The Implementation of Disruptive Measures to Enhance Productivity in an Advanced-Manufacturing Environment

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Abstract— **The performance of a manufacturing process and the need to increase throughput and reduce the cost of production are of the highest interest among modern manufacturers. Classical mathematical models developed were used to describe the operation of a robot during a complex pick and place task in a virtual manufacturing environment. The design parameters of the conveyor system were examined. Existing designs were studied and modeled to select the best operating speed to optimize throughput during the manufacturing system. The modeled design parameters were analyzed using MATLAB. The results were presented graphically with an optimal throughput obtained at an operating speed of 390m/seconds, operating time of 0.4secs, and power consumption of 12700W. The operation of the robotic arm was manipulated during service to determine the angle of placement that yielded a consistent and efficient throughput during the pick and place task. Consequently, an optimal throughput was reached when setting the manipulator at an angle of 88 degrees.**

Keywords- Automation of manufacturing process; modelling of robotic arm; simulation of results.

I. INTRODUCTION

The goals of the fourth industrial technology were to improve the efficiency of the manufacturing process, improve product quality, and enhance safety and security in manufacturing industries. Industry 4.0 involved the integration of intelligent, disruptive technologies into the manufacturing environment by focusing on automation, real-time data, artificial intelligence, machine learning, etc. The new technology uses its automation approach to boost productivity and output, increase efficiency, and create an intelligent manufacturing environment. [1][2]. Industry 4.0 has emerged with various disruptive technologies that can transform multiple manufacturing sectors from labor-intensive processes to a modernized automation process [3][4]. Implementing robotics in an advanced manufacturing environment has been a trending technology that requires further studies, innovations, and adaptations.

Robotics has been used in a wide range of applications. Applications include transporting materials and parts from conveyor systems to various stations, assembling parts, painting, sorting, packaging and labeling, inspection and testing, picking and place, materials handling, palletizing, etc. [5]. The applications of robotic technology to various systems were achieved with appreciable high speed, precision, and endurance limit [6][7]. The implementation of robotics in the manufacturing sector has improved the economic situation of various industries by enhancing the production process, product quality, and throughput rate. The robotic system uses several innovative sensory devices and control techniques to improve agility and productivity [8][9]. The importance of research in robotics in a recent study is to find solutions to manufacturing problems [10].

Enhancing a manufacturing process has become more apparent due to its technological impact on an advanced manufacturing environment. Recently, there have been various attempts to improve the service of industrial robots to perform some complex and time-consuming tasks in the manufacturing environment [11]. Implementing industrial robots as a disruptive technology in performing tasks has enabled technological growth in the manufacturing sector [12]. The behavior of a manufacturing system can be better expressed with classical models. In this paper, the throughput rate of a manufacturing system was enhanced. Classical mathematical models were used to describe a manufacturing environment, whereas robot was used to perform a complex pick and place task. The scenario was analyzed using various mathematical tools. The manufacturing scenario was validated by manipulating the robotic arm motion to select the best operating angle.

II. LITERATURE REVIEW

Effective implementation of various automation tools adequately increased production performance and machine up-time. Industry 4.0 introduced various disruptive technologies and has supported manufacturers to have outputs at a reduced cost. Automation of services in an advanced manufacturing environment has reshaped the global market for higher productivity [13]. The uses of disruptive manufacturing technologies have brought about numerous improvements in productivity in the manufacturing process. In recent technological advancements, robots have been disruptive tools and have introduced tremendous changes in the advanced manufacturing environment. Robots have been widely used among manufacturers due to their exceptional efficiency and ability to perform complex tasks within the shortest period [14][15]. Robotics applications reinforced the manufacturing industries and enabled competitiveness among manufacturers [16].

