variation of the decision variables, defining the constraints and the objective function, analyzing the number of replication and discussions about the length of the warm-up period and simulation-run length, the following approach was proposed for searching for the optimal solution to our problem.

1) Firstly, we ran the optimizer only with single replication with the values of decision variables. The simulation-run length for this experiment is 11 days with an additional warm-up period of 3 days. The objective function *profit* was computed from the final 11 days of each 14 days evaluation.
2) On the basis of the best results analysis the range of decision variables variation is reduced.
3) The optimizer was run with 5 replications with a reduced range of decision variables. The simulation-run length for this experiment was 25 days with an additional warm-up period of 3 days. The objective function *profit* was computed from the final 25 days of each 28 day evaluation.

A. The Witness optimization solution

The Witness Optimizer package offers an optimization suite in its experimental framework. The main optimizer option (see Fig.3) offers the easy selection of parameters (decision variables) to change, constraints, run/warm-up duration, algorithm choice and is also the place to choose whether the objective function should be maximised or minimised. This engine also includes other useful and time-saving devices. As mentioned above, it is possible to use the simple analysis of experiments to determine the variability of typical runs which helps to determine the number of replications required. Then we can set a tolerance to abort multiple runs if the first replication is so far removed from the optimal found as to make further replications a waste of time and unnecessary or, we can optionally track for any other parameters that may be of interest in the results set from the simulation.

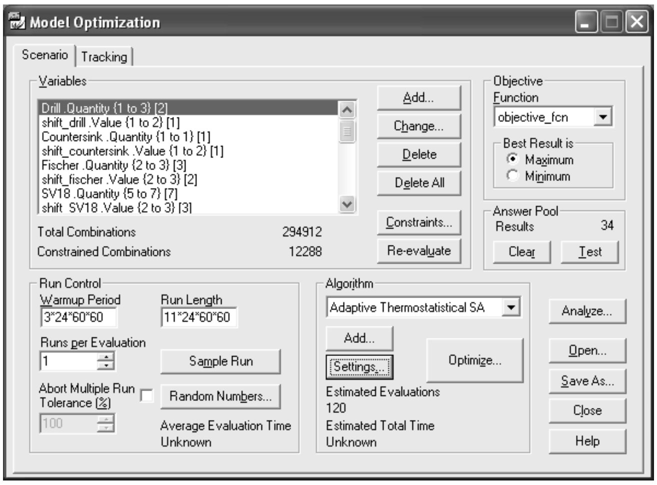

Fig. 3: The main Witness Optimizer control dialog

The Witness optimizer offers a wide choice of options for experimentation. We use the Hill Climb. For this algorithm, we can set some parameters to control optimum searching. Namely it is possible to specify a stopping rule that lets the optimization algorithm run until a user-specified number of configurations (combinations of decision variables) has been completed and the number of configurations for which there is no improvement in the value of the objective function. With the WITNESS optimizer for typical simulation experiments, Lanner's experience is that if there are around 20,000 different configurations then the optimizer needs around 200 experiments to come up with an optimal or near-optimal answer. For 2,000,000 configurations, 300 to 500 experiments are usually necessary. Of course, these figures are not cast in stone – they vary with the nature of the solution space. However, these figures illustrate the remarkable value of optimization. With 20,000 options, it is likely that by running just 1% of the possible experiments, good results can be achieved. According to this consideration, for example, we can use 200 for the maximum number of configurations and 20 for the number for which there is no improvement. What does this mean? Suppose that the objective function value at configuration i is the largest up to that point. Then the algorithm will terminate at configuration $i + 20$ if the objective function values at configurations $i + 1, i + 2, \ldots, i + 20$ are all less than, or equal to, the objective function value at configuration i; however, the algorithm will never go beyond 200 configurations.

VI. Results for the Hill Climb algorithm

According to the above defined settings and proposed approach, the experiments were carried out using the Hill Climb algorithm. The Hill Climb settings dialog in the Witness Optimizer enables one to specify that the optimization run is to stop after a certain number of evaluations or a certain number of consecutive evaluations without an improvement in the best result found, whichever is first.

