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A SIMULATION MODEL TO IMPROVE PRODUCTION PROCESSES IN AN IMPLANT MANUFACTURING PLANT

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ABSTRACT
Developments on economy and technology have forced the manufacturing companies to be competitive. The process improvement has become a critical issue for determining and eliminating the production losses. To improve its ability to compete in the market, implant manufacturing, which is a distinct and innovative sector, needs effective methods to analyze current situation and improve manufacturing processes. Simulation-based models are proven beneficial when dealing with managerial decisions, especially in manufacturing systems. In this study, real data is used and a simulation model is developed for an implant manufacturing plant which produces many products including implants in different shapes and sizes in Turkey to analyze the production process and evaluate alternative scenarios to increase the throughput. The facility where the case study conducted consists of CNC machining, washing, inspection, automatic cleaning, surface treatment and packaging processes. The proposed simulation model is expected to reach several outcomes such as volume throughput, machine and worker utilization and queue time.
Keywords: Discrete event-simulation (DES), scenario analysis, process improvement, implant manufacturing.

1. INTRODUCTION
Implant is an artificial tooth root placed in the jawbone and made from an appropriate material to restore function and aesthetics of missing teeth. In the light of the reports of international research companies, it is predicted that in 2018, the dental implants and prosthetic world market will reach 9.1-billion-dollar trade volume. In 2020, the total market size is expected to exceed 13 billion dollars. There are more than 300 dental implant brands worldwide, and it is determined that 224 of these firms are producers. The world dental implant industry is divided into five regions as North America, Europe, Asia Pacific, Latin America and Central Asia-Africa. The world dental implant demand accounts for 45-50% of European countries, 25-30% of North America, 15-20% of Asia Pacific countries and 5-10% of Latin America and other countries. While South Korea, Italy and Spain are the countries with the highest usage compared to the population; the highest dental implant use is in the United States without considering population [1]. The figures of a research by IMPLANTDER for the year of 2014 shows 350,000 implants were sold and it is estimated that 56% of these numbers were used by private dental hospitals and private polyclinics, 29% by freelance dentists, 14% by university dentistry faculties and 1% by public hospitals. The fact that the annual income per capita in Turkey is lower than the European Union average, the number of dentists is lower than the EU

average, and the lack of knowledge and experience about implant treatment especially in regions other than big cities are the main factors that enable dental implant treatment numbers to be much lower than developed countries. Given this development in the sector, it is expected that the improvement of the production processes will be a trigger for the use and sales of the implant. To analyze the production processes and to obtain information on the current efficiency levels is necessary for analysis of the efficiency of the operations. This also enables improving the efficiency of production processes. Process improvement using system analysis has been studied by many scholars in different industries [2-3]. System analysis takes into consideration many interacting, stochastic, and complex components [4]. However, it is possible to follow classical production process improvement tools such as Value Stream Mapping (VSM), they are inadequate for providing a high level of detailed and dynamic representation of the real systems. Therefore, discrete event simulation (DES), which is a popular computer simulation methodology, is frequently applied to analyze production processes in different sectors. Using simulation modeling during the implementation of continuous improvement can contribute to the stakeholders by providing an increased throughput value and satisfaction level. There are many DES applications in manufacturing industry. For instance, Opacic et al. [4] developed a DES based-decision support tool to improve the production process at an engineered wood products mill. Öner-Közen et al. [5] studied efficiency of paced and unpaced assembly lines under consideration of worker variability using DES. Güner Gören [6] combined DES with VSM to assess the impact of proposed improvements in furniture industry. Andrade-Gutierrez et al. [7] optimized the production in a flexible die-casting engine-head plant via DES using a Plant Simulation software package. Sarda and Digalwar [8] analyzed performance of a vehicle assembly line using Arena simulation software. Şen et al. [9] implemented DES combined with six-sigma methodology and presented a case study in a manufacturing firm.
In this research, a DES model is developed to determine the efficiency performance of existing operations and to seek a potential for improvement in the production process of a major implant manufacturer in the Eastern Black Sea region of Turkey. The model is used to assess the impacts of changes in the production process on the implant throughput, utilization of CNC machines, and queuing time. This study contributes by the aspect of that the current DES study is the first attempt to consider production processes of implant manufacturing based on real industrial data.