Various disruptive technologies have been developed to support and enhance the smooth running of multiple stages of the manufacturing processes [17][18]. The use of automation in augmenting human activities has increasingly improved the efficiency of the manufacturing processes. Industrial robots are efficient automation tools with higher flexibility and can be programmed to perform various tasks within a short time [19][20]. The research presented in [20] [21][22] showed how robotic manufacturing systems were optimized for optimal efficiency and productivity. The part's positioning to be picked up can affect the robot's performance in an advanced manufacturing environment [23][24]. In this present work, robots were implemented to perform a pick and place task. The scenario was studied to determine the best angle of twist that can produce an optimal throughput rate. The research showed that at an angle of 88 degrees, the manipulator performed excellently as when performing the desired task. This research outcome can be useful among manufacturers in the competitive market.

III. METHODOLOGICAL APPROACH

A virtual manufacturing scenario was developed and studied to determine the impact of using a robot to perform the complex pick and place task in a manufacturing environment. Classical mathematical models were developed to describe each process involved. The design parameters of an existing conveyor system were studied and simulated to obtain the best design parameter that can yield an optimal throughput rate during a manufacturing process. Also, the waiting time involved during the packaging stage was modeled and studied. The manufacturing process involved parts arriving via a conveyor system from multiple stations to a buffer station. The arriving parts were picked up and placed by a robot.

The arrival behavior followed a Poisson process with varying mean arrival rates. The arrival of the parts from the buffer station took the form of a negative exponential distribution and observed the impatient behavior of customers in the M/G/I queuing system. The M/G/I queuing system follows a Poisson process varying with mean arrival rate λ with a general service time distribution. The repeatability motion of the robotic arm ensures the system has a deterministic feeding time μ (mean service time). Parts that were not picked up during the initial cycle were redirected for service in the next cycle.

Mathematical models were developed and analyzed using the queuing mathematical theory. The average queuing time was modeled. This enabled proper optimization of the performance of each robot with its corresponding queue. Various mathematical expressions were developed and solved using the Newton-Rap son iteration method. Some values were assumed and implemented into the equation to test the efficiency of the models.

A. Model analysis for an optimal throughput rate

During the complex pick and place task, the robot does not pick up all arriving parts as the conveyor move past the vision camera. Other parts were redirected to join the following arriving parts. During the traveling period of parts, there existed a continuous movement of parts with a minimum distance/gapα between the work envelope and the boundaries within which the arriving parts exist. The number of visible parts was fed along with the conveyor system and denoted as N_f. The center point of the arriving part was determined within the Height and width of the work envelope. The Diameter of the part fed into the process was assumed to be less than 20mm. The velocities of the conveyor belts were the same.

Assumptions

- The system was not saturated or starved.
- There exist continuous motion in the conveyor system
- The Height and width of the work envelope were assumed to be equal
- All parts were well guided to avoid slipping off

The following notations and parameters were used to arrive at a suitable expression that was implemented to obtain higher throughput.

Notation/parameters

N_f=Number of part fed through the work envelope
c = Centre of work envelope
d = Diameter of fed part
α = Minimum clearance required = d/2
w = Height, and width of the workpiece
P_b= probability that work has been fully cleared
v= Velocity of the belt
T_r= The robot throughput rate
R_b=The arrival rate of parts from the conveyor (parts/mm^2).

An impatient customer's renewal theorem was implemented to obtain a suitable mathematical expression for optimal throughput. In (1), the Velocity of the conveyor system v is expressed as:

$$V = \frac{\pi D n}{60} \quad (1)$$

Equation (2) was developed to represent the probability that the work piece has been fully cleared from the work envelope.

$$p_b = \frac{(w-d-2\alpha)^2}{(w-d)^2} \quad (2)$$

In equation(3), the center of the work envelope c was modeled while considering the width and height of the work envelope and the Diameter of the conveyor belt with speed (v).

$$c = \frac{w\pi(\alpha+d)^2}{(w-d)^2 v} \quad (3)$$

Similarly, in (4), the expression for the arrival rate of parts from the conveyor to the server (robot) was modeled as:

$$r_b = \frac{1}{c}\frac{(w-d)^2 v}{w\pi(\alpha+d)^2} \quad (4)$$

In (5), the number of parts fed through the work envelope was obtained by considering the width and height of the work envelope, the Velocity of the conveyor, the probability of cleared work from the work envelope, the center of the work envelope, and the arrival rate of parts from buffer station to the pickup point.

