A Simulation Model to Optimize Pre-sewing Operations in the Apparel Industry: A Case Study from Sri Lanka

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***Abstract*— The most crucial factor in apparel manufacturing is catering for due dates. The unoptimized, ad-hoc scheduling and static routing of Production Orders (POs) result in late deliveries of orders. The inability to analyze the available pre-sewing capacity against the demand results in last moment revelation of resource over utilization. This study proposes a systematic approach in analyzing pre-sewing capacity against the demand. A mathematical model in estimating pre-sewing job completion times for six chosen pre-sewing departments is proposed. Operation Flexibility and Routing Flexibility in pre-sewing section are analyzed and integrated in scheduling through Precedence Diagramming Method (PDM) and priority scheduling algorithm. An optimized scheduling approach with a simulation model to facilitate the visibility of resource utilization and PO completion times is adopted. The simulation model provides approximated PO completion time with optimized criterion, provides measures on resource utilization and queue wait times, thus facilitating proactive measures for the management at an early stage of the production.**

Keywords*— *Routing Flexibility, Operation Flexibility, PDM, Optimization, Simulation

I. INTRODUCTION

Apparel industry is a giant industry in Sri Lankan economy, contributing 44% to the national export. Having a $5.3 Bn export revenue earned in year 2019, the industry is rapidly growing becoming the regional apparel hub [1]. Given the gravity of economic contribution of the apparel industry, the sustainability of regional industry leadership is of utmost importance. This is a challenging mission with new market trends which has made the industry a very competitive place. The competitiveness of apparel manufacturing industry is caused due to the highly fluctuating and diversified market demands. The apparel manufacturers are compelled to adjust the manufacturing processes to produce Production Orders (PO) with shorter life cycles with uncompromised standards of garments. Under these circumstances garment manufacturers are becoming more focused on shrinking the lead times of manufacturing processes optimizing the available resources and the capacity.

The lack of proper scheduling and the neglected opportunity of routing flexibility and operation flexibility in optimizing resources within pre-sewing sections have resulted in extended production lead times, ultimately resulting in late order deliveries.

Routing flexibility and operation flexibility are two characteristics existent within an apparel manufacturing pre-sewing section. Routing flexibility of a manufacturing system is its ability to produce a part by alternate routes through the system. Alternative routes may use different machines, different operations, or different sequences of operations. Typically, these different machines are those capable of essentially the same processes. Operation flexibility, also known as sequence flexibility refers to a parts' ability to be produced in different ways. Operation flexibility is a property of the part, and means that the part can be produced with alternate process plans, where a process plan means a sequence of operations required to produce the part [2].

In garment manufacturing there are multiple operations that one product should undergo from raw material receipt to needle point or the sewing start, which is varied from one product to the other based on the style. Each of these styles has a pre-determined set of operations from a set of pre-sewing operations that can be carried out within the plant. Not every style has the same set of operations or the operation sequence (routes). Thus, the chain of pre-sewing operations to be carried out vary from style to style and there's a possibility for a style to have multiple possible routes to be taken. This proves the existence of operation flexibility within pre-sewing section.

Further, a client order is converted to a Sales Order (SO) within the manufacturing plant for further proceedings. One Sales Order is broken down to Sales Order line Items (SO/LI) and one SO/LI is broken down to Production Orders (PO). The manufacturing processes are carried out in PO level within the plant. It is these POs which will be scheduled for jobs to be carried out by machines or laborers within each department responsible for carrying out each pre-sewing operation. Since there exist multiple identical machines within a department, there exist multiple routes a single PO can take in machine level, which gives the existence of routing flexibility within the pre-sewing chain of operations.

These two types of flexibilities: routing and operation flexibilities are opportunities which can be exploited in better resource utilization if analyzed at an early stage of production and made use of in job shop scheduling in the pre-sewing chain of operations.

II. LITERATURE REVIEW

Optimizing pre-sewing resources against the demand is inevitably bound with the Job Shop Scheduling Problem (JSSP) which is a complex combinatorial optimization problem [10]. The conventional scheduling problem can become Flexible Job Shop Scheduling Problem (FSSP) if there are a set of machines available and each operation is allowed to be processed on any one of the available ones. A FJSSP is more troublesome than the established JSP, because it adds a level of decision yet beside that sequencing i.e. job routes [3].

