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Optimizing robotic motion in dynamic manufacturing environments

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ABSTRACT

The field of robotics has been a trending technology over the years due to its ability to revolutionize industries. This study highlights the role of optimized robotic motion in enhancing productivity in dynamic manufacturing environments using MATLAB simulations. By modeling the arrival of manufactured parts in batches via a conveyor system governed by a negative exponential distribution in a Poisson process, MATLAB is employed to design optimal robotic trajectories for pick-and-place operations. The research carefully analyzes parameters such as arrival rates and cycle times to manage the stochastic nature of part delivery. The result reveals a significant improvement in operational efficiency, with throughput increasing by up to 20% due to real-time optimization of robotic motion. The non-linear relationship between throughput and arrival rates highlights the system's complexity, with optimal conditions observed at specific arrival rates, such as 0.16 s for peak efficiency. MATLAB's Polynomial Trajectory Planning tool generates smooth, continuous paths, ensuring that robotic operations dynamically adapt to changing conditions. This foundation supports future innovations in robotic system integration and automated production lines, offering a significant step forward in the application of advanced simulation tools an advanced manufacturing environment.

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1. INTRODUCTION

The emergence of Industry 4.0 represents a revolutionary shift in manufacturing practices, characterized by the integration of advanced technologies such as the internet of things (IoT), big data analytics, artificial intelligence (AI), and robotic automation. This new industrial revolution aims to create smart manufacturing environments. By implementing disruptive technologies, companies can not only optimize their production processes but also improve responsiveness to market demands. Robotics plays a critical role in advancing automation within manufacturing environments. Robots have evolved significantly, transitioning from simple, repetitive tasks to sophisticated systems capable of performing complex operations with high precision [1], [2]. Modern robotic arms, designed to mimic human movements, consist of several limbs connected by joints, allowing both rotational and translational movements. These arms are now capable of performing a variety of tasks, including assembly, welding, painting, and material handling [3]. The end effectors of robotic arms—similar to human hands—improve functionality by enabling robots to grasp, manipulate, and perform complex tasks [4]. These end effectors are controlled by servo motors, offering precise movement capabilities [5]. Additionally, motion sensors and computer algorithms enable automated control, allowing robots to work continuously with minimal human intervention [6].

This level of automation not only improves productivity but also enhances safety by delegating dangerous or monotonous tasks to robotic machines [7]. Implementing AI in robotics further extends the capabilities of these systems. AI algorithms allow robots to learn from their environment and adapt their behavior accordingly [8], [9]. This capability is critical for optimizing motion planning and allows robots to respond effectively to changing conditions in an advanced manufacturing environment [10]. Despite advances in robotics and AI, many manufacturing environments still face challenges in efficiency and productivity. Traditional motion planning methods often rely on predefined trajectories that fail to consider variability in part arrival and operational dynamics [11]. As a result, robots may experience delays, longer cycle times, and reduced throughput rates [12]. These inefficiencies hinder the full potential of automation, resulting in suboptimal resource utilization and increased operational costs [13]. Furthermore, the increasing complexity of manufacturing systems demands a more sophisticated approach to robotic motion planning. Current methods often lack the flexibility required to optimize robotic operations fully. Adaptive and intelligent systems capable of processing real-time data and making instant decisions are critical in dynamic environments [14]. Using real-time data from IoT-enabled sensors, simulation framework generates adaptive trajectories for robotic arms performing pick-and-place operations. This approach not only reduces cycle times but also improves overall throughput rates, overcoming the limitations of traditional motion planning methods [15].

Various operational scenarios have been conducted using MATLAB simulations model, allowing the system to adapt to the stochastic nature of part arrivals and effectively minimize delays, optimizing task execution [16]. The flexibility of this approach allows robots to dynamically adjust their movements based on real-time conditions, improving performance in advanced manufacturing environments [16]. The contribution of this research lies in its potential to transform the landscape of robotic automation in Industry 4.0. By integrating MATLAB simulation into robot motion planning, we provide a solution that not only eliminates existing inefficiencies but also aligns with the broader goals of intelligent manufacturing [4], [17]. Findings have significant implications for the future of industrial automation, paving the way for more intelligent, responsive, and efficient manufacturing processes where throughput rate required to be improved [11].

