Framework for Operational Performance Measurements in Small and Medium Scale Industries Using Discrete Event Simulation Approach

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Abstract—**Globally, production systems must cope with limitations arising from variabilities and complexities due to globalization and technological advancements. To survive in spite of these challenges, critical process measures need to be closely monitored to ensure improved system performance. For production managers, the availability of accurate measurements which depict the status of production activities in real time is desired. This study is designed to develop an operational data decision support tool (ODATA-DST) using discrete event simulation approach. The work-in-process and processing time of each workstation/buffer station in a bottled water production system were investigated. The status of each job as they move through the system was used to simulate a routing matrix. The production output data for 50cl and 75cl product from 2014-2016 were collected. A mathematical model for routing jobs from the point of arrival to the point of departure was developed using discrete event simulation. A graphical user interface (GUI) was designed based on the factory's performance measurement algorithm. Simulating the factory's work-in-process with respect to internal benchmarks yielded a cycle time of 4.4, 6.23, 5.04 and throughput of 0.645, 0.455, 0.637 for best case scenario, worst case scenario and practical worst case scenario respectively. The factory performed below the simulated benchmark at 26%, 28%, 28% for the 50cl and at 51%, 54%, 59% for 75cl regarding the year 2014, 2015 and 2017 respectively. Performance measurement decision support tool has been developed to enhance the production manager's decision making capability. The tool can improve production data analysis and performance predictions.**

Keywords-performance measures; production system; discrete event simulation;decision support system

I. INTRODUCTION

The need for continuous performance improvement in a production system despite the complexities arising from market fluctuations will continue to drive the desire for innovative research. Performance measurement, a sub-division of performance evaluation involves the selection of appropriate quantitative measures to aid decision making in a system. These measures are vital input into any decision support tools (DST) [1, 2]. Also, such measures are required to assist executives at different decision levels. Ultimately, these decisions will contribute to the actualization of the strategic goals of the organization [3-7]. Authors in [8] classified performance measures into: (1) measure focus, and (2) measure tense. The former comprises of financial (monetary) and operational (non-monetary) data, while measure tense entails studying the past to improve the present. Diverse studies have been carried out on how to measure system performance using DST [6, 9-11]. This is necessary as the profitability, productivity, and survivability of any production system largely depend on the quality of the decisions obtained from such tools. DST in a production system can be deployed at operational, tactical and strategic levels. However, due to the ambiguities associated with most decision processes, the need to smoothen the complexities associated with choosing the best alternative cannot be ignored [12].

Decision support tools relevant to the production system include the following: (1) thermodynamics and exergy analysis, (2) optimization, and (3) simulation [13-16]. On simulation, the aim is to imitate real-world process over time [17, 18]. Also, in a simulation model, discrete mathematics can be employed in which events of various kinds are kept and governed in a queue for each object [19]. Discrete event simulation (DES) considers state changes at discrete points (points which an event occurs). It can be used to answer "what if" scenarios, diagnose the occurrence of certain phenomena and enhance system development over time [12, 17, 20-22]. Despite the increase in the research work on using DES as a DST, empirical studies have shown that it is minimally used in production systems [1, 12, 23-25]. In Nigeria, one of several challenges limiting the performance of small and medium scale enterprises (SMEs) involved in production process is the lack of access to proprietary DST [7, 26, 27]. Based on this reality, in this study the objective is to develop an operational data DST (ODATA-DST) for a bottled water factory using DES analytical approach. The rest of this paper is structured as follows: A brief discussion on DST and DES is the focus of section II. In section III, ODATA-DST was developed using an illustrative example. Results from the example and conclusion are the focus of sections IV and V respectively.