Job shop Scheduling problem is an optimization problem where jobs are assigned to resources in such a way that one or many of the objectives are satisfied. These objectives can be minimizing the total make span, maximizing the resource utilization or reducing the Work in Progress (WIP). At a given context a combination of the above objectives might need to be achieved.

Although research focusing specifically on apparel manufacturing pre-sewing section FJSSP are scarce, there is an extensive body of literature on FJSSP underlying the same fundamental flow [3,4,6,8,10]. These researches belong to multiple approaches like heuristic approaches, meta-heuristic approaches, mathematical models and simulation-based optimization approaches.

One study proposed a branch and bound algorithm for fixed pre-assembly scheduling on multiple fabrication machines. Minimizing the total weighted completion time of a finite number of products is considered as the scheduling measure. Two lower bounds are derived and tested in a branch-and-bound algorithm. Also, an efficient greedy-type heuristic algorithm is developed to generate near-optimal schedules [4].

FJSSP has been mainly approached for solving in meta heuristic approaches due to its NP-Hardness. Among these meta heuristic algorithms are: simulated annealing, tabu search and genetic algorithms [5,6,7,8,9,10].

Feldmann and Biskup in 2003, considered the problem of scheduling a number of jobs on a single machine against a restrictive common due date. A new problem representation has been developed and meta-heuristics, namely evolutionary strategies, simulated annealing and threshold accepting have been applied in solving the above. The study demonstrates that the application of above meta-heuristics is efficient in obtaining near-optimal solutions by solving 140 benchmark problems with up to 1000 jobs [11].

In 2014, a survey on multi objective evolutionary algorithm for manufacturing scheduling problems was conducted. focus is on the design of multi objective evolutionary algorithms (MOEAs) to solve a variety of scheduling problems. Firstly, a fitness assignment mechanism and performance measures for solving multi-objective optimization problems are introduced along with evolutionary representations and hybrid evolutionary operations especially for the scheduling problems. Then these EAs are applied to the different types of scheduling problems, including job shop scheduling problem (JSP), flexible JSP, Automatic Guided Vehicle (AGV) dispatching in flexible manufacturing system (FMS), and integrated process planning and scheduling (IPPS). Through a variety of numerical experiments, the study demonstrates the effectiveness of these Hybrid EAs (HEAs) in a wide range of applications of manufacturing scheduling problems [12].

In 2018, Salma and Eltawil proposes a decision support system based on simulation metamodeling optimization approach to assist in making timely and informed decisions, using emerging technologies like industry 4.0 and cyber-physical system concepts. The DSS is comprised of a simulation model with a simulation metamodel combining the merits of simulation modelling and design of experiments by providing optimal solutions [13].

In a study conducted in 2011, Joseph and Sridharan proposes a simulation-based metamodels for the analysis of routing flexibility, sequencing flexibility and scheduling decision rules on the performance of an FMS. Three routing flexibility levels, five sequencing flexibility levels and four scheduling rules for part sequencing decision are considered. The performance of the FMS is evaluated using measures related to flow time and tardiness of parts. Multiple regression-based metamodels have been developed using the simulation results. The results show that deterioration in system performance can be minimized substantially by incorporating either routing flexibility or sequencing flexibility or both. However, the benefits of either of these flexibilities diminish at higher flexibility levels. When flexibility exists, PSRs, such as earliest due date and earliest operation due date, provide better performance for all the measures [14].

In another study conducted in 2014, an estimation of distribution algorithm-based approach coupled with a simulation model is developed to solve the FJSSP and implement the solution. The focus of the study is to employ simulation with estimation of distribution algorithm where three probabilistic models are utilized. The first one generates the processing sequence of operations on the machines; the second produces the assignment of operations on machines, and the third obtains the start time for each work shift. The objective is to generate schedules that can obtain a small amount of WIP as a performance measure. Using the proposed approach, the shop performance could be noticeably improved when different machines are assigned to different schedules [15].

Given that the research question is bound with the visibility available for management at an early stage of production, an optimization model concerning routing and operation flexibilities, integrated with a simulation model for performance measure analysis is proposed in this study.

The study site is an apparel manufacturing plant which produces garments for orders. The information of the pre-sewing section of the plant is mainly handled by ERP system. The plant produces embellishment orders, normal orders and sub-contracting orders. Since the internal capacity of the plant is concerned in this study, sub-contracting orders are not taken in to consideration. The production planning is carried out based on the technical details of the POs and data available in ERP system.