Related work of key contributions to the field of advanced manufacturing environment focuses on trajectory optimization, machine learning applications, and the integration of modern technologies such as the IoT and simulation tools. Benotsmane *et al*. [18] introduced an innovative "whip-lashing" method for trajectory optimization of industrial robot arms, demonstrating substantial reductions in cycle times and enhanced operational efficiency. This technique highlights the importance of advanced trajectory planning, particularly in environments where minimizing motion time while maintaining precision is crucial for reducing production costs and improving throughput. The concept of minimum jerk trajectory planning has been studied extensively to achieve smoother and more efficient robotic movements. Devi *et al.* [19] applied artificial neural networks (ANN) to minimum jerk trajectory planning for the Puma560 robot, significantly improving task execution times by generating smoother motion profiles. The application of ANN in this context ensures that robotic systems can adapt to real-time operational demands, enhancing efficiency in high-demand industrial processes. In high-speed applications, Wu *et al*. [20] developed an optimal time-jerk trajectory planning algorithm for delta parallel robots using an improved butterfly optimization algorithm. Their findings demonstrate that optimized trajectories not only enhance responsiveness but also improve overall performance in demanding manufacturing environments. These advanced optimization techniques allow robotic systems to maintain efficiency even in dynamic, fast-paced conditions. The use of reinforcement learning in robotic motion optimization has emerged as a promising solution for dealing with the complexities of dynamic environments.

He *et al*. [21] proposed an integral reinforcement learning-based approach to multi-robot path planning, which addresses challenges such as collision avoidance and adaptation to unknown environmental disturbances. This adaptability is essential for ensuring operational efficiency in manufacturing environments where conditions, such as part arrival rates and obstacles, frequently change. Similarly, Lopez *et al*. [22] demonstrated how reinforcement learning can dynamically adjust robotic trajectories based on real-time data, achieving significant improvements in task efficiency and system performance. Incorporating IoT technologies into robotic systems has further enhanced their ability to adapt to dynamic manufacturing environments. Kim [23] explored how IoT devices can provide real-time feedback, enabling robots to adjust their motions according to the current state of the production line. This real-time adaptability allows for seamless synchronization between robotic operations and other automated systems, improving overall operational efficiency and reducing downtime. Simulation-based approaches have also become integral in validating and optimizing robotic motion strategies. Salawu *et al.* [24] presented a simulation framework using MATLAB, which enables the evaluation of various robotic motion strategies in dynamic manufacturing environments. By simulating real-world scenarios, including fluctuating part arrival rates and varying obstacle configurations, MATLAB allows engineers to identify the optimal configurations for robotic systems. This simulation-based approach ensures that robots are well-equipped to handle the unpredictable conditions often encountered in advanced manufacturing systems.

Continual learning has also played an important role in improving robotic performance in dynamic environments. Lesort *et al.* [25] discussed continual learning frameworks that enable robots to learn and adapt continuously, improving performance over time as they interact with new environments. The ability to learn from past experiences and adjust to new challenges is crucial for optimizing robotic motion in ever-changing manufacturing environments. The integration of human-robot collaboration has further influenced the optimization of robotic motion in dynamic settings. Kruse *et al.* [26] explored collaborative handling of highly deformable materials, demonstrating that optimizing interactions between humans and robots can significantly enhance productivity and reduce errors in manufacturing processes. Similarly, Matsas and Vosniakos [27] evaluated the effectiveness of virtual environments for assessing human-robot collaboration, emphasizing the importance of seamless collaboration for achieving optimized production outcomes. Disruptive technologies, such as those studied by Feder [28], have had a profound impact on productivity in manufacturing environments. These technologies enable the reconfiguration of production systems to better handle dynamic and complex tasks, resulting in more flexible and efficient operations. The growing trend of integrating AI and robotics into manufacturing has provided new opportunities for optimizing processes and enhancing overall system performance.

