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Validation of a Digital Simulation Model for Maintenance in a High-Volume Automated Manufacturing Facility

Patrick Ruane*. Patrick Walsh. John Cosgrove*****

**Johnson & Johnson Vision Care and Technological University of the Shannon, Limerick, Ireland (e-mail: patrick.ruane@tus.ie)*

*** Technological University of the Shannon, Limerick, Ireland (e-mail: patrick.walsh@tus.ie)*

**** Technological University of the Shannon, Limerick, Ireland (e-mail: john.cosgrove@tus.ie)*

Abstract: Digitalization in manufacturing is the conversion of information into digital format, the integration of this digital data and technologies into the manufacturing process and the use of those technologies (eg: simulation) to change a business model to provide new revenue and value-producing opportunities. Digitalization may be seen as the increased generation, analysis, and use of data to improve the efficiency of the overall manufacturing system. Simulation in manufacturing is often applied in situations where conducting experiments on a real system is impossible or very difficult due to cost or time to carry out the experiment is too long. A key input to the simulation model of automated equipment is the acquisition of valid data in relation to cycle time and reliability of various workstations on this line. As a consequence of being able to simulate equipment processes and interact with this validated simulation model, both the understanding of how the production system will perform under varying reliability and cycle time conditions is achieved. The simulation model then enables the experimentation of 'what if scenarios' that can be tested easily, while also providing a valuable tool to inform the maintenance personnel what station reliabilities they need to target in order to sustain a high performing manufacturing line.

The author has adopted an open source simulation tool (JaamSim) to develop a digital model of an automated production line in a Johnson & Johnson Vision Care (JJVC) manufacturing facility. This research demonstrated how a digital model was validated for use. The validated digital model can then be used by the author/facility engineering teams to perform scenario testing during the design stage of the line. This simulation model can also be used as a subset of an optimization system to determine recommended optimum line parameters to maximize line performance, either during the line design or when line is in operation.

Keywords: Simulation Model, Digital Model Validation, OEE, MTBF, MTTR, Reliability.

1. INTRODUCTION

Digital manufacturing technologies, such as simulation models, have been considered an essential part of the continuous effort towards improving the OEE (Overall Equipment Efficiency) of automated manufacturing equipment and processes.

1.1 Overall Equipment Efficiency (OEE)

The concept of OEE, introduced by (Nakajima, 1988), is being used increasingly in industry. It looks at the wider manufacturing aspects, not only the equipment availability and performance, but the efficiency losses that result from rework and yield losses. According to (Tajiri, 1992) the relationship between OEE and losses depends on equipment availability, their performance rates, and the quality of the product. OEE monitors the actual performance of a machine relative to its performance capabilities under optimal manufacturing conditions. According to (Grzegorz Gołda, 2016) Manufacturing Line efficiency can be expressed, using the OEE metric that depends on three factors: availability, performance, and quality.

OEE = (Availability) x (Performance) x (Quality)

Availability is the ratio of the time spent on the realization of a task to the scheduled time. Availability is reduced by disruptions at work and machine failures. According to (Grzegorz Gołda, 2016) the term of availability contains planned work time and unplanned events e.g., the disturbances at work and random machine failures. Any unplanned event that causes the equipment to be unavailable results in reduced efficiency. The reliability of systems or devices such as sensors, robots, conveyors are defined as the probability that they will work correctly for a given time under defined conditions of work. The most popular method for estimating reliability parameters uses the theory of probability to forecast a value of MTTF (Mean Time to Failure), MTBF (Mean Time

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Between Failures) and MTTR (Mean Time to Repair). The use of normal, exponential, triangular distributions to describe both failure and repair times are often used. In practice, for description of reliability, the parameter MTTF is normally used, which is the expected value of exponentially distributed random variable with failure rate λ. In the case of repairable objects, the parameter MTBF and the MTTR are used.

