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# Simulation of Autonomous Vehicle in Manufacturing

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## Abstract

A Discrete Event Simulation (DES) approach was used to study and analyze the transition from a manual material handling system to an automated system of Autonomous Mobile Robots (AMRs) in a manufacturing plant. The plant currently relies on a manual system where a hand truck operator services multiple injection molding machines with varying cycle times, transporting parts bins to the warehouse. Transitioning to AMRs is expected to improve efficiency, reduce labor costs, and sustain high production rates. However, determining the optimal number of AMRs is critical to balancing operational efficiency with capital investment. Using the ARENA® simulation software, the project models the manufacturing floor to analyze machine cycle times, service requirements, and distances between tasks. The objective is to identify the minimum number of AMRs required to maintain seamless operations and high robot utilization while avoiding delays and overcapacity. The study ensures accurate and actionable insights by replicating real-world constraints and production metrics. The findings will provide a cost-effective, efficient solution for deploying AMRs, supporting the plant's transition to automated material handling.

## Keywords
Simulation modeling, Autonomous Mobile Vehicles, Material Handling in Manufacturing

## 1. Introduction
In modern manufacturing environments, automation continues to redefine operational efficiency. While traditional material handling relies heavily on manual labor, integrating Autonomous Mobile Robots (AMRs) presents a scalable solution to meet the increasing production demands in today's global and competitive markets.The hypothetical facility under study currently relies on a traditional manual material handling system to support four injection molding machines, each producing parts with unique geometries and cycle times. Once a bin is filled with molded parts, a hand truck operator must manually transport it to a designated warehouse area and return an empty bin to the machine. Since each machine can only hold one bin at a time, timely exchange is critical to avoid production delays. However, due to the variability in operator availability and the overlapping demands of multiple machines, this system often results in idle time, inconsistent throughput, and a lack of scalability as production volumes increase.

To address these inefficiencies, this study explores the integration of Autonomous Mobile Robots (AMRs) to automate the material transport process. AMRs can autonomously navigate the facility, respond dynamically to pickup and delivery requests, and operate continuously without fatigue. The objective is to determine the optimal number of AMRs required to maintain or improve throughput while minimizing capital investment. Arena® simulation software is used to simulate the production environment, incorporating variables such as machine cycle times, bin handling logic, AMR speed, and environmental constraints. By running scenario-based simulations with varying AMR fleet sizes, the study evaluates system performance, identifies operational bottlenecks, and proposes a cost-effective configuration for transitioning from manual to automated bin handling.

### 1.1 Objectives

- Identify optimal fleet size of AMRs for continuous production support.
- Simulate real-world constraints including machine cycles and distances.
- Evaluate system performance across multiple AMR configurations.

## 2. Literature Review

There has been a noticeable shift in how manufacturing floors are being imagined whether its new facilities being built with the latest technologies or existing ones seeking to modernize and streamline their processes. Technologies like AGVs and AMRs offer a practical path toward automating manual tasks, helping manufacturers improve efficiency without fully overhauling their operations. As Omron Automation notes, "Implementing Autonomous Mobile Robots (AMRs) holds tremendous potential for transforming manufacturing processes by streamlining material handling and enabling flexible production… AMRs offer a range of benefits that can drive operational efficiency, reduce costs, and improve overall productivity." [5] Their ability to reduce downtime, enable real-time routing, and adapt dynamically to production demands makes them well-suited for modern manufacturing environments.

Simulation tools like Arena® give engineers the ability to test these concepts virtually before making real-world investments. According to Banks et al. , "Simulation modeling allows decision-makers to evaluate system behavior under various configurations without disrupting real operations." [1] Arena® is widely used to simulate queuing systems, machine scheduling, and material flow especially under conditions of uncertainty or limited resources[3]. This makes it particularly useful when evaluating automation strategies such as AMR deployment.While past research shows the value of AMRs and validates simulation as a reliable planning tool, few studies tie the two together in a practical way, especially in molding environments with real-world constraints. This study fills that gap by using Arena® to model bin movement based on machine output, incorporating travel time, charging logic, and other operational parameters. The resulting simulation framework is flexible and can be adapted for future use in other smart manufacturing facilities.

## 3. Methods

Arena simulation software was used to model a layout consisting of four injection molding machines and three primary travel routes. AMR behavior was defined by speed, charge requirements, and bin-carrying limitations. Key assumptions included one bin per AMR, variable cycle times, and 30% downtime due to charging.