The ongoing research into these areas underscores the importance of robust optimization techniques and the integration of advanced technologies in improving robotic motion in dynamic manufacturing environments. By leveraging trajectory optimization, machine learning, IoT integration, and simulation tools, researchers have made significant strides in ensuring that robotic systems can operate efficiently and adaptively, ultimately driving productivity gains and reducing costs in modern manufacturing systems. This study proposes an innovative optimization technique that leverages MATLAB simulation software to improve robot motion planning in dynamic manufacturing environments.

2. METHOD

In this study, a robotic system was integrated to perform a pick-and-place task on a conveyor system to optimize its operation for an improved productivity. The manufactured parts arrived in batches via a conveyor system governed by a negative exponential distribution in a poisson process. The arriving parts were further picked up randomly by the robot and the parameters were studied. The average cycle time was studied with other working variables to determine the effect of optimization on the throughput rate.

The methodology consists of several key components, which are described as follows:

i) Conveyor system setup: the conveyor system transports parts arriving from the buffer station in batches following a negative exponential distribution process modelled by poisson's principle. This configuration ensures that part arrival is stochastic and reflects real-world manufacturing scenarios. The distance between the work area and the recording boundaries was described by a minimum distance, referred to as α. This distance is significant to creating a safe operating work area for the robotic manipulator which adequately enables effective pick-up and placement of parts.

ii) Robot manipulation and motion planning: the robotic arm was programmed to perform the pick-and-place operations using a set of predefined motion trajectories. These trajectories were originally determined based on kinematic equations that take into consideration the physical limitations and operating parameters of the robot. The robot arm's end effectors are designed to firmly grasp parts as they move through the conveyor system.

iii) To enhance the throughput rate during pick-and-place tasks, the process began with continuous data collection on part arrivals, cycle times, and the operational status of the robotic system, which served as the training foundation for the model. Parameters were varied against each other using a deterministic approach in MATLAB. The MATLAB learning tool was designed to simulate this data, predicting optimal trajectories based on input parameters such as part arrival rate and robotic arm status, while aiming to minimize a loss function that quantifies the difference between predicted and actual performance metrics. Various optimization techniques, including gradient descent, were utilized to iteratively refine the model, resulting in improved efficiency and effectiveness of the robotic system in real-time operations.

iv) Implementation of equations: equations from previous studies were integrated into the model to improve the optimization results. These equations provided a mathematical basis for the motion planning and control strategies, ensuring that the robotic arm operated within its defined constraints while maximizing efficiency [26].

v) Validation and performance evaluation: the optimized robot motion was validated through a series of experiments on the conveyor system. Performance metrics including average cycle time and throughput rate were recorded and analyzed. The results have been compiled in Table 1 and illustrate the improvements achieved through the optimization process.

Table 1. The average cycle time for the pick-place task

Motion	Task	Average service time (seconds)
0.1	The home poses to view the arriving art from the conveyor	4
0.2	Reach to grasp the item	3.2
0.3	Moving to the item drop pose	3.0
0.4	Moving from an item dropped pose back to home pose	3.41

Kinematic analysis of a 6-DOF manipulator was performed to study its motion mechanisms for pick-and-place tasks without considering the forces driving the motion. Both direct and inverse kinematics was used to analyze the performance of the manipulator, using the Denavit-Hartenburg (D-H) method to derive the equations for its motion [26]. The D-H parameters including joint rotation angle (θ), distance along the z axis (d), twist angle between joints (α), and twist length (a) were presented in tabular form.

The homogeneous transformation matrix for the manipulator was created, where each transformation depends on the configuration of the previous joint. This approach enables effective modeling of the manipulator's connections and joint configurations, regardless of the complexity of the robot arm. The homogeneous transformation matrix of the motion manipulator is provided below based on the D-H representation in [26]. Every frame undergoes a uniform change in relation to the joints of the preceding frames. T is dependent on a single joint variable. In relation to frame 0, the forward kinematics model of frame n.