MTBF = MTTF + MTTR

Machinery failures affect the availability of means of production and may cause severe disturbances in production processes. The average availability is given by:

Availability = MTTF/ MTBF

1.2 Equipment Reliability & Maintenance of Manufacturing Lines

Manufacturing equipment reliability is a significant factor that plays an important role in the ability of equipment to perform to the required levels in operation. Reliability is a measure of an equipment's ability to operate efficiently within set limits and confines of time (Thoma, et al., 2016). Optimizing reliability is paramount for the successful operation of equipment and the minimization of costs associated with downtime and unexpected breakdowns (Rosita & Rada, 2021). Equipment that spends most of its time running efficiently under continuous operations, indicates that reliability is being achieved due to regular maintenance activities being done thus delivering smooth operation. Maintenance is an important consideration in the enhancement of equipment reliability. Measures such as MTTF, MTBF and MTTR help define the reliability of a given station/line (Forsthoffer, 2017) (Prasetyo & Rosita, 2020). Consistent maintenance ensures that manufacturing lines operate to their optimum performance and achieve their business targets (Roy, et al., 2016). MTTR is easily determined using the number of repair hours divide by the total number of repairs within that specified period. The higher the MTTR the greater it negatively affects line throughput. Another measure of line reliability is MTTF and is determined by dividing the total number of operation hours within a predetermined period by the number of failures (Pancholi & Bhatt, 2016). Mean Time Between Failure (MTBF) is the sum of MTTF and MTTR. Maintenance is a set of organised activities that are carried out to keep an item in its best operational condition with minimum cost acquired. The cost at times may appear high in the beginning, but they are intended to keep the overall condition of the equipment better and its operating and other expenses low (considered over its life span) (Jawalkar, 2016). It is also important to improve equipment reliability throughout an equipment's life to meet the business goals and objectives (Rosita & Rada, 2021).

A goal of high performing manufacturing companies including Johnson & Johnson Vision Care (JJVC) are as follows:

1. Eliminate/reduce the unplanned maintenance activities (station set-up after component changeout, minor station adjustments/tweaking to improve station performance) by designing out these non-value add and sometimes repetitive activities during the original equipment design.
2. Reduce the planned maintenance activities (component changeout) to a minimum, and then design the line to require the minimum time to replace this component/system with little/no set-up thereafter.

The equipment design has a significant influence on all these factors. More reliable components are selected requiring less frequent maintenance and the equipment design is such that it allows components to be replaced quickly with minimal/no set-ups post change-out. Simulation is a key technology for the development of planning and exploratory models to optimize decision making including the design and operation of these complex and smart production systems (Ferreira, et al., 2021). Simulation is a tool that was used by the author to verify and aid in helping to confirm the performance capability of the equipment design before it is built. Reducing both the planned and unplanned maintenance activities has the effect of increasing the available time that the manufacturing line is available to run, thus increasing line efficiency. Simulation is one approach that can be used to predict the performance capability of new manufacturing lines during the design stage. If the new line is not already built/running, the simulation model can use data (station cycle times and reliability) from pervious similar equipment designs or actual component data supplied by the Original Equipment Supplier (OEM).

2. DEVELOPMENT, VERIFICATION AND VALIDATION OF THE TRAY LOADER DIGITAL MODEL

2.1 Industrial Use Case Overview

A digital model of an industrial system (Fig 1) known as a Tray Loading System was developed using JaamSim software.

