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SIMULATING THE EFFECT OF WORKERS' MOOD ON THE PRODUCTIVITY OF ASSEMBLY LINES

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ABSTRACT

Production lines have various components, from workers to loads and machines, each of which can influence the productivity of the entire system either directly or indirectly. One of the most vulnerable parts of an assembly line is the human element. Studies have been conducted on the methods to improve assembly line productivity, both from a worker's ergonomic perspective and from a system simulation perspective, but neither approach has considered the worker's mood. This study uses systems simulation capabilities to address some of the major psychological difficulties that may affect worker efficiency beyond the ergonomic conditions, such as emotional and cognitive factors. This study aims to present feasible solutions for increasing the productivity of an assembly line in a backpack company in Montana, with regard to an employee's mood, and cognitive and physical states.

1 INTRODUCTION

Despite the fact that industries tend to replace humans with robots/machines due to their higher productivity, it is crucial to maintain a focus on humans when considering workplace improvements. Industries have shown a preference for the escalation of automation (Cummings 2014), which can lead to job loss and, ultimately, an increase in worker poverty. Instead of replacing humans with machines in all sectors, increasing the productivity of workers wherever possible would be a better alternative that would cause less damage to society. To improve workplace systems and thereby increase or sustain worker productivity, the physiological and psychological needs of humans must be considered.

Workers' general status in industries has been largely explored. Most of these studies have evaluated the physical conditions of workers by implementing human factors and ergonomic principles (Perez et al. 2014; Longo, Mirabelli, and Papoff 2006; Reid et al. 2010). The resulting recommendations are being actively enforced across most industrial and non-industrial sectors. However, the growth in production and competition in the global market has caused increased awareness of human inefficiency and has led ultimately to a downsizing in the number of employees (Luthans et al. 2008). Industries are disinclined to consider employee mood which beside industrial/organization psychology negligence to research more on the impact of moods in the workplace (Muchinsky 2000), has influenced dozens of depression among workers (Mcternan, Dollard, and Lamontagne 2013). Yet, there is still a need for novel methods to address human working conditions, both physical and psychological, to increase the efficiency and productivity of manufacturing systems.

Simulation has been applied for research in diverse segments of industry, such as manufacturing, services, defense, and healthcare (Hosseinpour and Hajihosseini 2009, Qayyum and Dalgarno 2010, Brailsford 2010). However, none of the studies have addressed human emotional states in the simulations; rather they have focused on the ergonomic/physical aspects of working conditions. The current research has proven unreliable as a result of focusing solely on observed data and simulating it without attention paid to workers' mood.

The aim of this study is to provide a proof of concept on the importance of considering workers' mood and its role in employee efficiency in a given assembly line in order to then see the concept applied in a successful, discrete event simulation (DES) model. Due to the nature of DES, two general simulation components of input-system and output-system were used to analyze the current productivity of the system (by means of output), as well as to analyze changes in employee (as the server) status. Workers were modeled as servers; raw materials and processed materials were the input and output, respectively. The novelty of this study is in the integration of manufacturing and the psychological aspects into the same simulation model. It should be noted that in the current study, workers' mood and worker emotional states were considered to have the same meaning (Grandey, Tam, and Brauburger 2002; Lavis 2001).

2 BACKGROUND

2.1 Simulation in Manufacturing

A fair amount of research has been conducted using simulation to prove how diverse changes to components can impact a manufacturing system (Perez et al. 2014). The implementation of simulation is not limited to one type of manufacturing. In lean manufacturing, Carlson and Yao (1992) employed simulation in the early stage of design to improve their system. Additionally, simulation has been used to study assembly production, which is the most common type of manufacturing design. Assembly lines consist of workstations, whether they be run by workers or machines, arranged in a sequence or linked by a conveyor. Simulation has been used for finding bottlenecks to reduce queue lengths. Kumar et al. (2015) used simulation to analyze the assembly line of an automobile manufacturing company to increase the capacity of the existing system. Ultimately, assembly machines and workers have to perform continuously, operating at a similar speed during the entire workday. Glonegger and Reinhart (2015) have recently studied the different components of an assembly line by using simulation. In their study, the need to reduce the workload of assembly line workers due to the physical and cognitive pressure of completing a given task in a limited time was considered from each individual worker's perspective. However, more study still needs to be done on humans individually, considering more criteria such as emotional aspects, to enhance assembly line productivity.