TABLE V: RESULTS FOR EXPERIMENTS WITH SINGLE REPLICATION USING THE HILL CLIMB ALGORITHM

Evaluation	Profit [Euro]	n_drill	shift_drill	shift_countersink	n_fischer	shift_fischer	n_SV18	shift_SV18	n_liberty	shift_liberty	n_grind	shift_grind	n_chamber	shift_chamber	n_polish	shift_polish
11	231156	2	1	1	2	2	6	3	5	2	5	2	3	3	1	3
16	230797	2	1	1	2	2	6	3	5	2	5	2	3	3	2	2
20	230680	2	1	2	2	2	6	3	5	2	5	2	3	3	1	3
22	230441	2	1	1	2	3	6	3	5	2	5	2	3	3	1	3
2	229753	2	1	1	2	2	7	3	5	2	5	2	3	3	1	3
3	229255	2	1	2	2	2	7	3	5	2	5	2	3	3	1	3
10	229100	2	1	1	2	2	7	3	5	2	5	2	3	3	2	2
4	228768	2	1	1	2	2	7	3	5	2	6	2	3	3	1	3
0	228646	2	1	1	3	2	7	3	5	2	5	2	3	3	1	3
21	228452	2	1	1	2	2	6	3	5	2	6	2	3	3	1	3
18	228178	2	1	1	2	2	6	3	6	2	5	2	3	3	1	3
1	227874	2	1	2	3	2	7	3	5	2	5	2	3	3	1	3
13	224092	2	1	1	3	2	6	3	5	2	5	2	3	3	1	3
27	221865	3	1	1	2	2	6	3	5	2	5	2	3	3	1	3

The first parameter was set to 120 and the second to 40. Table V shows the top results achieved after running the optimizer with a single replication using the Hill Climb algorithm. The simulation-run length for this experiment was 11 days, with an additional warm-up period of 3 days. The objective function *profit* was computed from the final 11 days of each 14 day evaluation. The optimal result of €231156, indicating a marginal profit, was found by the algorithm after 11 evaluations. On the basis of the results shown in Table V, the analysis of decision variable range was performed. The number of decision variables was reduced to 9, because the optimization parameters *shift_drill, shift_SV18, shift_liberty, shift_grind, n_chambers and shift_chambers* are constant. The list of reduced number of decision variables with constraints and suggested values is shown in Table VI. Thus, a reduced range of decision variables was used for the second experiment. This time, the optimizer was run with 5 replications of each set of decision parameters.

TABLE VI: LIST OF REDUCED RANGE OF DECISION VARIABLES WITH CONSTRAINTS

Variable name	Values	Suggested value	Constraint	Cumulative combinations
n_drill	2,3	2		2
shift_countersink	1,2	1		4
n_fischer	2,3	2		8
shift_fischer	2,3	2		16
n_SV18	6,7	6		32
n_liberty	5,6	5		64
n_grind	5,6	5		128
n_polish	1,2	1	2<n_polish*shift_polish	
shift_polish	2,3	3	n_polish*shift_polish<5	256

To save the optimizer time and effort, the suggested values were set in accordance with the best found from the single run experiment. The simulation-run length for this experiment was 25 days, with an additional warm-up period of 3 days. The objective function *profit* was computed from the final 25 days of each 28 day evaluation.

Table VII summarises the results of this experiment. This table also contains the standard deviation and 95% confidence interval of each 5 replications.

On average, over five replications, the first result in Table VI is the best - however the first 11 results are very close together. Therefore, the average busy time of all workplaces is tracked. Note that the standard deviation for the third result is lower and hence, this result should be more consistent. The 95% confidence interval and the average value of workplace utilization confirm this hypothesis. Therefore, the third result can be chosen as the optimal solution for our system.

TABLE VII: RESULTS FOR EXPERIMENT WITH 5 REPLICATIONS USING HILL CLIMB ALGORITHM (28 DAYS SIMULATION TIME)

Model number	Evaluation	Profit [Euro]	Standard deviation	95% confidence interval	Average busy time [%]	n_drill	shift_countersink	n_fischer	shift_fischer	n_SV18	n_liberty	n_grind	n_polish	shift_polish
1	9	555987	1450	554185 - 557789	80.84	2	1	2	2	7	5	5	2	2
2	7	555469	4272	550158 - 560780	82.87	2	1	2	2	7	5	5	1	3
3	6	555076	308	554693 - 555459	83.48	2	1	3	2	7	5	5	1	3
4	2	554744	1320	553103 - 556385	81.68	2	1	3	2	6	5	5	1	3
5	15	553917	131	553753 - 554080	81.57	2	1	2	3	7	5	5	2	2
6	26	553734	148	553549 - 553918	81.34	2	1	3	2	7	5	5	2	2
7	11	553630	1545	551709 - 555550	79.64	2	1	2	2	7	6	5	2	2
8	3	553222	1649	551172 - 555272	80.34	2	1	3	2	6	5	6	1	3
9	4	552884	2126	550240 - 555527	79.37	2	1	3	2	6	5	5	2	2
10	12	551577	6216	543850 - 559305	76.82	2	2	2	2	7	5	5	2	2
11	10	547083	14643	528878 - 565288	78.93	2	1	2	2	7	5	6	2	2
12	13	518962	20291	493735 - 544188	77.40	2	1	2	2	6	5	5	2	2
13	0	518424	22490	490463 - 546385	79.17	2	1	2	2	6	5	5	1	3
14	1	510833	23143	482060 - 539606	74.82	2	2	2	2	6	5	5	1	3