## 4. Data Collection

Table 1 represents the number of Molding machine and the respective cavitation mold producing parts at the specified cycle time. These base specifications were then used to calculate production output and bin generation rates. The numbers shown in this table are not sourced from an actual production environment but were randomly generated to represent a hypothetical use case for simulation purposes. These assumptions help define a consistent scenario for evaluating AMR performance in a controlled and repeatable way.

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Table 1. Molding Machine Specifications

| Machine List | Part Size | Cavities in Mold | Cycle Time (Seconds) |
|---|---|---|---|
| Molding Machine 1 | Large | 2 | 30 |
| Molding Machine 2 | Medium | 16 | 23 |
| Molding Machine 3 | Medium | 8 | 18 |
| Molding Machine 4 | Small | 64 | 12 |

Table 2 calculates the expected number of full bins generated per hour by each molding machine based on its cycle time and mold cavity configuration. These values were derived from assumed production specs and were used as input for bin generation timing in Arena®.These base specifications were then used to calculate production output and bin generation rates, using the following calculation methodology:

## Calculation Methodology

The number of parts produced and bins generated per hour are derived from basic manufacturing math, assuming each machine runs continuously.

1. Parts per Minute: Parts/min = (60 / Cycle Time in seconds) × Number of Cavities
2. Parts per Hour: Parts/hr = Parts/min × 60
3. Bins per Hour: Bins/hr = Parts/hr ÷ Parts per Bin
4. Time to Fill One Bin (min): Time per Bin = 60 ÷ Bins/hr

All part and bin values in Table 2 were calculated using these formulas. Assumptions about how many parts fit per bin were based on estimated part sizes and standardized container volume.

Table 2. Molding Machine Production Rates and Bin Generation

| Machine List | Part Size | Cavities | Cycle Time (Seconds) | Parts Per Minute | Parts Per Hour | How many parts est. per bin | Bin Created Per Hour | How long does it take to create one bin? (Minutes) |
|---|---|---|---|---|---|---|---|---|
| Molding Machine 1 | Large | 2 | 30 | 4 | 240 | 200 | 1.2 | 50 |
| Molding Machine 2 | Medium | 16 | 23 | 42 | 2504 | 600 | 4.2 | 14 |
| Molding Machine 3 | Medium | 8 | 18 | 27 | 1600 | 600 | 2.7 | 23 |
| Molding Machine 4 | Small | 64 | 12 | 320 | 19200 | 5000 | 3.8 | 16 |

Table 3 AMR speeds vary by load condition. These times were calculated using Time = Distance / Speed and adjusted ±50% to model best- and worst-case scenarios due to environmental interference. These values fed directly into route logic in Arena®. Calculation Methodology for AMR Travel Times Travel durations between facility points were computed based on assumed distances and AMR speeds using the following formulas:

1. Average Time (sec): Time (sec) = Distance (m) ÷ Speed (m/s)
2. Best Case (min): Best = (Time in sec × 0.5) ÷ 60
3. Average Case (min): Average = Time in sec ÷ 60
4. Worst Case (min): Worst = (Time in sec × 1.5) ÷ 60

These cases represent scenarios with minimal, normal, and high interference, respectively. For example, for the Molding to Warehouse route (400 m at 0.8 m/s):

- Average = 500 sec (8.3 min)

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- Best Case = 4.2 min
- Worst Case = 12.5 min

These time estimates were used as input parameters in Arena's ® route logic for modeling transit behavior.

Table 3. AMR Travel Time Estimates Between Facility Locations

| Starting Location | End Location | Average Time(sec) | **Best Case Time(MIN)** | **Average Time(Min)** | **Worst Case Time (MAX)** |
|---|---|---|---|---|---|
| Molding Machines | Warehouse | 500.0 | 4.2 | 8.3 | 12.5 |
| Warehouse | Charging Station | 333.3 | 2.8 | 5.6 | 8.3 |
| Charging Area | Molding Machines | 333.3 | 2.8 | 5.6 | 8.3 |

Table 4 shows the average speeds were assumed based on standard AMR performance under load. Routes involving loaded bins were assigned slightly slower speeds to reflect safety and real-world handling practices. Max forward travel speed for a MIR 200 is 1.1m/s for reference.

Table 4. AMR Travel Speeds by Route

| Starting Location | End Location | Average speed (m/s) |
|---|---|---|
| Molding Machines | Warehouse | 0.8 |
| Warehouse | Charging Station | 0.6 |
| Charging Area | Molding Machines | 0.6 |

## 5. Results and Discussion

### 5.1 Numerical Results

Simulation iterations ranged from 1 to 15 AMRs. Key metrics such as bin throughput and machine utilization were tracked. Results showed that 5 AMRs produced optimal throughput (~268 bins/hour) with machine utilizations above 90%.