The enormous capabilities of system simulations in creating the details of manufacturing components, such as transfer time and process times, make simulations a valuable tool for prediction. It is clear that simulations are a worthwhile tool to be used in manufacturing research, not only for their versatility, but also for predicting and resolving future issues (Perez et al. 2014). Perez et al. (2014) used DES to analyze early manufacturing system design from the ergonomic aspects. By employing their method, it is possible to predict the mechanical exposure patterns of workers. In another study, Longo, Mirabelli, and Papoff (2006) analyzed assembly line production by relating ergonomics and Methods Time Measurement (MTM) using simulation. Appling ergonomic principles in the simulation of assembly production revealed diverse problems caused by lifting, transportation and, especially, worker posture. Nevertheless, although these studies took ergonomic principles in manufacturing into account, neither of them considered the psychological aspects of humans.

Hosseinpour and Hajihosseini (2009) presented valuable tools for addressing certain manufacturing difficulties using simulation. Factors such as the time that each entity spends in queue, the timeliness of deliveries, the utilization of equipment or personnel, and the time in the system for each entity are all generally relevant to workers' performance. However, the simulation models used to analyze the manufacturing systems were mostly based on the normal (or typical) mood of operators. Unfortunately, human emotional states or moods transition, which may also influence performance, were not considered. This study combines the predicting and solving capabilities of simulations to address problematic features in manufacturing systems, specifically considering worker status.

2.2 Emotional States in Manufacturing

Human emotional intellect refers to aptitude of understanding, using, and regulating different types of emotions for personal space (Mayer et al. 2004, Gross et al. 2006). It is very interesting to learn about the machineries that have attempted to replicate the nature of human emotions in the past, where the comparison could result in the astounding realization of how the emotional states have repeatedly made their way into the technological aspects of today's world (Norman 2002, Smith and MacLean 2007).

Briner and Kiefer found that less than half (around 40 percent) of the papers on organizational psychological research defined emotions in line with basic psychological theories (Briner and Kiefer 2005; Gooty et al. 2010). It is significant that the definitions and components of emotional characteristics, such as affect, mood, emotions, and emotional capabilities, have produced considerable argument in psychological research (Barrett 2006, Izard 2009, Locke 2005, Russell 2003). This ongoing discussion on emotion has brought an agreement on the notable distinctive ideas on mood and emotions, but not on the emotional capabilities (Matthews, Roberts, and Zeidner 2004). Mood can be found to have an overlapping effect, where it is found to range from feelings to moods to actual physiological reactions (Frijda 1993, Ashkanasy 2003). The Cognitive Appraisal Theory (CAT) defines emotion as an organized mental response to an event or object (Ortony, Clore, and Collins 1990). Emotions are considered to last much less time yet be much more intense and target-centered than moods (Fisher 2002, Gohm and Clore 2002).

Although emotions are very real occurrences that we experience on daily basis, they have so far been challenging to clearly define. Assessment theories suggest that emotions are associated with different reactions towards an event, person, entity or situation. While there are no definite guidelines for evaluating scope, discrete emotional states have been characterized as having different outlines of valence, arousal, uncertainty, individual control vs. situational control, threat, goal-obstruction, etc. (Roseman 1991; Scherer 2001). In short, emotions are very brief yet intense reactions to an event, entity, person or situation. They have a distinct part to play in both the psychological and physiological characteristics of the functionality of the human being, depending on the situation (Beal et al. 2005; Fisher 2000, 2002; Frijda 1993; Mayer, Salovey, and Caruso 2004; Ortony, Clore, and Collins 1990; Weiss, Suckow, and Cropanzano 1999; Zelenski and Larsen 2000). For this reason, this study aims to explore the involvement of mood in determining the processing time in an assembly system and understand the effect on employee productivity in the system.