VII. RESULTS FOR ADAPTIVE THERMOSTATISTICAL SA ALGORITHM

The optimization experiments using the Adaptive Thermostatistical Simulated Annealing algorithm were carried out in a similar manner as with the previous algorithm. The Simulated Annealing (SA) Settings dialog in Witness Optimizer enables one to also set the maximum number of evaluations and the number of consecutive evaluations without any improvement in the best result found, after which the optimization run stops. The values of these parameters were set to 120 and 40. For this algorithm it is possible to set other parameters for the optimization. The setting dialog enables one to check the *Split large variables* box that specifies whether large contiguous variable ranges are split automatically into smaller ranges of a maximum of 10 values. Another parameter for the algorithm entitled *Schedule Parameters* can be calculated automatically or entered manually. The Schedule Parameters should only be set manually by users who understand the process of SA. This area enables one to define the values for the cooling schedule and for the adaptive search. For the cooling schedule, it is possible to define Initial Temperature in the simulated annealing, Cooling Rate (the multiplier used to reduce the temperature at each temperature step) and Cooling Steps (the number of times to reduce the temperature during the optimization run). The Adaptive Search checkbox controls whether the adaptive search method is used during optimization. We used automatic settings of these other parameters for our experiments. The top results achieved after running the optimizer with a single replication using the Adaptive Thermostatistical SA algorithm are shown in Table VIII. The suggested values of decision variables specified in Table IV were reused as starting parameters for the optimization procedure. The simulation-run length for the initial experiment using this algorithm was 11 days, with an additional warm-up period of 3 days. Thus, the objective function *profit* was computed from the final 11 days of each 14 day evaluation. The optimal result of €230797, indicating a marginal profit, was found by the algorithm after 22 evaluations. Similarly as with the Hill Climb algorithm, the analysis of decision variable range was performed according to the results shown in Table VIII. The number of decision variables was reduced to the same nine parameters as for previous algorithm.

TABLE VIII: RESULTS FOR EXPERIMENT WITH A SINGLE REPLICATION USING THE ADAPTIVE THERMOSTATISTICAL SIMULATED ANNEALING ALGORITHM (14 DAYS SIMULATION TIME)

Evaluation	Profit [Euro]	n_drill	shift_drill	shift_countersink	n_fischer	shift_fischer	n_SV18	shift_SV18	n_liberty	shift_liberty	n_grind	shift_grind	n_chamber	shift_chamber	n_polish	shift_polish
22	230797	2	1	1	2	2	6	3	5	2	5	2	3	3	2	2
20	230133	2	1	2	2	2	6	3	5	2	5	2	3	3	2	2
4	229753	2	1	1	2	2	7	3	5	2	5	2	3	3	1	3
17	229100	2	1	1	2	2	7	3	5	2	5	2	3	3	2	2
0	228646	2	1	1	3	2	7	3	5	2	5	2	3	3	1	3
18	228581	2	1	2	2	2	7	3	5	2	5	2	3	3	2	2
24	228472	2	1	1	2	2	6	3	5	2	6	2	3	3	2	2
14	227955	2	1	1	3	2	7	3	5	2	5	2	3	3	2	2
2	227874	2	1	2	3	2	7	3	5	2	5	2	3	3	1	3
8	227595	2	1	1	3	2	7	3	6	2	5	2	3	3	1	3
5	227072	2	1	1	3	3	7	3	5	2	5	2	3	3	1	3
9	226962	2	1	1	3	2	7	3	5	2	6	2	3	3	1	3
40	226344	3	1	1	2	3	7	3	5	2	6	2	3	3	2	2
33	225191	3	1	1	2	3	6	3	5	2	5	2	3	3	2	2
36	224980	3	1	1	2	3	6	3	6	2	5	2	3	3	2	2
39	224215	3	1	1	2	3	6	3	5	2	6	2	3	3	2	2
6	224092	2	1	1	3	2	6	3	5	2	5	2	3	3	1	3
27	223211	3	1	1	2	2	6	3	5	2	5	2	3	3	2	2
25	222388	3	1	1	2	2	6	3	5	2	6	2	3	3	2	2