### 5.2 Graphical Results

Figure 1 illustrates how the average utilization of Autonomous Mobile Robots (AMRs) changes as more robots are added to the system. It helps identify the point at which adding additional AMRs no longer provides meaningful efficiency gains. It supports decision making regarding the optimal fleet size by showing when AMR utilization begins to plateau.

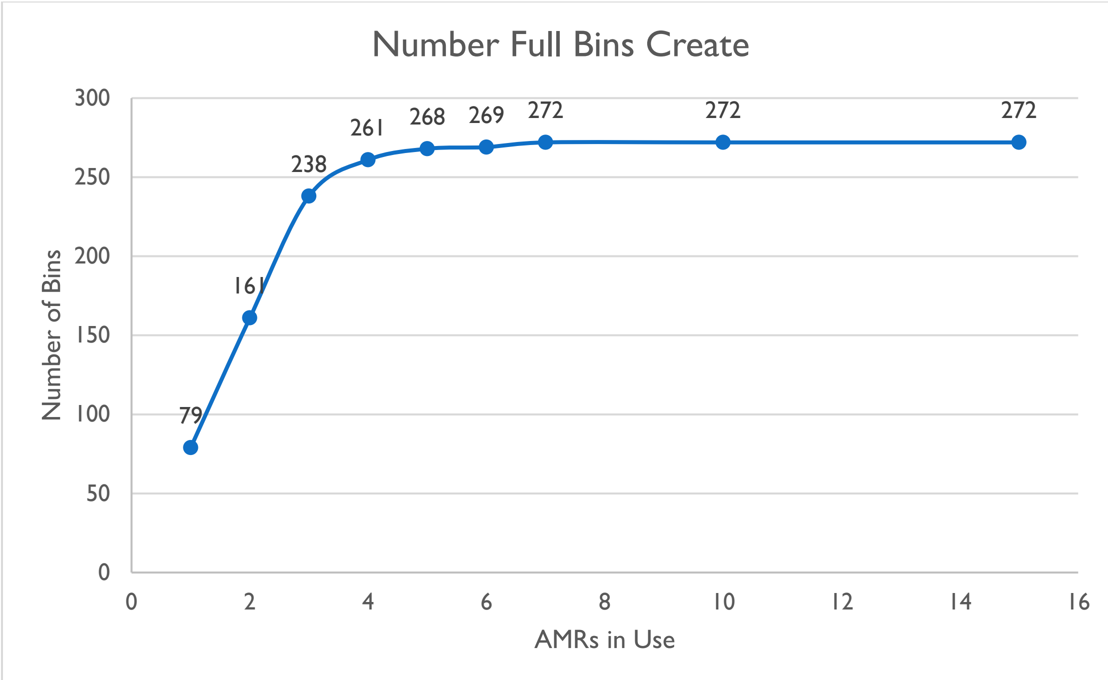


Figure 1. AMR Utilization vs. Number of AMRs

Figure 2 shows the relationship between the number of AMRs in the system and the total number of full bins transported to the warehouse. It visually confirms throughput increases with each additional AMR up to a certain point, after which bin production levels off. This data validates the simulation's outcome and reinforces the conclusion that 5 AMRs is the optimal fleet size for the scenario studied.