III. DATA COLLECTION

This study makes use of five main documents as data sources. Those are:

- Style Spec/Style Sheet – A document prepared by plant technical team, comprising of set of due pre-sewing operations for one style and their technical dependencies. A style can run in multiple POs.
- Resource Pool – A database comprising of per-sewing resource details and technical constraints.
- Production Plan – The document comprising of list of POs to be processed and the Production Start Date and Time (PSD/PST) which is deemed as the due date of PO for pre-sewing section.
- BOM Details – Bill of Materials for each finished good extracted from ERP system.

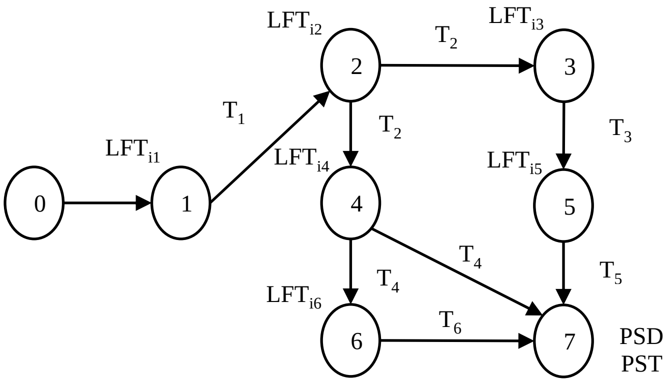

Figure 1 - Precedence Diagram for PO$_i$

- Master data – Technical and other detail maintained by Production Planning and Controlling Unit (PCU).

These data are acquired from the pilot plant from which the experimental scenario is adopted.

IV. METHODOLOGY

This study proposes a separate mathematical model to estimate job completion time in each pre-sewing department. This model integrates operation flexibility into scheduling through PDM (Precedence Diagramming Method), resulting a job list with latest finish time for each job, for each pre-sewing department. Studies [14, 17] have adopted similar approaches to PDM in analyzing part paths with critical path method and operation graphs.

Precedence Diagramming Method (PDM) maps the sequences and dependencies of pre-sewing operations for POs in the PO list which is provided to be processed by the PCU of the apparel manufacturing plant. Fig. 1 shows the precedence diagram formed based on the Table 1 for a sample PO. Through this approach, the operation flexibility is analyzed and integrated.

A. *Mathematical Model for Job Completion Time Estimation*

The model is built for a scenario of a PO list consisting styles comprised of following 6 pre-sewing operations:

Fabric Picking, Fabric Spreading, Fabric Cutting, Trims Picking, Molding and Strap Making.

Assumptions

In this study, the proposed model is built upon the following assumptions:

(A1): SMV values for all pre-sewing operations are maintained and pre-given.

(A2): All master data are maintained within ERP system and pre-given.

(A3): All Strap jobs are plastic material.

(A4): Cut SMV does not vary on size.

Table 1- Operation Sequence & Dependencies of PO$_i$

Process No.	Sub Process	Dependent	Next
1	Fabric Picking	0	2
2	Spreading	1	3,4
3	Cutting	2	5
4	Trims Picking	2	6,7
5	Molding	3	7
6	Strap Making	4	7
7	Line In	4	0

Following is the operation process time (T$_i$) formula development.

The following notation (Table 2) is utilized in analyzing the routing flexibility and formulating calculations for process time estimation in this study:

Table 2- Nomenclature

PO$_i$	i^{th} Production Order (PO) which will be produced
Qty$_i$	Quantity of PO$_i$
SZ$_{il}$	l^{th} size of PO$_i$
SZQty$_{il}$	Quantity of SZ$_{il}$
St$_i$	Style of PO$_i$
Dc$_{il}$	l^{th} docket of order PO$_i$
DcQty$_{il}$	Docket ratio quantity of *l*th docket of order PO$_i$
PPDc$_{il}$	Plies per docket Dc$_{il}$
MQty$_{il}$	Pieces per marker of Dc$_{il}$
Panel$_{il}$	Panel *l* of PO$_i$
FbQty	Fabric quantity per one panel, one piece of POi (Extracted for BOM)
UPP$_{il}$	Units per piece of unit *l* of order POi (Extracted for BOM)
TrmCat$_{il}$	Trim category *l* of PO$_i$
TrmQty	Trim quantity per one unit of POi (Extracted for BOM)
MatQty	Roll/Box quantity for material type (Extracted form master data)
Trm $_{(1\text{ to }n)}$	Trim categories for PO$_i$ (Extracted for BOM and master data)
PE	Picking Efficiency for material category (Extracted form master data)
PTT $_{(1\text{ to }n)}$	Fabric picking travelling time for geographical zone (Extracted form master data)
SprdSMV	Material wise SMV (Standard Minute Value) for spreading per one lay (Extracted form master data)
CutSMV	Panel wise SMV for cutting (Extracted form master data)
BnSMV	Binding SMV (Length per minute - Extracted form master data)
StrpInsSMV	Strap Insertion SMV (Extracted form master data)
StrpComSMV	Strap Completion SMV (Extracted form master data)
MoldDT	Molding Dwell Time (Style Wise Maintained)