3 METHODOLOGY

3.1 Case Study

Four different assembly stations in the production line of a mountain backpack manufacturing company in the state of Montana were explored in this study. The company had a production line consisting of twenty workstations; however, due to limited time and resources, only four workstations were considered in this study. The four workstations consisted of 1) sewing on both sides of a zipper, 2) attaching two straps on two sides of a bag, 3) inspecting the pockets, and 4) putting a plastic foam piece into the front pocket and inspecting the zipper, which is the last step in assembling a mountain backpack.

Since all the workstations followed a roughly similar procedure of assembling or inspecting, a logical flow diagram was drawn to display the sequence (Figure 1). Each of the aforementioned workstations had different cycle times. Calculating an average cycle time yielded a processing time for each operator over an observation period as presented in Table 1.

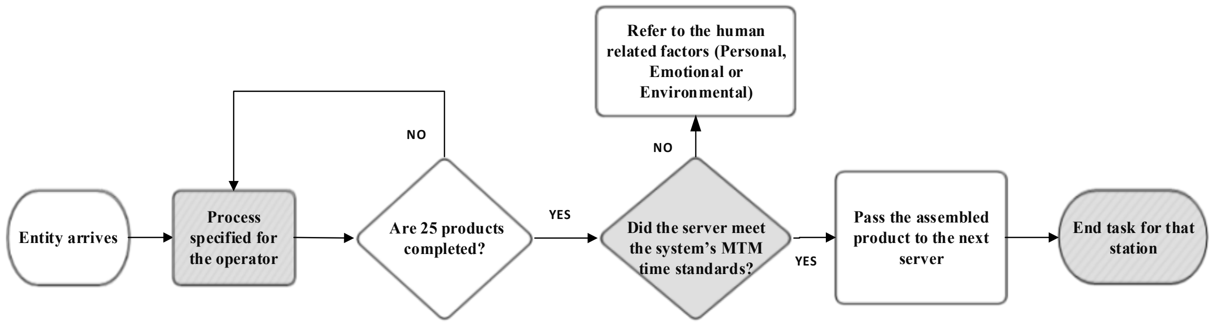

Figure 1: Logical flow diagram.

The average cycle times for the four workstations were 26.73, 23.63, 25.12, and 39.13 seconds, respectively. Since the last worker inserted a foam piece into the pocket and inspected the zipper, the process time required was higher. The work could be characterized as being highly repetitive, low-end muscular activity requiring relatively low effort (Hansson et al. 2009). Thus, the workers were not physically fatigued by the work. Nevertheless, the company provided variety in the tasks by switching the workers to different stations, along with allowing a ten-minute break in each one-hour session to prevent high levels of sadness.

A similar case was previously described by Looze, Bosch and Rhijn (2010), who recognized perceived fatigue in system operators and realized the significant impact of work/rest schemes on production output. For the purpose of the project as well as for simplicity, only one regular work session as defined by the company (about an hour), or about two sequenced tasks, were used in the current study.

Table 1: Average cycle time.

Process	Observed average cycle time (sec.)	Number of processes observed
Sewing on both sides of a zipper	26.73	11
Attaching two straps on two sides of a bag	23.63	10
Inspecting the pockets	25.12	10
Putting a plastic foam piece into the front pocket and inspecting the zipper	39.13	9

3.2 Assumptions

Since discrete event simulation generates models based upon various assumptions, the following are the data and the structural assumptions used to construct the simulation model in this study:

- The simulation system only includes the first pair of workstations and the last pair of workstations and assumes that the inter-arrival times for the other assembly line stations (which lie between the two pairs) remain constant.
- Servers are idle at the beginning of the system.
- System timing starts from zero seconds.
- No entities were rejected in the process.
- Servers had no break times and no shift changes occurred.