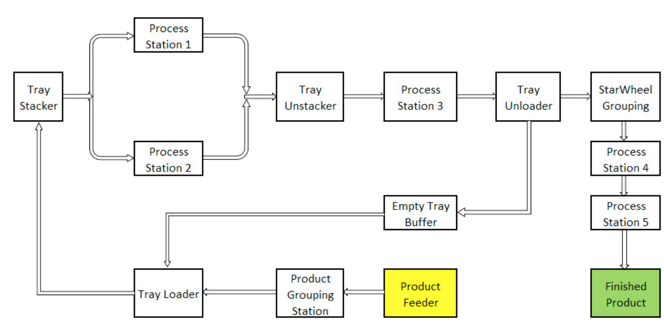


Fig 1: Automated Tray Loading System Industrial Case

This system consists of individual product (p) that arrives from an upstream line to a product feeder at defined arrival times. These are then grouped into multiples of 10. The group of products are then loaded into empty plastic trays that can hold up to 660 parts. Once filled the plastic tray moves at a defined cycle time to a tray stacker. The tray stacker accumulates the filled trays into groups of 30. This group of 30 trays then undergoes a batch process in either Process station 1 or 2 under defined conditions. Upon completion of this batch process, the trays of product leave Process Station 1 or 2, where a tray unstacking operation takes place. Each individual tray of product undergoes a further process step (Process Station 3), again under defined conditions. Once a tray is finished at Process Station 3, the product is removed from the tray at the Tray Unloading station and is then passed to the Star Wheel grouping station, where the product is now grouped into batches of 30. These groups are then passed to Process Station 4 and 5 for the final finishing process. The empty trays from the tray unloading station, are returned to the empty tray buffer and finally back to the tray loader operation, to repeat the overall process. The digital model developed, will simulate this whole operation, considering the following 5 points:

1. Entities (units of Product) per arrival.
2. Service times for process stations, travel times for conveyors
3. Probability distributions for reliability and repair of stations.
4. Conditions for process stations to process and pass product to the next station.
5. Queue size and location.

2.2 Verification of the Tray Loader Digital Model:

A detailed verification process was undertaken on the Tray Loader digital model following the Logical/mathematical verification, program/code verification steps outlined by *(Davis, 1992)* and the detailed knowledge of the author on the actual system. All the Tray Loader Objects, Service Times, Steps, Thresholds, Maintenance conditions and Threshold condition logic were all verified and confirmed to be correct to how the actual line operates. A detailed verification checklist was completed on the Tray Loader digital model. As part of the digital model verification process it was important to verify that the product flow into and out of the various simulation objects (as seen from the JaamSim GUI) are identical to what actually occurs on the tray loader line. This verification process allowed any additions or changes to the simulation logic to be corrected, verified, and visualised immediately. It was through the ongoing and iterative model verification and the testing process during model development, that a realistic model of the actual dynamic interactions was developed and fine-tuned. During this phase of model verification, the weak points of the system were discovered and corrected. It is extremely advantageous to find these early-stage simulation bugs, thus allowing a well-tested and robust system to be developed.

2.3 Validation of the Tray Loader Digital Model

The approach taken for developing the Tray Loader digital model followed the steps described by (Law, 2019).
Step 5 of this approach deals with confirming that the programmed model is valid. The model is run using the standard basic settings from the actual tray loader system. The simulation model output data for the system was compared with the comparable output data collected from the actual system. This is called results validation. If the results are consistent with how the system should operate, then the simulation model is said to have face validity. Sensitivity analyses is performed on the programmed model to see which factors have the greatest impact on the performance measures and, thus, must be modelled carefully (Law, 2019). According to (Kleijnen, 1995), validation is concerned with determining whether the conceptual digital model (as opposed to the computer program) is an accurate representation of the system under study. (Kleijnen, 1995) outlines the following three (3) steps to validate a simulation model.

1. Obtaining real-world data from the actual system.
2. Tests for comparing simulated and real data (namely graphical, Schruben-Turing or t tests).
3. Sensitivity analysis (using statistical design of experiments with associated regression analysis).

The above approach was used to validate the Tray Loader digital model, see section 3 for more detail. Actual Tray Loader system data was collected from the historian database for all the relevant process stations used in the digital model. The data collected included input feed rate, yield, throughput and uptime per minute for each process station. Excel macros were then developed to calculate the equipment reliability metrics namely: Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) for each of the process stations using the uptime/minute data. The Input feed rate, yield, output data and the MTBF/MTTR for each process station was analysed, outliers removed, and distributions determined along with the distribution parameters. Minitab® is used to analyse all the data obtained. Minitab® is a statistical analysis software that assists in the analysis of data collected from any process and provides a simple, effective way to input the data, manipulate that data and statistically analyse it. The methodology used to determine the MTTR and MTBF for the actual Tray Loader System will be described in section 3.