MoldHT	Molding Handling Time (Style Wise Maintained)
O_{il}	lth operation of order PO_i
A_i	Arrival time of ith PO
CP_i	Actual completion time of PO_i
PT_{il}	Processing time of operation O_{il}
FT_{il}	Actual finish time of O_{il} (Through simulation model)
LFT_{il}	Latest finish time of O_{il} (Estimated)
PST_i	Due date and time of PO_i
TD_i	Tardiness of PO_i (CP_i - PST_i)
PT	Process Time

Fabric Picking Process Time Estimation:

$$PT = \sum_{Panel(1-l)} [(FbQty * Qty_i * UPP_i / MatQty) * PE + PTT] \quad (1)$$

Fabric Spreading Process Time Estimation:

$$PT = \Sigma_{Dc\,(1-l)} (SprdSMV * PPDc_{il}) \quad (2)$$

Fabric Cutting Process Time Estimation:

$$PT = \Sigma_{Dc\,(1-l)} (CutSMV * MQty_{il}) \quad (3)$$

Trims Picking Process Time Estimation:

$$PT = \Sigma_{TrmCat(1-l)} [(TrmQty * Qty_i * UPP_i / MatQty) * PE + PTT] \quad (4)$$

Molding Process Time Estimation:

$$PT = \Sigma_{SZ(1-l)} [(SZQty_i * MoldDT) + (SZQty_i * MoldHT)] \quad (5)$$

Strap Making Process Time Estimation:

$$PT = Qty_i [(TrmQty * StrpInsSMV) + (TrmQty_n * StrpComSMV)] \quad (6)$$

Based on Standard Minute Values (SMV) of pre-sewing operations and PO quantities, the time durations for each pre-sewing operation of a given PO are estimated (Ti). Starting form PSD/PST (Due date and time for a given PO) a back calculation is carried out by using the estimated time durations above, the latest finish date & time (LFT_{il}) for each job, for each pre-sewing department is calculated (Fig. 1).

Once the above analysis is carried out for all POs in the list, each pre-sewing department gets a job list with a time value (LFT_{il}) for each job. These jobs for each pre-sewing department is scheduled, using priority scheduling algorithm. This algorithm will assign the job having the earliest date and time value for LFT_{il} calculated above, to the firstly available resource out of multiple identical resources in the department in scenario 1. For the priority scheduling algorithm and chosen dispatching rules to be implemented and to analyze the performance of the manufacturing system, the study implements a simulation model of the pre-sewing manufacturing system of an apparel manufacturing plant.

B. Simulation Model Development

A simulation model is built to test the experimental scenario, Table 3. Six pre-sewing operations are simulated along with the resources as shown in Fig 2. Five main input sources have been integrated. The dynamic routing of a PO is enabled based on the style through the simulated pre-sewing model. The simulation model is tested under three different dispatching rules.

Scenario 1:

- Tested scheduling algorithm: Priority scheduling algorithm (Non-preemptive) *

*Given that the jobs for each pre-sewing department (O_{il}), are non-related.