- The equipment and tools used at each station remained the same.
- No failures occurred in the system.
- The servers at each workstation dealt with the same type of work.
- The entities had a continuous First-In-First-Out (FIFO) flow in the system.
- The server capacity remained constant throughout the timed sessions.
- Only Friday from 10:00 a.m. until 12:30 p.m. was considered (due to the limited time and resources) in the data collection. Furthermore, it was assumed that this shift portrayed the idle conditions for this specific mass production.
- Workers were healthy on the day of observation.
- The simulation assumed a transient state matrix for the purpose of determining the probability of remaining in the same state or change from one to another emotional state. The transient state matrix is given by equation 1.

$$\text{Emotions Transient State Matrix: } P_{ij} = i \begin{array}{c} \\ 1 \\ 2 \\ 3 \end{array} \overset{\displaystyle j}{\begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{bmatrix} 0.80 & 0.15 & 0.05 \\ 0.10 & 0.80 & 0.10 \\ 0.05 & 0.15 & 0.80 \end{bmatrix} \end{array}} \qquad (1)$$

1 = Happy; 2 = Normal; 3 = Sad

The matrix provides the probability of an individual to move from a current emotional state i to a state j. For example, given that an employee is currently in a normal mood (i=2), s/he has an 80 percent chance of remaining in a normal mood (j=2) for the next assembly. Therefore, we express the previous probability as P_{22}= 0.8.

3.3 Data Acquisition

The data for the model was acquired by visiting the company. From among the twenty assembly line workstations, data collection was narrowed to four stations within one observation period. Workers at each station selected for the study were observed in random order. The work at each observed station was fulfilled by one individual. Two males and two females were observed during the study.

Regarding the purpose of the project, a baseline was needed to compare each unique assembly project with previous ones. Therefore, two different procedures were conducted to find a reliable baseline. First, due to the limited time and the company policy concerning changing tasks, the first ten tasks were timed. MTM was used to obtain the time required for each task. After the first ten processes had been timed, the average cycle time for each workstation was calculated. The average time obtained in this manner was the first baseline needed for comparing each process cycle (Table 1). The second set of measurements considered the psychological state of the workers. Once the average time was obtained, each worker was asked how he/she felt during a work period. Twelve questions were selected to measure the psychological conditions, and emotional, physical and environmental influences on the workers. The questions are presented in Table 2. The workers were asked to orally answer the questions before starting the next work period. The measurements obtained in this manner revealed how internal and external conditions affected the productivity of the workers.

Once measurements were gathered, each worker's cycle time was noted on a worksheet. Whenever the observed time was longer than the expected time (average time), four repetitive questions were asked and scored by using a Likert scale method. Non-repetitive questions that needed similar answers during the study were asked only at the beginning.

Table 2: Questionnaire.

Conditions	Questions	Scale				
		1	2	3	4	5
Emotional	What would you say about issues related to your family/relative?	Lots of issues		Neutral		No issue at all
	How do you feel right now?*	Unhappy		Neutral		Very happy
	What is your level of tiredness now?*	Very tired		Neutral		Not tired
	Have you argued with somebody during last five days?	More than three		Neutral		Not at all
	Have you had tough days during last five days?	More than three		Neutral		Not at all
Perceived Physical	Do you feel pain on your fingers now?*	Very bad		Neutral		Not at all
	Do you feel pain on your shoulders now?*	Very bad		Neutral		Not at all
	Have you felt pain during last five days?	More than three		Neutral		Not at all
	Do these tools hurt you?*	Very painful		Neutral		Very convenient
Environmental	Do you feel satisfied with lighting and light directions?	Not at all		Neutral		Very satisfied
	Do you feel satisfied with air quality?	Not at all		Neutral		Very satisfied
	Have you noticed that someone at work was having a bad day?	Several times		Neutral		Not at all