II. RELATED LITERATURE

In [18] authors suggested some performance measures peculiar to most production systems, these include, but are not limited to, the following: (1) throughput under mean and peak load resources, (2) labor and machine utilization, (3) bottlenecks and choke points, (4) staff requirements, (5) queuing and delays caused by material handling, (6) work in process and (7) scheduling effectiveness. On the need to improve efficiency of the supply chain, author in [11] designed a performance measurement system for Thai automotive industries using data categorization, clustering, and examination. Author in [10] developed a fuzzy data warehouse model to measure business performance as a result of the ever-increasing complexity and heterogeneous nature of the data available to organizations. He concluded that fuzzy sets and linguistic variables have the ability to deal with imprecision, vagueness and uncertainty nature of production data for better decision making. Authors in [13] commented that the decision making process is driven by the following: (1) communication, (2) documentation, (3) knowledge and (4) model development. Models are used to demystify the complexity associated with many problems. Authors in [28, 29] identified some of the processes in modeling as: (1) data assessment and reduction, (2) state estimation, (3) monitoring, (4) diagnosis, (5) prediction, (6) hypothesis generation, (7) creation of mathematical image to a problem, and (8) decision making. Discrete event simulation (DES) model is a computer simulation method universally suitable for modeling the performance of a production system. The method can be used to abstract the dynamic and stochastic behavior of a system as a set of discrete sequence of events by considering event in instants of time [30]. Also, DES demands less computer resources and is useful in solving statistical uncertainties and discrepancies in simulated environments. On the use of DES in production systems, authors in [31] developed a simulation based real-time decision making tool for a manufacturing automation system. Authors in [32] presented the use of DES for planning, production and scheduling decisions. In [33], authors utilized DES for customer driven manufacturing system design. Author in [19] combined simulation and optimization to improve decision support in an energy efficiency industry.

III. METHODOLOGY

The mathematical model proposed in [34, 35] on factory's performance measurement was adopted. In Table I, the various operational performance measures required to understand the behavior of the production line are defined.

A. Descriptive Problem Definition

The flow process of a small scaled bottled water production plant is described in Figure 1. The process consists of a production line with 9 workstations (A1-A9) defined in Table II. The workstations are arranged in series with each job following the same processing sequence. In designing a discrete event simulation framework, the study of the production line will be limited to workstations A2 to A9 because their activities are discrete events. For each discrete event, there is a change in the state of the product as it moves from one workstation to another until it becomes a finished product. Each workstation (A2-A9) has at least one sub-workstation. Job routing of the production system is presented in Figure 2.

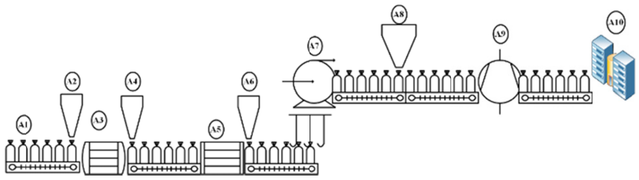

Fig. 1. Plant layout of the bottled water production plant.

B. Model Assumptions

- The bottled water factory is a serial production line with finished goods buffers.
- The cycle time of the machines is constant while the throughput time varies with respect to its state (in terms of been empty or saturated).
- Processing time in each workstation is deterministic but varies from one workstation to the other.
- Buffer capacity between successive work stations is finite.
- The production line is reliable with a steady state exponential distribution failure rate.
- Blockage of a station occurs if the jobs at the downstream buffers are beyond its capacity.
- The factory production line model has no machine downtimes, no loss in production due to waste and it is constantly in operation.

TABLE I. BASIC NOTATIONS

Notation	Definition
WIP	Work–in–process
CT	Cycle time
CT_{best}	Cycle time at best case performance
T_{approx}	Time for a job to go through an uncongested line
C_{approx}.	Capacity of the line
TH	Throughput
CT_{worst}	Cycle time for worst case performance
PR	Production rate
W0	Critical Work–in–process
THbest	Maximum throughput at best–case performance scenario
N	Number of stations
W	Level of work–in–process
To	Raw process time
T	Average processing time
THworst	Throughput for worst case performance scenario
r_b	Bottleneck rate

C. Mathematical Model

To model ODATA-DST using DES framework, the following measures were adopted.

- Cycle time

Case 1: When the production line is relatively empty

$$CT = T_{approx} \quad (1)$$

Case 2: When the production line is saturated

$$CT = max\left\{T_{approx.}, \frac{WIP}{C_{approx.}}\right\} \quad (2)$$

- Machine Capacity

$$C_{approx.} = \frac{1}{CT} \quad (3)$$

- Throughput

$$TH = C_{approx} * PR \quad (4)$$

- Work-in-process (from Little's Law)

$$WIP = TH \times CT \quad (5)$$

- Bottleneck rate

$$r_b = \frac{1}{T} \quad (6)$$

- Average time at a station

$$W_0 = r_b T_0 \quad (7)$$

TABLE II. PLANT NAMING CONVENTION

Conventions	Name	Description
A1	Belt conveyor	Belt conveyor
A2	Buffer station 1	Buffer station 1
A3	Workstation 1	Automatic rinsing machine
A4	Buffer station 2	Buffer station 2
A5	Workstation 2	Automatic filling machine
A6	Buffer station 3	Buffer station 3
A7	Workstation 3	Automatic capping machine
A8	Buffer station 4	Buffer station 4
A9	Workstation 4	Automatic Packaging machine
A10	Warehouse	Warehouse