$$T01 = 0_{T_1}(q_1) = \begin{bmatrix} -cos(q_1) & 0 & -sin(q_1) & 150\,cos(q_1) \\ -sin(q_1) & 0 & cos(q_1) & 150\,sin(q_1) \\ 0 & 1 & 1 & 450 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

$$T12 = 1_{T_2}(q_2) = \begin{bmatrix} -sin(q_2) & -cos(q_2) & 0 & -600\,sin(q_2) \\ -cos(q_2) & -sin(q_2) & 0 & 600\,cos(q_2) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$$T23 = 2_{T_3}(q_3) = \begin{bmatrix} -cos(q_3) & 0 & -sin(q_3) & 200\,cos(q_3) \\ -sin(q_3) & 0 & cos(q_3) & 200\,sin(q_3) \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$T34 = 3_{T_4}(q_4) = \begin{bmatrix} -cos(q_4) & 0 & -sin(q_4) & 0 \\ -sin(q_4) & 0 & cos(q_4) & 0 \\ 0 & 1 & 0 & 640 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$T45 = 4_{T_5}(q_5) = \begin{bmatrix} -cos(q_5) & 0 & -sin(q_5) & 0 \\ -sin(q_5) & 0 & cos(q_5) & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$T56 = 5_{T_6}(q_6) = \begin{bmatrix} cos(q_6) & -sin(q_6) & 0 & 0 \\ sin(q_6) & cos(q_6) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

Therefore, the base end effectors gives:

$$0_{T_6} = (0_{T_1})\,(1_{T_2})(2_{T_3})(3_{T_4})(4_{T_5})(5_{T_6}) \tag{7}$$

Considering all the matrixes, initial configuration.

$$0_{T_6} = \begin{bmatrix} 0 & 0 & 1 & 790 \\ 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 1250 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (8)$$

The step-by-step algorithm for the process is presented as follows:

Step 1. The objectives of the research were defined with the specific requirements for optimizing robotic motion in a dynamic environment. Factors such as productivity metrics, safety, efficiency, and adaptability to changes in the environment were considered.

Step 2. The characteristics of the dynamic environment where the robotic system will operate were studied. Potential challenges such as moving obstacles, changing terrain, and unpredictable disturbances were studied.

Step 3. Mathematical optimization methods and machine learning were used to study the process.

Step 4. The Monte Carlo simulation in MATLAB was used to generate multiple random scenarios (e.g. varying part arrival times, changing obstacles) and evaluate how different trajectories perform under stochastic conditions.

Step 5. Mathematical models that represent the robotic system, its dynamics, and the environment were created and studied. This involves kinematics, dynamics, and other relevant mathematical concepts.

Step 6. Control strategies were developed that allow the robot to navigate and adapt to changes in the dynamic environment. This involves trajectory planning, path following, obstacle avoidance, and other control techniques.

Step 7. Implementation of the algorithm in a simulation environment was carried out. Simulation that allows for testing and validating the algorithm under various scenarios was also done.

Step 8. Performance was evaluated.

Step 9. Based on the evaluation results, iteration of the algorithm to improve its performance and addresses identified issues was finally performed.

The mathematical equations as follows served as a working tool to achieve the present research.

$$PPr = \frac{t_{pick}+t_{place}+t_v}{V_c} \quad (9)$$

$$d = R_v \times sin\alpha \times t_{pick} \quad (10)$$

$$p_b = \frac{(w-d-2\alpha)}{(w-d)^2} \quad (11)$$

$$r_b = \frac{1}{c}\,\frac{(w-d)^2 v_v^{max}}{w\pi(\alpha+d)^2} \quad (12)$$

$$V = \frac{\pi dn}{60} \quad (13)$$

$$T_r = \frac{r_b}{\frac{w}{v}+r_b+t_{place}} \quad (14)$$

$$P_{x1} = V_c \times t_{pick} \quad (15)$$

$$P_{X2} = \Delta x + R_v \times cos\alpha \times t_{pick} \quad (16)$$

The parameters considered in this present work include; r_b = arriving rate of parts from conveyor system, T_r = throughput rate, p_b= probability that work is been cleared, pp_r= pick up rate, d= diameter of fed part, V= velocity of conveyor belt drive, p_x= product position, and the diameter of the fed part. Using the equations modeled, functions were assigned to each parameter and the scenario was studied to achieve an optimal productivity.

3. RESULTS

The result obtained from optimizing robotic motion in a dynamic manufacturing environment, through MATLAB simulations, examined the relationship between average cycle time and throughput rate in a pick-and-place task. Various working variables were optimized to study their impact on operational efficiency.