$$[N_f] = \left(\frac{w}{v}\right) r_b p_b e^{-rbc} \quad (5)$$

The throughput rate was also determined by finding the relationship between the number of parts fed through the work envelope, the width of the work envelope, and Velocity of the conveyor system, as indicated in equation (6).

$$T_r = \frac{N_f}{[\left(\frac{w}{v}\right) + t_p + [N_f]t_c]} \quad (6)$$

B. Mathematical Model for Queuing Theory and Newton-Rap son.

The model used in the research described the waiting time during the packaging stage in a virtual manufacturing environment. The system performance was modeled using a Poisson distribution function where the service times were exponentially distributed. Classical mathematical models were developed for describing and making a decision in the packaging stage of the virtual manufacturing process.

Parameters were assumed under operating conditions, and values were effectively used to describe the manufacturing system. Parameters that were used within the waiting line model include the cost of waiting per hour (C_w), the average number of product in queue (L_s), the cost of robot/hour (C_p), the average number of product arriving from the machine per unit time (λ_i), packaging rate which represented the service rate per unit time measured per hour (μ), utility factor of the server which is the robot(ρ_n).

The queuing mathematical theory was then used in analyzing the classical models, and the queuing mathematical theory was used in analyzing the classical models. The models that were used in representing the packaging stage is summarized below:

The products arrival rate was presented as

$$\sum_{i=1}^{n} \lambda_i \,(\mathrm{t}) = n\lambda(t) \quad (7)$$

A discrete value was assumed for the total number of products arriving during the packaging stage and was expressed as:

$$N = n\lambda_t \mathrm{x}\ \mathrm{t} \quad (8)$$

Total product packed by available robots was expressed as:

$$\mu_j(t) \times t \times m \quad (9)$$

During the packaging phase, the utility factor of robots was expressed as:

$$\rho_n(t) = \frac{\lambda_i(\mathrm{t})}{\mu_j(t)} \quad (10)$$

The mean queue time required by each robot and the production rate of each robot was expressed as:

$$p_j(t) = (\lambda_i + \mu_j)\rho_n(t) + \lambda_i\rho_{n-1}(t) + \rho_{n+1}(t) \quad (11)$$

The overall productivity rate of the system $\rho_n(t)$ was modeled as:

$$\rho_n(t) = \left(\sum_{i=1}^{n} \lambda_i + \sum_{j=1}^{n} \lambda_i\,\mu_j\right)\rho_n(t) + \sum_{i=1}^{n} \lambda\,\rho_{n-1}(t) + \sum_{j=1}^{m} \mu_j\rho_{n+1}(t) fort \to \infty \quad (12)$$

For a discrete value of time t;

$$\rho_n(t) = \rho_n(\mathrm{t}) + \lambda n\rho_{n-1}(t) + \mu(t)\rho_{n+1}(t) \quad (13)$$

The waiting time denoted by W is expressed in 14:

$$W = \sum_{j=1}^{m} \mu_j - \sum_{j=1}^{m} \lambda_i, \quad \mathrm{w} = \frac{1}{\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i}} \quad (14)$$

Waiting time (unit/hour) expressed as:

$$L_s = \frac{\mathrm{n}_{\lambda i}}{\mathrm{n}_{\lambda t - \mathrm{m}_{\mu_j}}} \quad (15)$$

The cost of production T is given in (16)

$$T = mcp\mu_j + c_w\rho_n wL_s \quad (16)$$

After substituting the parameters into (16), the production cost gives:

$$T = mC_p\mu_j + C_w\left(\frac{\lambda_i^{\,2}}{(\mu_j(\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i})^2}\right) \quad (17)$$

The system's performance was optimized using the waiting time model expressed in (15). The optimization process was achieved by differentiating the model to the service rate of each robot.

$$C_p + \frac{\lambda^2[(\mu-\lambda)^2 + 2\mu(\mu-\lambda)]}{\mu^2(\mu-\lambda)^4} = 0 \quad (18)$$