*Repetitive questions

3.3.1 General Methodology

Figure 2 presents the data collected from the four different processes observed at the company when considering mood. The data has been color coded according to the ranges calculated, with the tolerance interval calculated by Microsoft Excel NORMINV (probability, mean, standard deviation). The mean and the standard deviations were calculated for each of the servers to obtain the number used for the MTM calculation. The individual cells below indicate the mood considered with respect to each servers.

Operator 1	27.56	27.00	29.45	26.53	25.26	**23.06**	29.53	**23.01**	27.03	28.90	26.73	28.53	38.72	**22.80**	25.70	34.93	25.35	----	----	----
Operator 2	**21.08**	22.08	22.56	**20.76**	23.45	27.45	25.11	29.47	**20.38**	23.90	26.42	**21.47**	28.53	21.98	25.00	23.89	**20.79**	21.89	**20.89**	23.71
Operator 3	**19.00**	**22.33**	28.13	28.22	**22.48**	27.72	28.42	27.92	23.86	23.15	**20.33**	22.96	24.95	23.90	24.10	24.35	24.61	22.96	24.00	26.12
Operator 4	**30.43**	41.55	42.28	38.60	38.05	42.72	38.61	41.23	38.72	40.16	**33.56**	39.10	42.20	42.56	38.56	36.75	38.35	39.20	38.76	38.30

Happy	
Normal	
Sad	

Figure 2: Cycle time for each workstation along with the legend for mood.

Based upon the observations, it was hypothesized that the operators had various emotions during their processing time. By understanding the relationship between the mood of the operators and their processing time, an emotional matrix was built. Each row represents the ratio of the special average mood to the normal average mood. A discrete-event random process occurs when a system, which is normal in a certain state at each step, changes states randomly between the steps. The emotional processing rate matrix is given by equation 2. For example, for operator 3 (j=3) if the worker feels happy (i=1), then the assembly time will be 15 percent faster than the normal rate. Therefore, the processing time rate for happy when compared to normal for operator 3 is denoted by R_{13}, which is equal to 1.15 times the normal processing time.

$$\text{Emotional Processing Rate Matrix: } R_{ij} = i \begin{array}{c} \\ 1 \\ 2 \\ 3 \end{array} \overset{j}{\begin{array}{c} \begin{array}{cccc} 1 & \quad 2 & \quad 3 & \quad 4 \end{array} \\ \begin{bmatrix} 1.15 & 1.12 & 1.15 & 1.22 \\ 1.00 & 1.00 & 1.00 & 1.00 \\ 0.83 & 0.83 & 0.86 & 0.92 \end{bmatrix} \end{array}} \qquad (2)$$

i_1 = Normal/Avg. happy; i_2 = Normal/Normal; i_3 = Normal/Avg. sad; $j_{1\text{-}4}$= Operator

3.3.2 Discrete Event Simulation Model

A DES model was created using Rockwell Arena (version 14.7) based on the assembly with the four workstations. All the DES model inputs, such as the service times and arrival times, were determined from observation. Operators used similar sewing machine brands as well and similar facilities such as desks and chairs. In addition, the workstations' environmental situation was counterbalanced among the considered workstations. Task time means were obtained from the MTM analysis and an 11.9 percent coefficient of variability with a variety of distributions was applied in the model to account for normal human variation. All the data was analyzed with Arena's Input Analyzer to find the best fit distribution for all the cycle times. Thus, the ideal distribution for each of the four workstations was found to be: Erlang, Lognormal, Gamma and Normal. Each distribution was implemented in the assigned process time with limited entities during each implementation.