TABLE IX: LIST OF REDUCED RANGE OF DECISION VARIABLES WITH CONSTRAINTS

Variable name	Values	Suggested value	Constraint	Cumulative combinations
n_drill	2,3	2		2
shift_countersink	1,2	1		4
n_fischer	2,3	2		8
shift_fischer	2,3	2		16
n_SV18	6,7	6		32
n_liberty	5,6	5		64
n_grind	5,6	5		128
n_polish	1,2	2	2<n_polish*shift_polish	
shift_polish	2,3	2	n_polish*shift_polish<5	256

The suggested values were set in accordance with the best found from the single-run experiment. Note that these values are different for variables *n_polish* and *shift_polish* as for Hill Climb algorithm. The list of reduced number of decision variables with constraints and suggested values is shown in Table IX.

For searching for the right solution, the optimizer was run with 5 replications of each set of reduced decision parameters. The simulation-run length for this experiment was 25 days, with an additional warm-up period of 3 days. Thus the objective function *profit* was computed from the final 25 days of each 28 day evaluation. The top results of this experiment are presented in Table X.

TABLE X: RESULTS FOR EXPERIMENT WITH 5 REPLICATIONS USING THE ADAPTIVE THERMOSTATISTICAL SIMULATED ANNEALING ALGORITHM (28 DAYS SIMULATION TIME)

Model number	Evaluation	Profit [Euro]	Standard deviation	95% confidence interval	Average busy time [%]	n_drill	shift_countersink	n_fischer	shift_fischer	n_SV18	n_liberty	n_grind	n_polish	shift_polish
1	4	557503	285	557149 - 557857	79.63	2	1	2	3	6	5	5	2	2
2	5	555987	1450	554185 - 557789	80.84	2	1	2	2	7	5	5	2	2
3	27	553734	148	553549 - 553918	81.34	2	1	3	2	7	5	5	2	2
4	10	553527	367	553071 - 553984	77.76	2	1	3	3	6	5	5	2	2
5	3	552884	2126	550240 - 555527	79.37	2	1	3	2	6	5	5	2	2
6	12	552196	521	551548 - 552843	74.01	2	2	3	3	6	5	5	2	2
7	21	551741	908	550613 - 552870	81.47	3	1	3	2	7	5	5	2	2
8	26	550948	666	550121 - 551776	80.07	2	1	3	2	7	6	5	2	2
9	28	550661	1143	549240 - 552082	79.39	2	1	3	2	7	5	6	2	2
10	24	549267	835	548228 - 550305	80.08	3	1	3	2	7	6	5	2	2
11	22	549005	814	547993 - 550017	80.08	3	1	3	2	7	5	6	2	2
12	13	548867	135	548700 - 549035	75.66	2	2	3	3	7	5	5	2	2
13	17	548616	137	548446 - 548787	79.22	3	1	3	3	7	5	5	2	2
14	46	548018	751	547084 - 548952	78.35	2	1	3	2	7	6	6	2	2
15	15	547491	145	547311 547672	78.04	2	1	3	3	7	6	5	2	2
16	40	546480	812	545471 547489	79.04	3	1	3	2	7	6	6	2	2
17	14	546268	137	546098 546438	74.25	2	2	3	3	7	6	5	2	2
18	16	545998	136	545830 546167	77.88	3	1	3	3	7	6	5	2	2

It can be seen that the objective function values (*profit*) of all displayed results are very close together. Therefore, this table also contains apart from the standard deviation and 95% confidence interval of each 5 replications, the average busy time of all workplaces. These parameters helped us to choose the right solution for our system.

Due to very close results achieved using the Adaptive Thermostatistical Simulated Annealing algorithm and values of average busy time, it is very difficult to choose the right (optimal) result. The first 3 results can be the right solution therefore the detail analysis of these results was carried out in the next section

VIII. Summary and Evaluation of the Results

Due to ambiguity of previous results it was necessary to carry out a more detailed analysis of the proposed solution. Therefore, another experiment with 4 proposed models was performed. The model No. 3 proposed according to Hill Climb algorithm and the first three models proposed according to the Thermostatistical SA algorithm are chosen to detailed analysis. The simulation-run length for this experiment was 6 weeks - which means 39 days, with an additional warm-up period of 3 days. The simulation experiment was run with 5 replications. Apart from the *profit* variable, the other parameters of the investigated process are tracked. The values of these parameters were computed from the final 39 days.