The model for optimal service was modeled as:

$$C_p\mu^5 - 3C_p\mu^4\lambda + 3C_p\mu^3\lambda^2 - C_p\mu^2\lambda^3 + 3\mu\lambda^2 C_w - C_w\lambda^3 = 0 \quad (19)$$

C. Simulation Using Newton-Raphson Method.

The Newton-Rap son Iteration method determined the approximate values used in the simulation of the models presented in the thesis. Newton-Rap son iteration method based its strategy on finding an approximate value for the root of a valued function of x [25]. Using the Newton-Rap son equation reduced the errors that were likely to set in when calculating the roots of functions. The efficiency of the Newton-Rap son method was the advantage it has over other methods. This method converges fast when compared with the Gauss Seidel, and other methods used in finding roots of quadratic equations. If it converges we get root (answer) in less number of steps. It requires only one guess.

Formulation of this method is simple. The Newton-Rap son iteration method was used to find the zeros of the arbitrary equations that were implemented during the manufacturing scenario; here, the specific root of a function depended on the initial value. The Newton-Rap son's iteration strategy was utilized in the research as follows:

Given that the root of the derived equation was r, let x_0 be the estimated value of r, h represents a measure of the approximate value of x_0 from the exact value.
Where

$$r = x_0 + h, h = r - x_0 \tag{20}$$

h was very small and its linear approximation was represented as:

$$0 = f(r) = f(x_0 + h) \approx f(x_0) + hf^{'}(x_0) \tag{21}$$

The mathematical model was valid if, $f^{'}(x_0)$ was approximately equals to zero.

$$h \approx \frac{f(x_0)}{f^{'}(x_0)} \tag{22}$$

$$r = x_0 + h \approx x_0 - \frac{f(x_0)}{f^{'}(x_0)} \tag{23}$$

Therefore, the estimated value x_1 of r yielded:

$$x_1 = x_0 - \frac{f(x_0)}{f^{'}(x_0)} \tag{24}$$

Similarly, x_2 was derived as a function of x_1

$$x_2 = x_1 - \frac{f(x_1)}{f^{'}(x_1)} \tag{25}$$

For a required number of x, x_n is the next approximate value.
Therefore, x_{n+1} was modelled as:

$$x_{n+1} = x_n - \frac{f(x_n)}{f^{'}(x_n)} \tag{26}$$

The Newton Rap son Iteration was used for analyzing the service rate (μ), and modeled as:

$$\mu_{n+1} = \mu_n - \frac{f(\mu_n)}{f^{'}(\mu_n)} \tag{27}$$

Equations (28) and (29) represented the first and second-order of the Newton-Rap son iteration model of a production system [1].

$$f(\mu) = C_p\mu^5 - 3C_p\mu^4\lambda + 3C_p\mu^3\lambda^2 - C_p\mu^2\lambda^3 + 3\mu\lambda^2C_w - C_w\lambda^3 \tag{28}$$

$$f^{'}(\mu) = 5C_p\mu^4 - 12C_p\mu^3\lambda + 9C_p\mu^2\lambda^2 - 2C_p\mu\lambda^3 + 3\lambda^2C_w \tag{29}$$

The assumed values for the manufacturing scenario were (C_p = R2/hour, C_w = R0.1/hour, $\lambda_i = 5$ units/hour for 10 machines, μ = 2 units per hour). The values were implemented into the general equation, solved, and the mathematical models were analyzed. Outcomes were simulated using the Newton-Rap son iteration expression. Close approximates values obtained were varied against each other to obtain the presented results graphically.

D. Variation of the Robotic Arm for an Optimal Throughput.

During the complex pick and place task, the robotic arm motion was manipulated to determine the best operating angle that gave an optimal throughput. Three different grasps were involved: the pre-grasp, the grasp, and the post grasp. The pre-grasp provided the suitable positioning of the end-effectors away from the object position and coordinated the trajectory motion to avoid the occurrence of collision during service. Grasping involved positioning the end-effectors with their fingers ready to grip the object for the designated task, while the post-grasp involved moving away of the end-effectors from the point where the object was grasped. The operation was controlled by computing the desired action for the end-effectors to perform the placing down task [25].