D. ODATA-DST Graphic User Interface

The computer implementation of ODATA-DST was achieved using visual basic application (VBA) integrated development environment. The following motivated the use of VBA: (1) compatibility, (2) availability across multiple platforms, (3) interactive nature, and (4) ease of numerical programming. A screenshot of ODATA is shown in Figure 3.

E. Best-Case Scenario, Worst-Case Scenario and Pratical Worst- Case Scenario of the Production Line

Analyzing the production line based on the best-case scenario, worst-case scenario and practical worst-case scenario is essential. These parameters are required to measure performance, determine the possible behavior, and areas requiring improvement at any time period.

1) Best-Case Performance (BCP)

This can be classified into minimum cycle time and maximum throughput. Minimum cycle time for a given WIP level (w) is given by:

$$CT_{best} = \begin{cases} T_0 \; if \; w \leq W\_0 \\ \frac{w}{r_b} \; otherwise \end{cases} \quad (8)$$

Maximum throughput for a WIP level given by TH_{best}:

$$TH_{best} = \begin{cases} \frac{w}{T_0} \; if \; w \leq W_0 \\ r_b \; otherwise \end{cases} \quad (9)$$

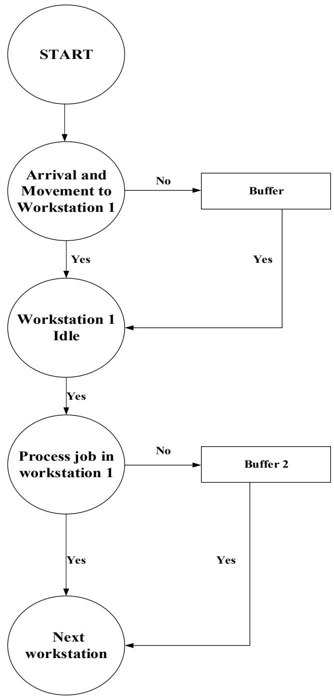

Fig. 2. Flow chart of job routing.

2) Worst-Case Performance (WCP)

This involves the maximum cycle time and minimum throughput possible for a line with bottleneck rate r_b and raw process time (T_0). Equation (10) is the worst-case cycle time for a given WIP level w.

$$CT_{worst} = wT_0 \quad (10)$$

Equations (11)-(13) are the worst-case throughput for a given WIP level w.

$$TH_{worst} = \frac{1}{T_0} \quad (11)$$

$$CT = N\left(1 + \frac{w-1}{N}\right)t \quad (12)$$

$$= T_0 + \frac{w-1}{r_b} \quad (13)$$

Applying Little's law, the corresponding throughput will be:

$$TH = \frac{WIP}{CT} \quad (14)$$

$$= \left(\frac{w}{W_0 + w - 1}\right) r_b \quad (15)$$

3) Practical Worst-Case (PWC)

Equation (16) is the cycle time for a PWC.

$$CT_{PWC} = T_0 + \frac{w-1}{r_b} \quad (16)$$

The PWC throughput for a given WIP level is given by:

$$TH_{pwc} = \left(\frac{w}{W_0+w-1}\right) r_b \quad (17)$$

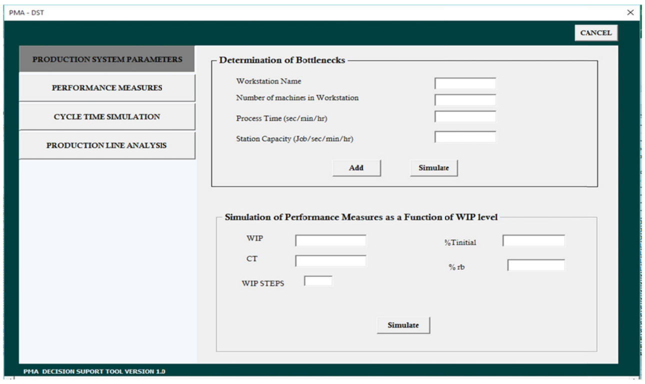

Fig. 3. ODATA – DST screen

IV. RESULTS

The results are presented in Table III. Workstation 4 has a bottleneck of 0.645jobs/minute, the critical work-in-process required to achieve maximum throughput at raw processing time of 2.2 minutes is 1.419 cartons. The raw process time was 2.2 minutes. This is lower than the sum of each workstation process time, as proposed in [34]. The relationship between the best-case, worst-case and practical worst case scenarios in relation to cycle time and throughput is presented in Table IV. For 50cl bottled water production, minimum and maximum output were 16% and 40% and occurred in March and November respectively. For the 75cl, minimum and maximum outputs were 28% and 83% in July and May respectively. The relationships between work-in-process and throughput for 50cl and 75cl are shown in Figures 4 and 5 respectively.

V. CONCLUSIONS

A performance measurement support tool has been developed to enhance production manager's decision making capability. Performance measures like cycle time, throughput, machine capacity, work–in–process, bottleneck rate and raw process time were used to derive a suitable benchmark. The tool is capable of improving production data analysis and performance predictions.

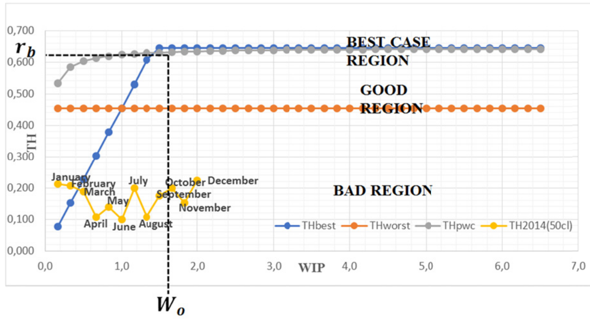

Fig. 4. Relationship between throughput and work in process (50cl bottle)

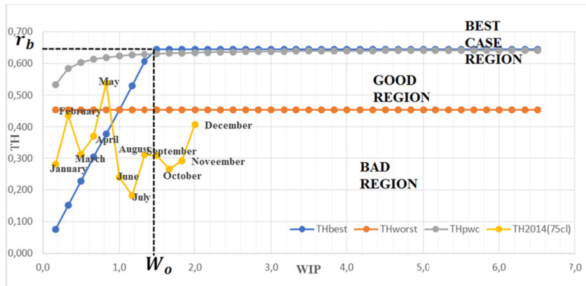

Fig. 5. Relationship between throughput and work in process (75cl bottle)

TABLE III. RESULTS FROM ODATA-DST

Station Number	Number of Machines	Process Times (secs)	Process Times (mins)	Jobs/Minute	Station Capacity (Job/sec)
Buffer 1	4	3	0.050	80	1.3333
WorkStation 1	4	8	0.133	30	0.5000
Buffer 2	4	4	0.067	60	1.0000
WorkStation 2	4	8	0.133	30	0.5000
Buffer 3	4	5	0.083	48	0.8000
WorkStation 3	3	3	0.050	60	1.0000
Buffer 4	4	21	0.350	11.428	0.1905
Work Station 4	1	93	1.550	0.645	0.0108
Average Processing time		18.125	**Raw Process time**		2.20
Bottleneck		0.645	**Critical WIP**		1.419

TABLE IV. INTERNAL BENCHMARK OUTPUT

W (Bottles)	W (Cartons)	Best Case Scenario		Worst Case Scenario		Practical Worst Case Scenario	
		CTbest (mins)	THbest (mins)	CTworst (mins)	THworst (mins)	CTpwc (mins)	THpwc (mins)
10	0.8	2.2	0.379	1.83	0.455	1.94	0.619
20	1.7	2.6	0.645	3.67	0.455	3.23	0.632
30	2.5	3.9	0.645	5.50	0.455	4.53	0.636
40	3.3	5.2	0.645	7.33	0.455	5.82	0.638
60	5.0	7.8	0.645	11.00	0.455	8.40	0.641
70	5.8	9.0	0.645	12.83	0.455	9.69	0.641

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