The discrete event simulation model presented in Figure 3 considers all the assumptions (Section 3.2) regarding the two first assembly processes: 1) sewing on both sides of a zipper, and 2) attaching two straps on two sides of a bag. Each station is portrayed as a block and is shown along with all the observed stations in a manner similar to the actual assembly line state. The following model shows the observed cycle time for each individual worker to accomplish the tasks, as recorded on the spreadsheets.

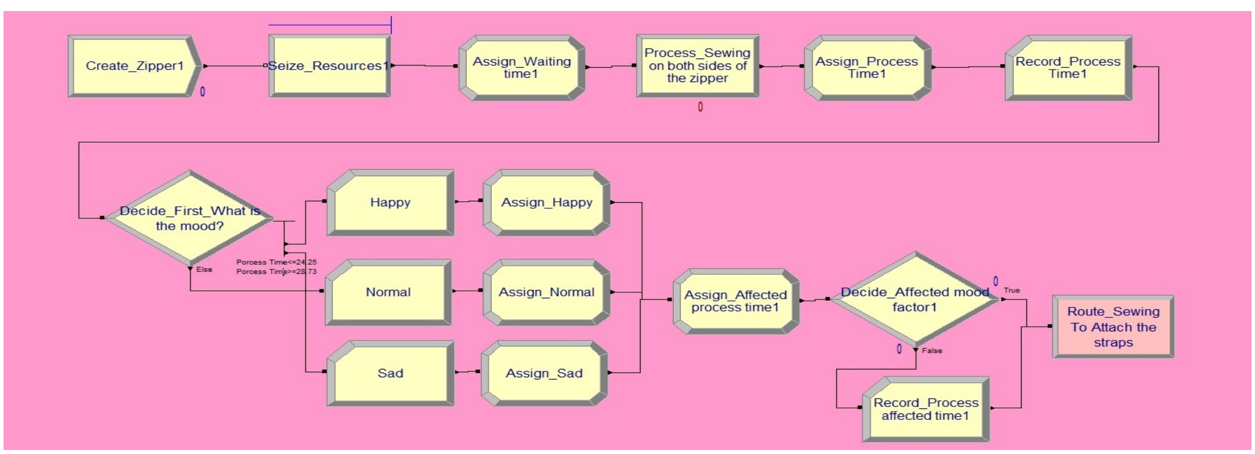

Figure 3: Portion of simulation model.

The simulation was conducted with one simple scenario, namely assemble or inspect to accomplish the allocated task, and was used to test how accurate the gathered real data was, based on the three mentioned moods (happy, normal, sad) in a dynamic system. The results showed that the proposed approach, the direct effect of various human conditions, leads to similar performance in a manufacturing system with flexibility such as in the observed company or with orders like most of the common assembly industries.

3.3.2.1 Discrete Event Simulation Model without Mood Consideration

Arena software was used to show the system from the beginning in order to perceive how prominent human factors are in the productivity of a system. Therefore, the simulation was conducted again in an ideal context, without any internal or external affective conditions. All the workers were assigned to a normal state (Figure 4).

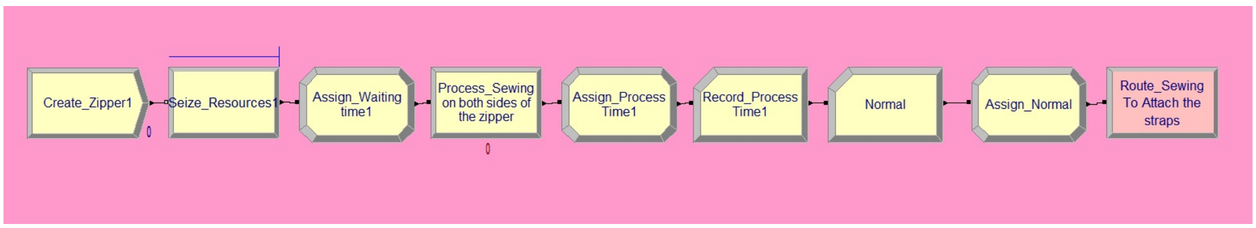

Figure 4: Portion of ideal simulation model.