The simulation showed that reducing cycle time directly enhanced throughput. Graphical representations confirmed the significant improvements in efficiency due to motion optimization. These results, with detailed analysis and implications for dynamic manufacturing, are comprehensively presented in this chapter.

The graph in Figure 1 provided a critical insight into the system's performance in dynamic manufacturing environments, highlighting a positive outcome when optimal operational conditions are met. During a time period between t=0.5 s to t=5 s, no task was fully completed, demonstrating that an arrival rate below the required optimal value leads to a probability of less than one for task clearance. At t=0.18 s, only 10% of the task was cleared, emphasizing that insufficient arrival rates hinder task execution. However, the sinusoidal pattern in the graph, followed by a fluctuating linear trend, signifies that when the arrival rate meets up with optimal conditions, the robotic pick-and-place system operates efficiently, as evidenced by peaks in the probability curve. These peaks reflect moments when the robot successfully synchronizes its operations with the incoming parts, maximizing productivity. The transition to a fluctuating linear trend represents a more stable performance, where dynamic trajectory planning and real-time monitoring allow the system to adapt to varying arrival rates, ensuring high throughput and minimized cycle times. This demonstrates that an efficient manufacturing process is achievable when the system dynamically adjusts to maintain optimal operational conditions, ultimately improving productivity and resource utilization.

The graph of throughput rate versus rate of arrival in Figure 2 demonstrates the significant impact of optimized robotic motion in dynamic manufacturing environments, illustrating a positive outcome in enhancing operational efficiency. Throughput increases substantially, with up to a 20% improvement when utilizing the motion planning algorithm, highlighting the system's ability to dynamically adapt to varying arrival rates. The real-time optimization of robotic trajectories ensures synchronization between part arrivals and robotic operations, minimizing idle time and maximizing overall throughput. The non-linear relationship between throughput and arrival rate, as shown in the graph, reflects the complexity of the system's operational states, with each state having its own local optimal arrival rate for maximum throughput. For instance, during the first positive half-cycle, the optimal arrival rate for peak efficiency was found to be 0.16 s, emphasizing that at each operational condition, there exists a specific arrival rate that maximizes throughput. This dynamic adjustment and optimization ensure that the system consistently operates at its highest potential, reducing delays and improving overall manufacturing efficiency. The results underscore the positive influence of efficient motion planning in enabling a seamless integration of robotic tasks with incoming parts, resulting in significant productivity gains.