Arriving parts from the conveyor were picked up randomly by the manipulator following the first-in, first-out order (FIFO). The vision camera determines the object's position at the robot workspace for immediate pickup. The average operating time was studied and presented in Table 1.

TABLE I. THE AVERAGE TIME SPENT ON THE PICK AND PLACE TASK

S/no	**Time Spent during the pick/place task**		
	Motion	***Task***	***Left/right***
1	Motion 1	The home pose to view an object on the conveyor	4.5
2	Motion 2	Reach object to grasp an object	3.2
3	Motion 3	Moving to the object drop pose	3.0
4	Motion 4	Moving from object dropped pose back to home pose	3.41

An operational variation of the manipulator motion was achieved by varying the angle between 81 degrees and 96 degrees. The effects of varying the angle and other operating parameters were studied to determine its impacts on the throughput rate of the manipulator.

IV. RESULTS AND DISCUSSION

The performance of the robots was examined to study its effects on the throughput rate during a pick and place task. The result in Fig. 1 shows the relationship between the packaging stages of manufacturing against the arrival rate of the products. Fig. 1 indicates that the packaging rates increased as the arrival rate also increased. The result shown in Fig. 1 implied that the number of robots assumed in the decision-making for the proposed model was suitable to solve the waiting line model.

 ISBN: 978-1-61208-966-9

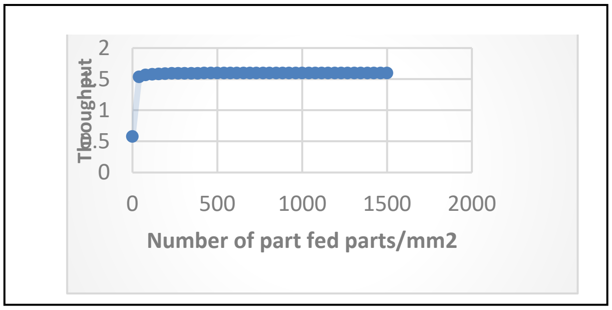

Figure 1. Throughput Rate against Part Fed Through the Conveyor System

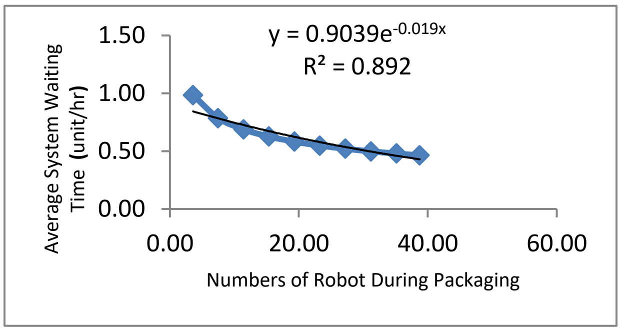

Figure 2. Average Waiting Time Against the Numbers of Robots Used.

During the packaging stage of manufacturing, the average waiting time gradually reduces as the number of robots used to perform the packaging task increases. If more robots were introduced to replace human labor, the lead time would be minimized an efficient production system can be obtained. This is illustrated in Fig 2.

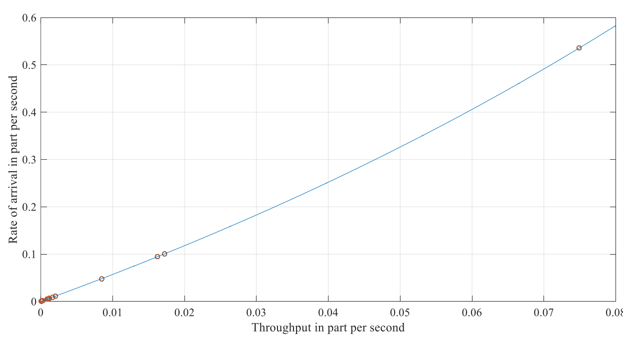

Figure 3. Products Arrival Rate Rb Against the Throughput Tr Rate (Parts/Secs).

The result in Fig. 3 shows an increasing throughput rate in correlation with the product arrival rate. The result shown in Figure 3 implies that the selected design parameters for the conveyor system were efficient.