4 VALIDATION AND VERIFICATION

The purpose of the validation of a simulation model is to apprehend if the simulation model created is capable of reconstructing the real system with reasonable precision. Among the validation methodologies and techniques that can be categorized, it can be done in four different groups: informal, static, dynamic and formal.

According to our model, it can be identified that the best methods of validation are the face validation and the historical data validation (Sargent 2005). Informal techniques are usually based on subjective estimates of system experts rather than on analytical formalisms. Among others, one of the most used informal validation techniques is the face validation. In this technique, the experts are presented with the most trustworthy results from both the simulation model and the real system where they are then asked to identify any differences between results from the simulation model and that of the real scenario. The face validation techniques are considered successful if the experts fail to find the difference between the two systems. Another validation measure is to ask individuals knowledgeable about the system whether the model's behavior is reasonable and in accord with reality (Longo, Huerta and Nicoletti 2013). In an historical data analysis (e.g., data collected on a system specifically for building and testing a model), a part of the data are used to build the model and the remaining data are used to determine whether the model behaves as the system does. The model that is developed in this paper follows the historical validation method, where the results of the simulation model are compared to a part of the real industrial data to check for reliability and accuracy.

5 RESULTS AND DISCUSSION

Lavis (2001) demonstrated how working with operators' moods can be used for improving productivity. Similarly, three moods (happy, normal, sad) were considered for each worker in the present study. The study speculated that mood has a profound influence on worker productivity, whether because happy workers show higher productivity (Oswald, Proto, and Sgroi 2009) or sad workers are more productive because they make fewer errors (Lavis 2001). The average task time was calculated for each observed workstation. The calculations were performed based on the arrival of the entities, following the FIFO system. The number of replications was restricted to one hundred. The desired number of replications of each workstation was calculated to give a 95 percent confidence with a half-width less than 1.5 percent of the average time in the system.

A paired t-test with 95 percent confidence interval was performed to analyze the mean differences between the actual observation and Arena calculations with mood consideration. The paired t-test shows that the hypothesized mean difference between the observed data set (28.67 sec) was not statistically different from Arena (27.39 sec; p-value on the difference = 0.375).

Table 3 compares the process time of the observed servers with the mean time obtained from Arena output with respect to moods. It is evident that the Arena average processing time for the entities and the actual observed mean time results mainly fall into the tolerance interval that was calculated as part of the outcomes from the observational data (Table 3).

Table 3: Observational and Arena average time.

Operator No.	Observational Average of the Process Time (sec)	Range of the Tolerance (sec)	Arena Calculated Average of the Process Time (sec)
1	27.66	25.22 – 28.25	27.86
2	23.55	21.62 – 25.64	23.34
3	24.48	22.85 – 27.39	19.52
4	39.03	36.62 – 41.64	38.87

Other factors that may have influenced the systems were considered. However, based upon the distributed survey (Table 2), the general physical conditions remained utterly similar during the observation. Moreover, employees also expressed in the survey that the environmental conditions, including air quality and the lighting, were excellent throughout the day regardless of the season of the year. Therefore, general physical condition and environmental factors were eliminated from the advanced analysis.