2. IMPLANT PRODUCTION PROCESS

The process at the implant manufacturing plant starts with receiving orders for four product types of implant: abutment, fixture, screw and measure equipment. Then, they are sent to be processes at CNC machines. CNC machining process is mandatory for each of four product types. As soon as they are processed at CNC machining area, three of them (abutment, fixture and screw) are proceed for first washing, first inspection and second washing, respectively. Measure equipment goes for heat treating process prior to first washing. Abutment and screw are inspected secondly and then labeled. By the labeling process, production process for abutment and screw is finalized. For fixture product, there is a resorbable blast media (RBM) process before third washing. After third washing, if the product type is fixture, the production flow is continued by second inspection and labeling. If not, it is proceeded to quality control followed by drying. The process flowchart is shown in Figure 1.

3. DES MODEL

The simulation model was developed using Arena 13.5 (Rockwell Automation Inc, 2010). The main inputs are customer orders and processing times for the processes of each product. The outputs are volume throughput, machine and worker utilizations queue time in each process (minutes). Several Arena modules such as create, process, decide, assign, batch, separate and dispose are used to model the plant. Entities are four type of implant products as follows: Entity 1 (Abutment), Entity 2 (Fixture), Entity 3 (Screw) and Entity 4 (measure equipment).

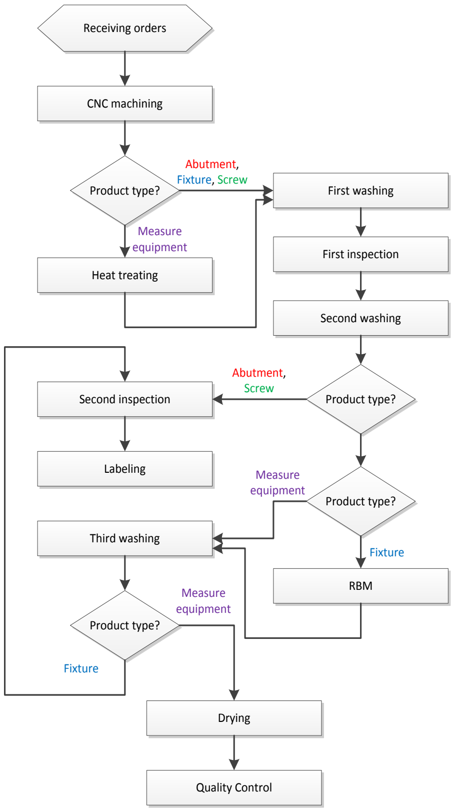

Figure 1. Production process

Table 1. Processing time distributions.

Process	Probability Distribution of Processing Time (minutes) for the product type:	
	Abutment	Fixture
CNC machining	TRIA(1.94[a],2.15[b],2.74[c])	UNIF(3.42,5.70)
First washing	JOHN(0.15[d],0.6[e],0.03[f],0.51[g])	TRIA(1.48,1.57,2.37)
First inspection	JOHN(0.47,0.57,0.22,1.5)	WEIB(1.75[j],11.33[k])
Second washing	JOHN(0.05,0.75,0.11,0.75)	UNIF(0.47,0.64)
Second inspection	UNIF(0.05[h],0.37[i])	-
RBM	-	NORM(0.44[l],0.04[m])
Third washing	-	BETA(4.20[n],0.90[o])
Process	Probability Distribution of Processing Time (minutes) for the product type:	
	Screw	Measure equipment
CNC machining	TRIA(1.83,1.95,2)	JOHN(0.52,0.67,0.65,2.71)
First washing	TRIA(0.38,0.47,0.62)	TRIA(2.71,2.74,3.38)
First inspection	UNIF(1.51,1.70)	UNIF(1.37,1.82)
Second washing	JOHN(0.64,0.76,0.28,0.34)	LOGN(0.90[p],1.14[r])
Second inspection	UNIF(0.05,0.37)	-
RBM	-	-
Third washing	-	-
TRIA: Triangular; UNIF: Uniform; JOHN: Johnson SB; WEIB: Weibull; LOGN: Lognormal; NORM: Normal; a: minimum value; b: most likely value; c: maximum value; d: shape parameter 1 (gamma); e: shape parameter 2 (delta); f: scale parameter (lambda); g: location parameter; h: minimum value; i: maximum value; j: scale parameter (alpha); k: shape parameter (beta); l: mean; m: standard deviation; n: shape parameter (alpha1); o: shape parameter (alpha2); p: lognormal mean; r: lognormal standard deviation		