- Tested dispatching rule: Lowest Attribute Value (Attribute = LFT_{il}) / Latest Finish Time First

Scenario 2:

- Tested scheduling algorithm: Priority scheduling algorithm (Non-preemptive)
- Tested dispatching rule: Lowest Attribute Value (Attribute = PT_{il}) / Shortest Process Time First

Scenario 3:

- Tested scheduling algorithm: Priority scheduling algorithm (Non-preemptive)
- Tested dispatching rule: First in First Out (FIFO)

Scheduling algorithms and dispatching rules are adopted with the following objectives:

1. Minimizing Tardiness (TD_i) / Due date delivery
2. Minimizing Queue Wait Times / WIP Reduction
3. Maximizing Resource Utilization

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

The simulation model was run under three experimental scenarios mentioned under *Simulation Model Development*. The simulation environment used is Arena discrete event

Table 3 – Experimental Scenarios

Scenario Number	**Description**		
	Scheduling Algorithm	***Dispatching Rule***	***Attribute***
Scenario 1	Priority Scheduling Algorithm	Lowest Attribute Value*	*Latest Finish Time
Scenario 2	Priority Scheduling Algorithm	Lowest Attribute Value*	*Shortest Process Time
Scenario 3	Priority Scheduling Algorithm	Frist in First Out	

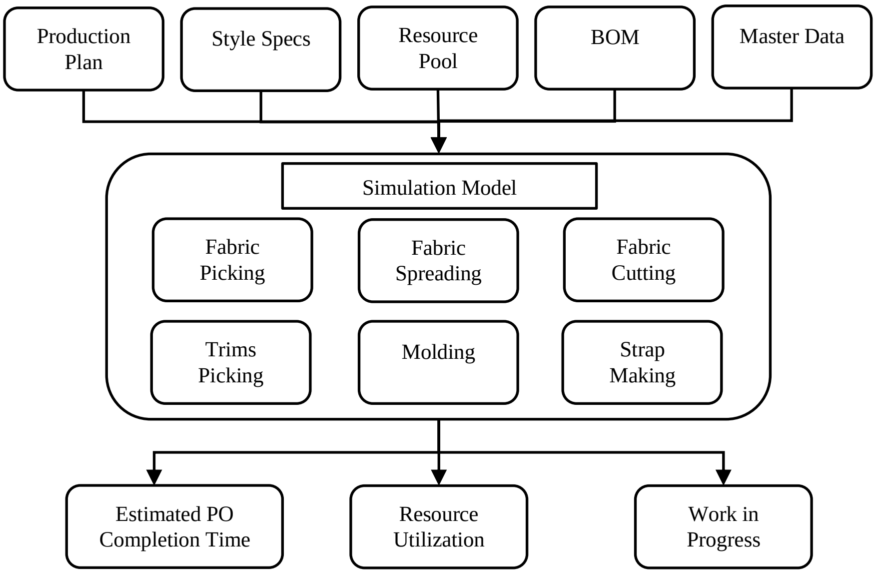

Figure 2 – Simulation Model Structure with Input Output Data

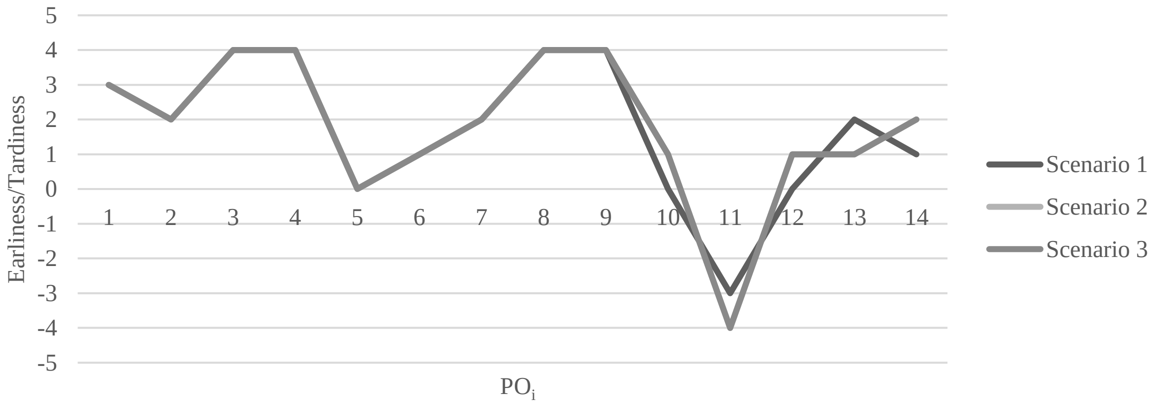

Figure 3 – Earliness and Tardiness of PO_i

simulation software. Resource capacities and all other attributes of the simulated manufacturing model were kept equal over all three experimental scenarios initially. The earliness and tardiness of each PO under different experimental scenarios is depicted in Fig. 3.