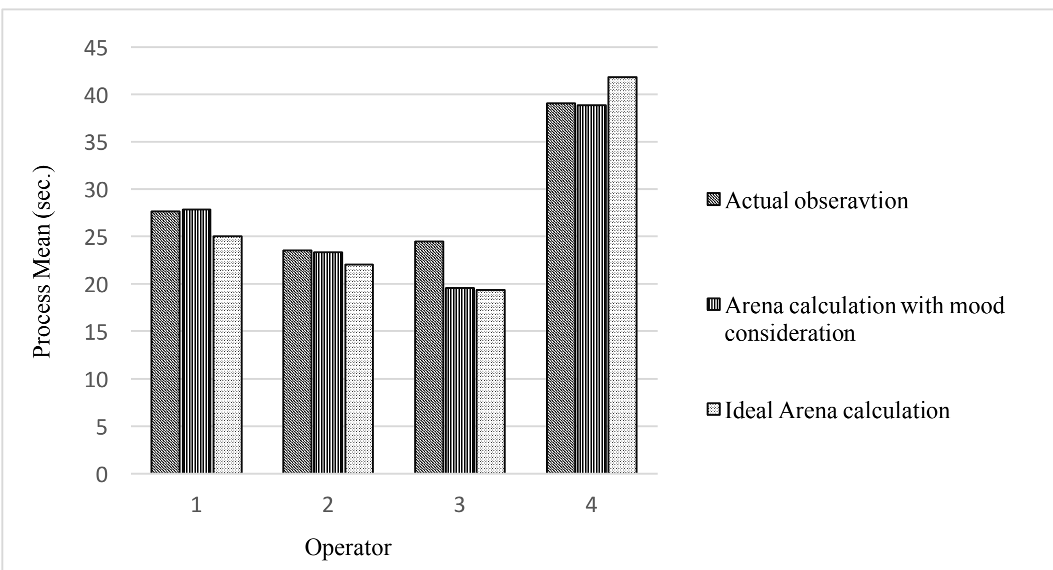

Figure 5: Process mean result for comparison between actual observation records, ideal Arena calculation and Arena calculation with mood consideration.

The average processing times in seconds as observed at the company during the data collection process are illustrated in Figure 5. The graph shows the variation in the observed time for each operator. In addition, the peaks and valleys observed in the graph reveal that processing time is affected by the operator's mood.

With the exception of the third operator, who had moderately different outcomes in terms of a major difference between the real time and the simulation time, the other operators all had similar outcomes, as expected. Therefore, the results support the hypothesis that in real-life situations, mood changes influence the productivity of the workers even though it is not observable. On the other hand, the comparison between the Arena ideal average processing times (without mood consideration) to Arena average processing time with mood consideration (Figure 5), indicates a significant difference, compared to the observation result. In other words, humans, who experience a variety of emotional states, will not have a consistent average outcome throughout the entire process. Hence, fluctuation of mood directly impacts worker efficiency. This indicates that, when simulating a process that involves humans, it is not sufficient to observe the data solely; the mood of the workers as well as mood changes over time must also be considered due to their direct impact on processing times.

6 CONCLUSION AND FUTURE RESEARCH

The objective of this research was to understand the impact of human-related psychological factors (especially the emotional) on the variances in the productivity of the servers in a manufacturing industry. In addition, it was proved based on the simulation model implemented in Arena that it was possible to use discrete event simulation (DES) to consider various conditions with respect to workers' moods.

Regarding the model's conclusions, it was evident that individual processing rates differ from one server to another and so the productivity of each, when mood changed, played a major role in deciding the time taken for each of the entities to be processed at each station. For the sake of explanation, the time taken by a specific worker for processing an entity was much shorter when the server was happy than when s/he felt sad, as was previously demonstrated by Oswald, Proto, and Sgroi (2009).

This paper is a proof of concept that DES has the capability to consider the fluctuating emotional states of humans as input in designing a model that seeks to increase the productivity of a system. Therefore, such a DES could be applied in the design sector for comparing human vs. machine outcomes, as well as for increasing the output of an existing system.

Ongoing research is currently focusing on collecting more data on assembly-line production in order to design a model that is closer to the real manufacturing process discussed in this paper. It can be noted that this study did not include all the stations that are part of this industrial assembly line. A more thorough study would have produced more accurate results for this project, which would have yielded a better understanding of the human factors involved and their influence on processing time, length of queue formed, and the overall productivity of the intended industrial manufacturing site. This aspect of the project opens up options for future research.

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