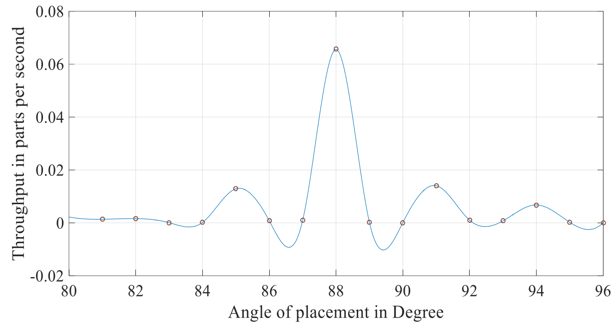

Figure 4. The Average Time Spent for Pick-Place-Task

The robotic arm was varied during the pick and place task to determine the best angle of operation that could produce the highest throughput rate. Result obtained is presented in Fig. 4. This showed that the operational variables of the robotic arm gave an optimal throughput rate at an angle of 88 degrees.

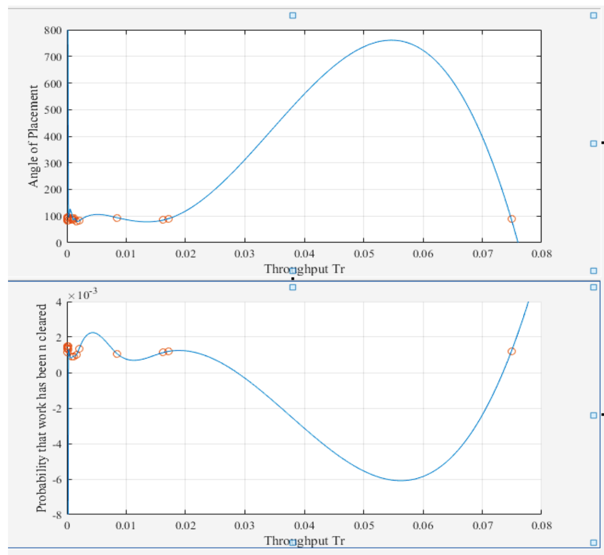

Figure 5. Probability That Work is Being Cleared From the Conveyor Against the Throughput Rates.

The graph in Fig. 5 indicates that the work's probability has been cleared from the conveyor system when measured against the throughput rate. The result showed a closed-looped graph which indicated that as the products arrived, the robots were efficient in picking up from the conveyor faster before it moved past it. The results confirm that the modeled design parameters selected for the conveyor system were efficient for optimal productivity.

V. CONCLUSIONS AND FUTURE WORKS

Classical mathematical models were used in describing a manufacturing process whereby robots were used to perform a complex pick and place task. The design parameters of a conveyor system were examined, and the best operating speed that gave optimal throughput during a complex pick and place task was achieved. This was successfully carried out by developing some mathematical models to study the effect of varying the loads below and above the rated speed of the electric motor. Standard equations were further developed and analyzed. MATLAB was used to simulate and analyze the mathematical models and solved using the engineering equation solver (EES). Results were simulated to obtain and select relevant results that gave optimal throughput at an operating speed of 390m/secs, using time at 0.4secs, and at a power consumption of 12700W.

The average waiting time of the robots during the packaging process was studied using the analytical queuing theory. The average queuing time was further differentiated to optimize the performance of each robot with its corresponding queue. A general equation was developed and further analyzed using the Newton-Raphson iteration method. The results confirmed that the suggested model could be suitable for use when the queuing time needs to be controlled during the packaging stage in a real-life manufacturing scenario.

Furthermore, the robotic arm motion was manipulated during the pick and place task to determine the best operating angle for an efficient production system. An optimal throughput rate during the pick and place task was achieved when the robotic arm was positioned at an angle of 88 degrees. This research outcome can be useful among manufacturers in the competitive market. The research is still in progress whereby further studies will be carried out to determine how effective the derived angle will be when the manipulator is slated for heavy task.

Acknowledgment

The authors acknowledge the support from the University of KwaZulu-Natal for the funding provided for the research work.

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