Earliness/Tardiness = Available Days for Completion - Simulation Completion Days (Positive values represent earliness while negative values represent tardiness.)

Fig. 3 depicts that scenario 2 and 3 has performed alike while scenario 1 has performed with less deviation from due dates. Both earliness and tardiness have negative impacts on the manufacturing process. Earliness means increased WIP while tardiness means inability to achieve due dates. Out of earliness and tardiness, it is best to eliminate tardiness first and then trying to achieve as less as possible of WIP by reducing the earliness. Given the above, it is best if POs can be completed on time. Under this criterion, when compared, experimental scenario 1 has performed better than other two scenarios in terms of due date delivery as well as in WIP reduction.

In relation with utilization performance measure, three instances of scenario 1 with different resource capacities were tested. Table 4 depicts instance wise capacity combinations against utilization percentages.

Analyzed with earliness and tardiness of PO completion with Fig. 4 along with capacity combinations and utilization percentages of Table 4, it is apparent that Instance 3 has outperformed instance 1 and 2 with higher resource utilization percentage not compromising on catering on due dates.

VI. CONCLUSION AND FUTURE WORK

Based on the above analysis, it is concluded that experimental scenario 1 outperforms other two experimental scenarios in terms of due date delivery and WIP reduction. Further, the simulation model provides the ability to test the manufacturing system with varied capacity combinations. It was deemed that instance 3 provides comparatively the best utilization along with due date delivery.

This study takes an effective approach of optimizing pre-sewing resources in scheduling through manufacturing flexibility. The simulation model facilitates the ability to process the PO list through existing resources prior to actual production starts, under different dispatching rules. The results of the simulation model provide management with

Table 4 – Instances Comparison

Resource	Instance 1 - Capacities	Utilization Percentage	Instance 2 - Capacities	Utilization Percentage	Instance 3 - Capacities	Utilization Percentage
Fab Picker	4	0.14%	1	0.55%	1	3.76%
SPRD MC	3	0.32%	1	0.96%	1	1.60%
Fab Cutter	2	1.13%	1	2.26%	1	3.76%
Trims Picker	2	0.81%	1	1.63%	1	2.71%
KEKI MC	1	99.60%	1	99.66%	2	82.91%
HAMS MC	5	19.92%	1	99.66%	2	82.91%
Molding MC	4	21.08%	1	84.39%	3	46.80%

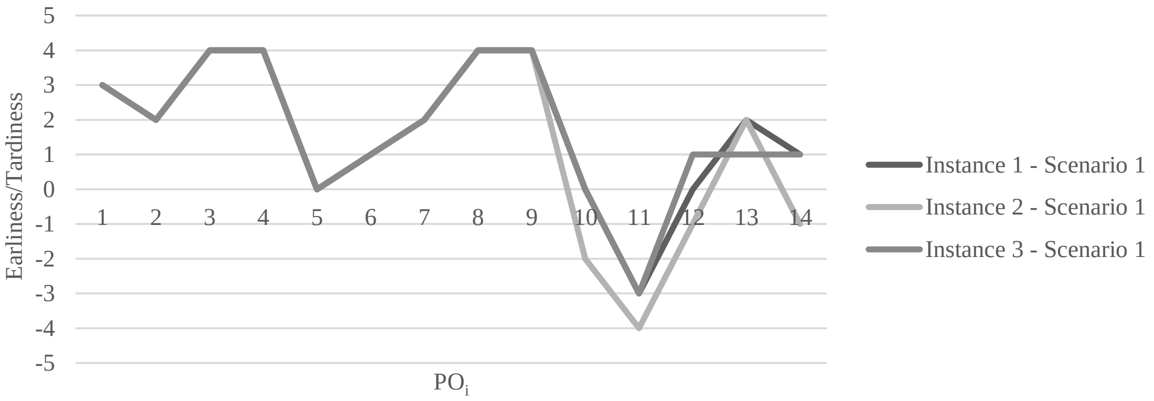

Figure 4 – Earliness & Tardiness of PO_i

insights as to the ability or inability to cater for the due dates, resource over or under utilization and WIP. This ultimately facilitates insights in making pro-active decisions. This study has tested the simulation model on three dispatching rules and one scheduling algorithm. The model can further be tested against other dispatching rules and scheduling algorithms as future work.

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