The results of this experiment for suggested models are presented in Table XI. It can be seen that it is not possible to suggest models B and C as optimal solution. The production line modelled through these models is going to be blocked and saturated. The values of *Average busy time* and *Average blocked time* confirm this fact. The full buffers before the high-usage machines were the cause of this problem. This blocked production system produces a limited number of products and subsequently, the values of the *profit* and *production costs* parameters are affected. In contrast, model A and model D achieve very good results. The results for both models are very close to each other. Therefore, it is possible to choose model A or model D as the right (optimal) solution for our production line.

The detailed settings and simulation results for these models are shown in Table XII. If we had to select only one model, we would have to choose the model A which provided a little bit better result anyway.

Table XI: Results for experiment with 4 suggested models (5 replications, 42 days simulation time)

Tracked parameters	**Model A** proposed according to the Hill Climb algorithm (the 3rd result)	**Model B** proposed according to the Adaptive Thermostatistical SA algorithm (the 1st result)	**Model C** proposed according to the Adaptive Thermostatistical SA algorithm (the 2nd result)	**Model D** proposed according to the Adaptive Thermostatistical SA algorithm (the 3rd result)
Evaluation	6	4	5	27
Profit [Euro]	881731	644019	533282	879629
Standard deviation of profit	322	22909	13595	334
95% confidence interval of profit	881331-882132	615537-672501	516379-550184	879213-880045
Average busy time of workplaces [%]	83.14	60.77	54.09	80.97
Average blocked time of workplaces [%]	0.41	9.01	11.55	0.45
Necessary staff	75	73	74	76
Total production (39 days period)	69779	53425	46112	69782
Production costs per part	2.36	2.95	3.436	2.39

TABLE XII. REPORT ON RESULTS OF TWO OF THE BEST MODELS

Workplace	Model A				Model D			
	Number of machines	Number of shifts	Busy Time [%]	Blocked Time [%]	Number of machines	Number of shifts	Busy Time [%]	Blocked Time [%]
Drilling	3	2	96.99	0	3	2	96.99	0
Countersinking	1	2	86.96	0	1	2	86.96	0
Turning-Lathe Fischer	3	2	69.05	0.24	3	2	68.96	0.04
Turning-Lathe SV 18	7	2	93.87	2.19	7	2	93.9	2.38
Turning-Lathe Liberty	6	2	95.22	1.59	6	2	95.12	1.76
Honing	2	2	77.81	0	2	2	77.67	0
Forging	2	3	95.32	0	2	3	95.13	0
Grinding	6	2	96.91	0	6	2	97	0
Turning-Lathe chambers	3	2	97.03	0	3	2	97.01	0
Polishing chambers	2	2	90.01	0	2	2	66.38	0
Manual treatment	9	1	16.15	0	9	1	16.15	0

IX. CONCLUSIONS

This paper presents the possibilities afforded by using computer simulation optimization for the design, optimisation and identification of reserves in production system. The aim was to propose an optimal solution for an increase of the productivity of the production system. Using the concrete example of an assembly line for short-barrels for pistols, the utility of the Witness simulation environment and especially of the Witness Optimizer has been demonstrated for searching for the optimal solution for this production process.

The optimization problem lies in the correct determination of an adequate number of machines in individual workplaces - or possibly, to set up an appropriate number of working shifts of these workplaces. This optimization case study is based on results and conclusions presented in [14]. These results, achieved and based upon an experimental approach, were verified by using of objective optimization method which the Witness Optimizer package offers. We have used the Hill Climb optimization algorithms. Our optimization problem (i.e. optimal settings of mentioned system) consists of maximizing a real objective function. The objective function calculates the marginal profit by subtracting the operational costs and staff costs from the marginal revenue received from selling the products. The solution rested upon the elimination of the number of machines in selected work-stations. In other workstations, it was suggested that they reduce - or as the case may be, increase the number of operational shifts.

The proposed solution leads not only to increases in productivity but also to savings in staff and production costs (namely energy). Subsequently, these savings and increased production dramatically affect the total marginal profit of the company. In our case it is possible to reach up to 25 times profit increase.

In terms of this case study, it is possible to say that simulation optimization is a very difficult field of research that has the potential of having a considerable impact on the practice - and particularly, when computers become significantly faster. Therefore, at present, every commercial simulation software programme contains a package that performs some sort of optimization.

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