3. DETERMINATION OF SIMULATION INPUT DATA

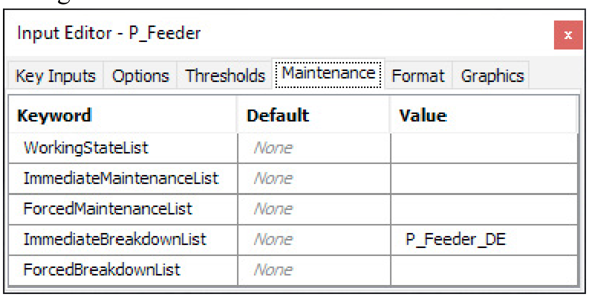
3.1 JaamSim Downtime Entity

Planned maintenance and breakdowns are modelled using the DowntimeEntity, which generates random or scheduled events based on either working time or calendar time. Normally, a maintenance activity is scheduled to occur at regular intervals based on calendar time. Breakdowns are normally modelled to occur randomly based on the working time for the object. The '*DowntimeEntity*' object in JaamSim is used to generate planned and unplanned maintenance events for various types of objects (workstations, buffers, conveyors). The *DowntimeEntity* generates the downtime events and their durations, but the objects that use one or more *DowntimeEntities* must provide their own logic for halting. See Table 1 for the list of *DowntimeEntity* Input parameters used in the Tray Loader application.

Table 1. JaamSim Downtime Entity Input Parameters.

Keyword	Description
Description	A free form string describing the Entity
FirstDowntime	The calendar or working time for the first planned or unplanned maintenance event. If an input is not provided, the first maintenance event is determined by the input for the Interval keyword. A number, an object that returns a number, or an expression can be entered.
IntervalWorkingEntity	The object whose working time determines the occurrence of the planned or unplanned maintenance events. Calendar time is used if the input is left blank.
DurationWorkingEntity	The object whose working time determines the completion of the planned or unplanned maintenance activity. Calendar time is used if the input is left blank.
Interval	The calendar or working time between the start of the last planned or unplanned maintenance activity and the start of the next maintenance activity. A number, an expression, or an object that returns a number can be entered.
Duration	The calendar or working time required to complete the planned or unplanned maintenance activity. A number, an expression, or an object that returns a number can be entered.
MaxDowntimesPending	The maximum number of downtimes pending for the downtime event

In JaamSim a DowntimeEntity object is then dragged and dropped from the JaamSim Model Builder to the application view window. On the Tray Loader digital model, one station called *P_Feeder*. One of the parameter settings to be configured is the *ImmediateBreakdownList* located within the maintenance tab. *ImmediateBreakdownList* is modelled in the Tray Loader application as it is unplanned, takes the production line immediately out of operation and is not accounted for in the business plan schedules. A *DowntimeEntity* object called *P_Feeder_DE* is referenced within the corresponding value cell for the *P_Feeder* object, see Fig 2.

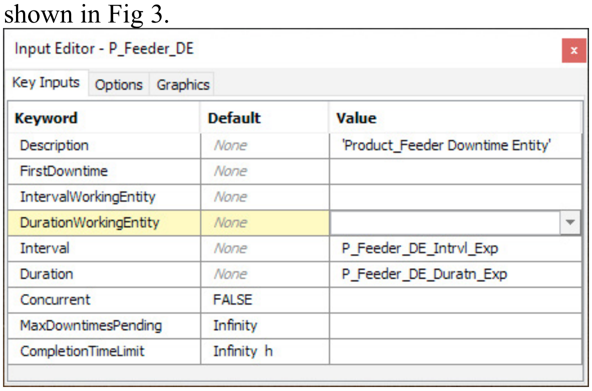

Input Editor - P_Feeder

Key Inputs | Options | Thresholds | Maintenance | Format | Graphics

Keyword	Default	Value
WorkingStateList	None	
ImmediateMaintenanceList	None	
ForcedMaintenanceList	None	
ImmediateBreakdownList	None	P_Feeder_DE
ForcedBreakdownList	None	