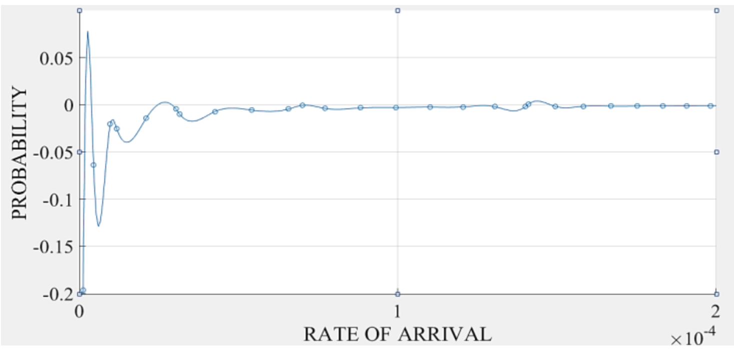

Figure 1. Graph of probability against rate of arrival

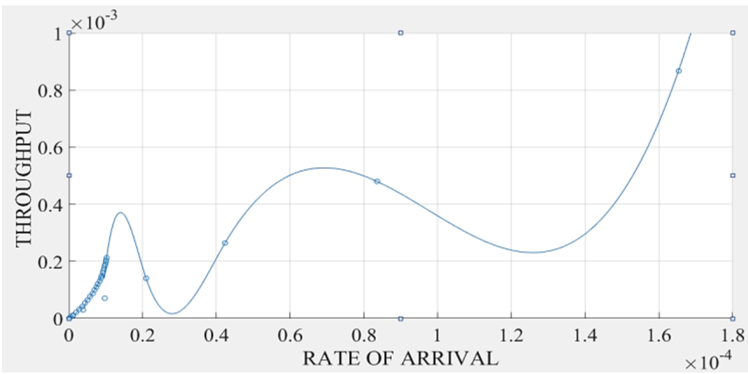

Figure 2. Graph of throughput against rate of arrival

Figure 3 illustrates the relationship between the robot's pick-up rate and the probability that work is cleared, providing valuable insights into achieving an efficient manufacturing task. Initially, as the pick-up rate increases, the probability of successfully clearing tasks also rises, demonstrating effective synchronization between the robot's motion and the demands of the manufacturing environment. This phase represents an optimal operational state where the robotic system performs efficiently, handling tasks with minimal delays and ensuring high throughput. However, beyond a certain threshold, the probability of clearing tasks begins to decline, signaling that an excessively high pick-up rate may lead to operational strain and inefficiency. This non-linear behavior highlights the importance of identifying and maintaining the optimal pick-up rate for each task. As shown in the graph, any pick-up rate below the required optimal value results in a probability of less than one, indicating incomplete task execution. Thus, for every manufacturing task, an optimal pick-up rate is critical for ensuring that the robotic system can clear all tasks effectively. This analysis underscores the importance of balancing pick-up rates to optimize performance, ensuring the system remains efficient and capable of managing workloads without being overwhelmed.

The relationship between the pick-up rate and the rate of arrival is presented in Figure 4. Optimizing robotic motion in dynamic manufacturing environments using MATLAB algorithms enhances task management, leading to improved productivity. MATLAB’s optimization tools enable robotic systems to adapt to fluctuating demands, improving operational efficiency. This dynamic relationship, illustrated on the graph, shows how MATLAB algorithms enhance the system's responsiveness to environmental changes. By addressing these complexities, the study contributes to advancements in automation; ensuring robotic systems are well-equipped to handle modern manufacturing challenges effectively.