3.1. Data Collection and Analysis

Data about processing times is obtained through the electronic enterprise resource planning (ERP) system of the plant. These processing times were fit to statistical distributions using EasyFit 5.6 Professional (MathWave Technologies, 2015). Table 1 shows the distributions used in the model.

3.2. Verification & Validation

The model was verified and validated using statistical t-test. Actual throughput data was provided by the implant plant and was statistically compared to results of the proposed Arena model over the same time period. The actual daily throughput for Abutment product was 3016 averaged in the year of 2016 (μ_0). The average throughput for 15 runs of the model was found to be 2999 with a standard deviation of 50. A t-test was performed to check if the means were statistically equal (indicating a valid model). The critical t-value (t_{critic}) was determined from the t-table to be nearly 2.14, for a two-tailed 95% confidence interval (1-α=0.995) with n-1 degrees of freedom (where n is the number of runs, 15). The hypotheses were as follows:

$$H_0 : \bar{X} = \mu_0$$

$$H_1 : \bar{X} \neq \mu_0$$

The t-statistic (calculated value) was calculated using Eq. (1) [4]:

$$t_{calculated} = \frac{\bar{X} - \mu_0}{S / \sqrt{n}} \quad \text{S: Sample standard deviation, n: number of runs} \qquad (1)$$

The $t_{calculated}$ value was found to be approximately 1.299. Since $t_{calculated} < t_{critic}$ (1.299<2.14), there was no significant difference between the accepted value and the average throughput obtained from the Arena model. This indicated the statistical validity of the model.

4. RESULTS AND DISCUSSION

The simulation model was run daily and included a warm-up period of one hour to ensure that no bias was introduced to the utilization, average throughput or queue times caused by an empty system at the beginning. Number of replications were computed based on the variance of output variables. Since the variance was low, it was determined that fifteen replications [10] are enough to make inferences with the outputs. The results for current state of the plant (base model) and an alternative scenario regarding the average throughput, machine and worker utilizations and average queue times for each process is summarized in Table 2.

Table 2. Summary of the results obtained from base and alternative Arena models.

Performance measures	Current state (Base model)	Putting an additional CNC machine into operation
Volume throughput (piece/day)	2999 (Abutment); 2435 (Fixture); 3299 (Screw); 1532 (Measure equipment)	4174 (Abutment); 3438 (Fixture); 4519 (Screw); 2114 (Measure equipment)
Resource utilization (%)		
CNC machine	100%	100%
Inspection worker	10.21%	10.34%
Washing worker	62.33%	63.09%
Labeling worker	6.23%	6.22%
Queue length (min)		
CNC machining	704.98	691.53
First washing	0.2664	0.096
First inspection	0	0
Second washing	0.3745	0.1187
Second inspection	0	0
Labeling	0.0038	0.0001

The CNC machining is the bottleneck process since its utilization is the highest overall. Moreover, the queue length is 11.75 hours on average. In order to overcome this state, an alternative scenario is designed considering putting an additional CNC machine into operation. This alternative state has improved the process by reducing queue length in CNC machining process and increasing the volume throughput of all four product types.

5. CONCLUSION

A DES model was developed and used as an analysis tool in this research to evaluate the production process of an implant manufacturing plant. No previous studies evaluated the production of an implant manufacturing plant using the DES modeling approach. This aspect highlights the contribution of this study. Conducting such a simulation study in an implant manufacturing environment can encourage other process improvement methods for their future attempts and provide a guide for the mangers in purchasing new specific machines that are actually expensive.

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