Fig 2: P_Feeder Object Maintenance Configuration

ImmediateBreakdownList is a list of DowntimeEntities representing unplanned maintenance performed immediately, interrupting any work underway at present. Other maintenance types such as *ForcedMaintenanceList*, *ForcedBreakdownList* or *ImmediateMaintenanceList* can also be configured depending on the user application to be modelled. A DowntimeEntity object is then dragged and dropped from the JaamSim Model Builder to the view window. The object is called *P_Feeder_DE* with input parameters configured as shown in Fig 3.

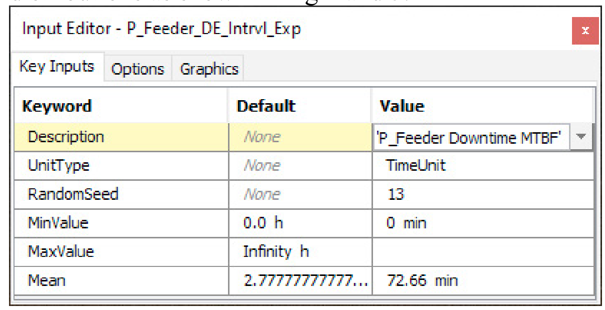

Input Editor - P_Feeder_DE

Key Inputs | Options | Graphics

Keyword	Default	Value
Description	None	'Product_Feeder Downtime Entity'
FirstDowntime	None	
IntervalWorkingEntity	None	
DurationWorkingEntity	None	
Interval	None	P_Feeder_DE_Intrvl_Exp
Duration	None	P_Feeder_DE_Duratn_Exp
Concurrent	FALSE	
MaxDowntimesPending	Infinity	
CompletionTimeLimit	Infinity h	

Fig 3: P_Feeder_DE Parameter Configuration

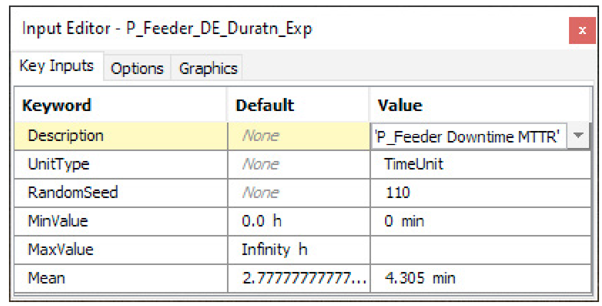
The *Interval* is the working time between the start of the last unplanned downtime activity and the start of the next downtime activity. A number, an expression, or an object that returns a number can be entered. The *Duration* is the working time required to complete the downtime activity. A number, an expression, or an object that returns a number can be entered. In this research, *Interval* is used to replicate the Mean Time Between Failures (MTBF), whereas *Duration* is used to replicate Mean Time to Repair (MTTR) for each object of the model. Two Exponential Probability Distribution objects are then dragged and dropped from the JaamSim Model Builder to the view window. The objects are called *P_Feeder_DE_Intrvl_Exp* and *P_Feeder_DE_Duratn_Exp* respectively to simulate the MTBF and MTTR respectively for the P_Feeder station. Input parameters are configured for both distributions as shown in Fig 4 and 5.