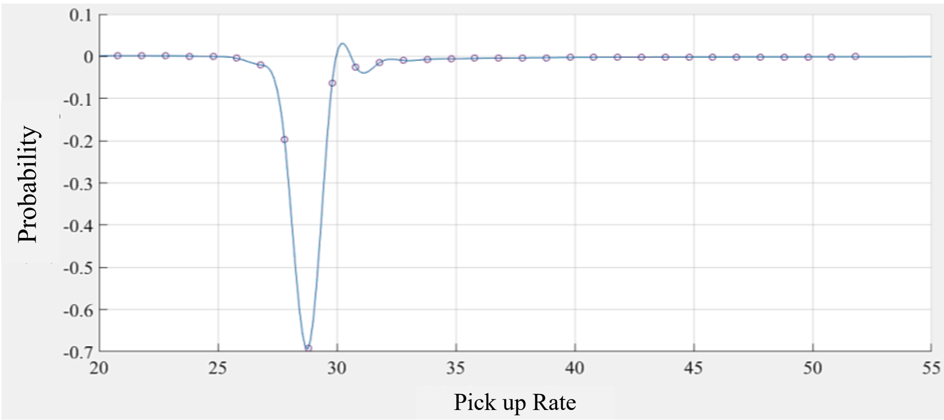

Figure 3. Graph of probability against pick up rate

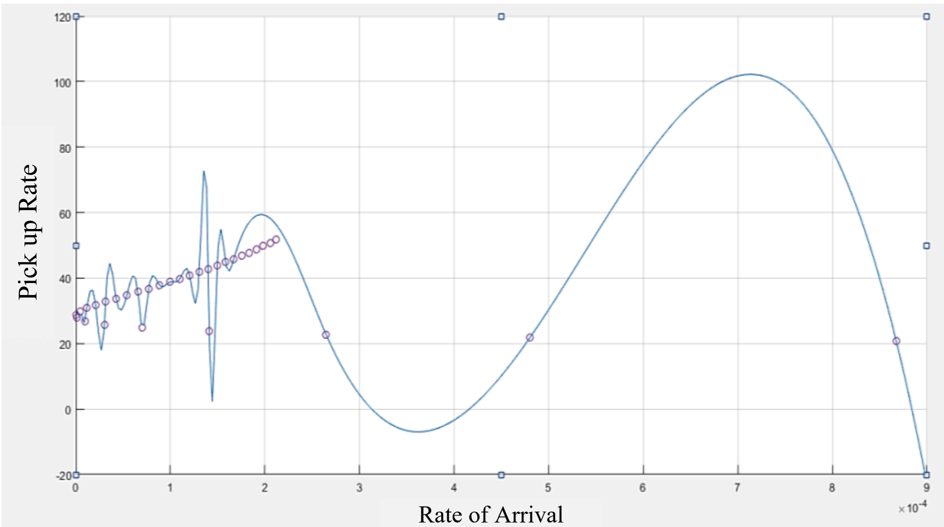

Figure 4. Graph of pick-up rate against rate of arrival

4. DISCUSSION OF RESULTS

The integration of advanced motion planning techniques for optimizing robotic motion marks a significant advancement in manufacturing, particularly in dynamic environments characterized by variability. This study demonstrated how these techniques can enhance productivity during pick-and-place tasks, achieving throughput rate improvements of up to 20%, as illustrated in Figure 2. This enhancement underscores the transformative potential of innovative technologies in manufacturing. Parts arrive in batches governed by a negative exponential distribution, reflecting the stochastic nature of production processes. The developed optimization technique effectively generates optimal trajectories, enabling the robotic system to adaptively synchronize its pick-and-place operations with the random arrivals of parts. By analyzing the throughput rate, the proposed optimization minimizes idle time while maximizing operational efficiency. The outcomes presented in Figure 1 reveal how the robotic system navigates through optimal performance periods and congestion, highlighting the importance of real-time monitoring and dynamic trajectory planning. The analysis of throughput rate against the arrival rate indicates that the system's performance is influenced by its ability to adapt to varying conditions. Furthermore, Figure 4 illustrates a complex non-linear relationship between the pick-up rate and the arrival rate. While higher pick-up rates initially enhance productivity, exceeding a certain threshold can lead to operational strain and reduced effectiveness. This finding emphasizes the necessity for systems that can manage workloads effectively, ensuring that operations remain efficient without becoming overwhelmed. Such insights correlate with the trends observed in previous figures, reinforcing the importance of optimizing not just the pick-up rates, but also the overall system dynamics to achieve sustained high efficiency in advanced manufacturing environments. By leveraging MATLAB for simulation, the study highlights a pathway toward more intelligent, responsive, and productive manufacturing processes.

In summary, this research highlights the effectiveness of optimizing robotic motion using MATLAB algorithms to improve productivity in advanced manufacturing environments. By leveraging MATLAB's optimization and control tools, this approach enhances operational efficiency and supports future innovations in robotic systems. The study reinforces the critical role of disruptive technologies in addressing challenges in dynamic manufacturing, enabling robots to respond efficiently to fluctuating demands. These findings underscore the importance of optimization in driving the evolution of production processes, contributing significantly to advancements in Industry 4.0, by improving throughput rate in an advanced manufacturing environment.

5. CONCLUSION

This research highlights the transformative potential of optimizing robotic motion in dynamic manufacturing environments using innovative motion planning techniques. By leveraging advanced simulation tools like MATLAB, the proposed approach demonstrates its ability to enhance productivity, reduce production time, and maximize throughput during pick-and-place tasks. These improvements are critical in today’s advanced manufacturing sectors, were operational efficiency and competitiveness drive industry success. The techniques discussed in this study enable robots to adaptively respond to changing conditions in real-time, further solidifying their value in dynamic, high-demand production settings. The findings underscore the effectiveness of these optimization methods in overcoming challenges in complex manufacturing systems, proving their practicality for streamlining operations and reducing costs. Moreover, the adaptability of this approach paves the way for future innovations, especially as manufacturers explore scalability across various industrial contexts. By incorporating real-time data feedback, further refinements in these optimization techniques could revolutionize how automation supports the evolving needs of Industry 4.0. In conclusion, optimizing robotic motion with advanced motion planning techniques offers a robust solution for improving productivity in advanced manufacturing environments. This sets a solid foundation for the future of automation, supporting the broader goals of efficiency, sustainability, and innovation in the manufacturing landscape.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Glen Bright		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no competing financial interests or personal relationships that could have influenced the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [GAS], upon reasonable request.

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