Input Editor - P_Feeder_DE_Intrvl_Exp

Key Inputs | Options | Graphics

Keyword	Default	Value
Description	None	'P_Feeder Downtime MTBF'
UnitType	None	TimeUnit
RandomSeed	None	13
MinValue	0.0 h	0 min
MaxValue	Infinity h	
Mean	2.77777777777...	72.66 min

Fig 4: P_Feeder Station MTBF Configuration


Input Editor - P_Feeder_DE_Duratn_Exp

Key Inputs | Options | Graphics

Keyword	Default	Value
Description	None	'P_Feeder Downtime MTTR'
UnitType	None	TimeUnit
RandomSeed	None	110
MinValue	0.0 h	0 min
MaxValue	Infinity h	
Mean	2.77777777777...	4.305 min

Fig 5: P_Feeder Station MTTR Configuration

The *UnitType* is selected as *TimeUnit*, *RandomSeed* is automatically selected by JaamSim and *MinValue* is set to 0 sec. A python program was developed to automatically take settings/parameters from an excel file and populate the values for means into both distributions automatically.

3.2 Determining the Actual values for MTBF and MTTR

It is important that the downtime distribution for both Interval (MTBF) and duration (MTTR) are correctly set-up for each station and are reflective of the reliability from the actual Tray loader system. If these distributions, their value's and/or parameter settings are not representative of the actual system, then all results obtained from the simulation model will be of little use. In order to determine the actual distributions and parameter values for the MTBF and MTTR for the Tray loader system, data was collected from the historian database over a period of 186 shifts (1 shift = 12hrs). Total uptime for each station was recorded every minute over a period of 129,000 minutes. The cumulative total uptime (sec) was recorded for each station of interest from the database. Briefly outlining how the data was captured and analysed, refer to Table 2 for example of how Mean Time Between Failures (Interval) and Mean Time to Repair (Duration) is determined for P_Feeder station. The cumulative uptime for a particular station is recorded at 1 min intervals. The uptime/min is then determined for each minute over the whole duration. From Table 2, the uptime for 7:05:00 is 155 – 115 = 40sec. The % uptime between 7:04:00 and 07:05:00 = $\frac{40}{60} \times 100$ = 66.6%. This process is repeated for each minute. For the purpose of calculating the MTTF and MTTR, the total uptime is calculated by adding the uptime for each minute until the station goes stops (< 60 sec uptime for that minute). This give the duration that the station was running until a stoppage occurs, thus Mean Time To Failure can then be calculated. Likewise, the number of seconds that the station was down is recorded which is then used to calculate the Mean Time to

Repair. Hence from Table 2, we can see that between 07:00:00 and 07:10:00, the station was down for 5 secs, running for 115 sec, down for 140 sec, running for 100 sec and down for 80 sec. MTBF is calculated as the sum of MTTF and MTTR.

Table 2. Sample MTBF and MTTR for P_Feeder Station

Station #	Time	Cumulative Uptime (Sec)	Uptime/ Min (Sec)	Interval - MTTF (Min)	Duration MTTR (Min)	Interval - MTBF (Min)
1	7:01:00	55	55		5	
1	7:02:00	115	60	115		120
1	7:03:00	115	0			
1	7:04:00	115	0			
1	7:05:00	155	40		140	
1	7:06:00	215	60	100		240
1	7:07:00	215	0			
1	7:08:00	255	40		80	
1	7:09:00	315	60			
1	7:10:00	375	60			
1	7:11:00	400	25	185		265
1	7:12:00	400	0			
1	7:13:00	400	0			
1	7:14:00	450	50		165	
1	7:15:00	490	40	90		255
1	7:16:00	490	0			

The durations/frequencies that this station was running will be used to calculate MTBF distribution, similarly the durations/frequencies that this station was down will be used to calculate MTTR distribution. This whole process is repeated for every station used in the Tray Loader JaamSim model over a period of 129,000 minutes. The Interval (MTBF) and Duration (MTTR) data just described above is determined. Excel macros were developed to automatically determine the MTTF, MTTR and MTBF data in Table 2. This data is then entered into Minitab where outliers are removed (See Fig 6).

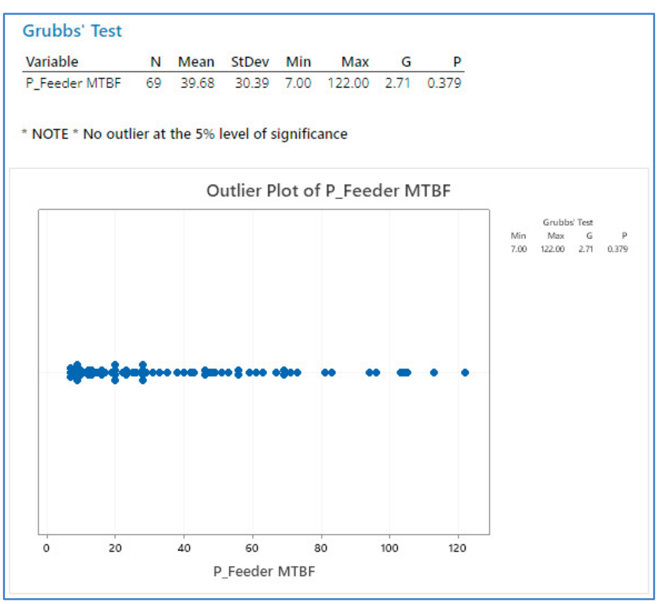


Fig 6: P_Feeder MTBF Grubbs Outlier Test

A Minitab outlier test is performed on the data using the Grubbs Outlier method (See Fig 6), where statistical outliers are removed first, then followed by any special cause outliers such as planned downtime activities. Once outliers were removed, the Grubbs outlier test indicated that there was no outlier MTBF data at the 5% level of significance. The same process was repeated for the P_Feeder MTTR data. A best fitting distribution identification process is then completed on both the MTBF and MTTR data again using Minitab. This analysis indicates that an Exponential distribution was the most appropriate fit for the *P_Feeder* MTBF data, with a mean (μ) of 72.68 Mins. See Fig 7 for Exponential distribution plot of the *P_Feeder* MTBF data.

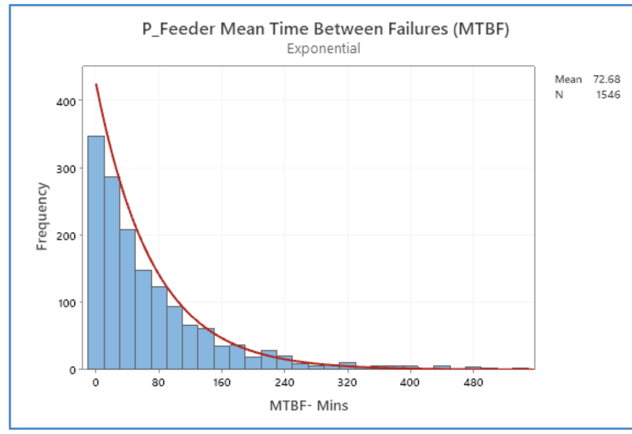


Fig 7: P_Feeder MTBF Distribution Plot

Likewise, a similar process is repeated for the *P_Feeder* MTTR data, where the data is entered into Minitab, outliers removed, and the most appropriate distribution selected. As can be seen in Fig 8, the Exponential distribution with mean (μ) of 4.305 min is the best fit to the *P_Feeder* MTTR data.

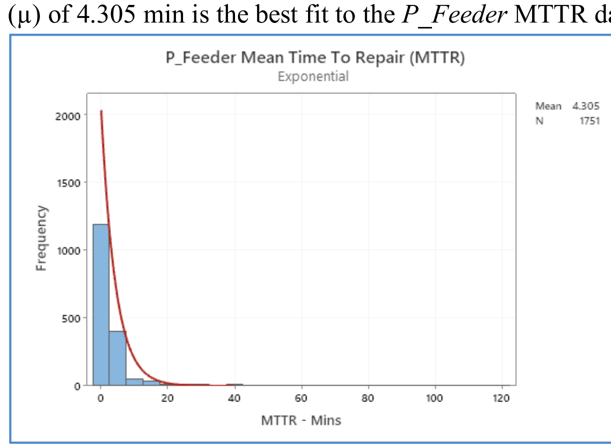


Fig 8: P_Feeder MTTR Distribution Plot

The above process outlined for calculating the actual distributions and parameters for *P_Feeder* MTBF and MTTR is repeated for the remaining 7 stations used in the Tray Loader simulation model.

3.3 Running the Tray Loader Digital Model

The digital model of the Tray Loader was set-up with an initial warm-up period of 8hrs. This enables the Tray Loader model to completely fill with product before the actual simulation run starts. Each simulation run is set to 12hrs, to replicate the 12hr shift that is used to operate the actual Tray Loader system. A simulation test run of 5000 replications was executed. The throughput data from each workstation along with the reliability data and tray buffer data from the 5000 simulation replications was written to a .csv file. The results from the simulation run were then compared with data from the actual Tray Loader system over an extended time period. The mean(μ) and standard deviation(σ) from the simulation results and actual line data are statistically compared to each other to confirm that the simulation model is a true representation of the actual Tray Loader system. This statistical analysis is completed for the P_Feeder workstation (both throughput and reliability) using a hypothesis tests known as a two-sample t-test, See Table 3 for results.

Table 3. Verification data of Tray Loader Digital Model

Station Name	Data Type	Data Source	Mean(μ)	Prediction Error	2-Sample t test P Value	Null Hypothesis	Null Hypothesis Result
P_Feeder	Throughput	Simulation (μ)	322,733	-0.20%	0.609	H_o: $pf_{savg} - pf_{aavg} = 0$	Accept
		Actual (μ)	322,096				
		Simulation (σ)	12,401	7.72%	0.281	H_o: $pf_{sstd} - pf_{astd} = 0$	Accept
		Actual (σ)	13,438				
P_Feeder	Reliability	Simulation	0.93862	-0.10%	0.352	H_o: $pf_{savg} - pf_{aavg} = 0$	Accept
		Actual	0.93769				

The summary statistics taken from the comparison of the actual *P_Feeder* throughputs and the simulation results are provided in Table 3 along with all the station reliability data for actual and simulated results. The maximum prediction error for all the mean data is 0.2% and the p-values for all the data are significantly greater than 0.05. The prediction error for the standard deviation on *P_Feeder* throughput is 7.72% which is expected, as the digital model has less variability/noise. This is not a significant factor in the model development and can be explained that some additional variability/noise occurs on the actual line due to human interactions, external factors such as materials availability, facility/utility system downtimes which have not been included in the model generation. Based on the analysis of the simulation model and the high level of accuracy with the empirical data gathered from the actual production line, the approach gives a high degree of confidence that the Tray Loader digital model is valid, accurately represents the real physical and operational production environment and provides a solid basis for the further use of this digital model.

4. CONCLUSIONS

As manufacturing capital equipment is expensive, it is necessary that the equipment once in operation is reliable and delivers to the business plan targets. Simulation is an invaluable tool to confirm that an automated manufacturing line can produce to the required business objectives before and after it goes into operation. Implementing the actual changes to equipment to improve reliability can be both time consuming and expensive. Simulation can be used to verify these improvements before the equipment is modified. Simulation can be a subset of an overall digital manufacturing system that enables the optimization of a manufacturing line during the line design stage or when the line is put into operation. The use of this technology gives a deeper understanding of what can occur on the manufacturing line when it is running. A simulation model when combined with optimization engine, can be used to identify problems before they occur and aid in the selection of optimum parameters to run the line before it is fully designed or built. Digital model technology supports other Industry 4.0 technologies such as predictive maintenance, OEE improvement, waste reduction, improve batch changeover times and to improve product quality (Shao, et al., 2019). It allows for efficient design and development, linking 3D models with simulation and emulation of equipment control code. In addition, having a digital model enables virtual line analysis, removing the physical restraints of expert engineers having to be on your location (Qi, et al., 2021). The author has demonstrated how the development of digital model can be validated for the study of equipment design, maintenance and reliability of an automated production line in the medical devices industry.

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