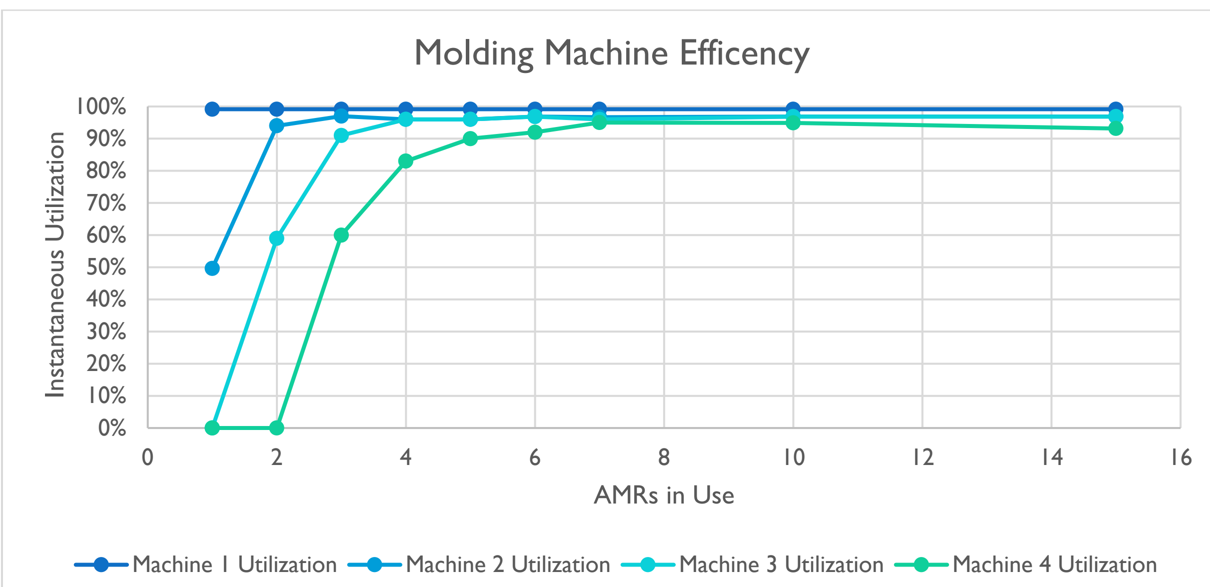


Figure 2 . Bins Produced vs. AMR Fleet Size

### 5.3 Proposed Improvements

While the current simulation focuses on single-bin AMRs, future iterations should explore models that include AMRs capable of transporting multiple bins per trip. This would reduce travel frequency and increase throughput per unit. Additionally, implementing dynamic path-finding algorithms capable of rerouting in real time to avoid congestion or

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delays could significantly improve system responsiveness and reduce average delivery times.Lastly, predictive maintenance strategies based on usage patterns, error logs, or idle behavior could be modeled to simulate how maintenance downtimes affect overall performance. This can help assess whether adding spare AMRs or rotating them based on predicted wear can ensure operational continuity.

### 5.4 Validation

Since the study was conducted entirely in Arena® simulation software, validation focused on internal consistency rather than real-world benchmarking. The model was reviewed to ensure that machine cycles, AMR behavior, and bin logic accurately reflected the intended manufacturing process. Scenario testing was conducted multiple times to confirm stability. While external validation is recommended for future studies, the current model was sufficient for comparative analysis and identifying optimal AMR configurations.

## 6. Conclusion

The Arena® based discrete event simulation modeling successfully captured the essential dynamics of integrating Autonomous Mobile Robots (AMRs) into a molding-based manufacturing environment. By analyzing machine utilization, bin throughput, and responsiveness under varying AMR fleet sizes, the study identified five AMRs as the optimal solution that balances high productivity with minimal capital burden.

Beyond confirming the feasibility of replacing manual transport with AMRs, the simulation also provides a foundation for broader strategic planning. As facilities scale or introduce more product variety, this model can be expanded to test multi-bin AMRs, variable scheduling strategies, and even traffic coordination across multiple workstations. Moreover, the simulation framework developed in this study is highly adaptable to other manufacturing scenarios. While the current case focuses on a specific injection molding environment, the model could be applied to diverse production settings with different pickup and drop-off locations. In such cases, the only variables that would change are the number of service points, the travel distances between them, and the AMR travel speeds based on environmental constraints. These inputs can be easily adjusted in Arena®, making it a powerful tool to simulate a wide range of factory layouts and logistics workflows.

Overall, the approach demonstrates that discrete event simulation is a valuable decision-support tool for evaluating flexible automation deployments in modern manufacturing. The insights gained offer both immediate recommendations and a long-term framework for iterative system improvements.

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## Biographies

**Kasra Fatemi** is a dedicated mechanical engineer with over eight years of industry experience and is currently completing his M.S. in Engineering Management and Operations at the University of New Haven, where he also earned his B.S. in Mechanical Engineering. He has a strong background and interest in plastics injection molding, tooling, and automation. As an Engineering Manager at Medtronic, he leads a team of engineers in developing and delivering plastic injection molds to produce critical-level components for patients. Kasra looks forward to applying his newly acquired degree to continue driving impactful innovations in the medical device space.

**Dr. M Ali Montazer** earned the BSIE, MSIE and the Ph.D. degrees from the University at Buffalo. He began his academic career at the University of New Haven in September 1984 and is now Professor of Industrial Engineering and Engineering Management. Dr. Montazer was honored with the Excellence in Teaching Award in 1987. After several years of fulltime teaching and research, he served as program coordinator for the MSIE and MSEOM, department chair, Associate dean and interim dean of the college prior to returning to the faculty and fulltime teaching in January 2016. He loves teaching and working with motivated and inquisitive students to work on application-oriented projects, especially those coming from and sponsored by local industry. Over the years, he has worked with students on projects sponsored by Hershey Metal, Sikorsky Aircraft, Asa Abloy-Sargent, Cheese-borough Ponds (Unilever), Remington, US Surgical (Medtronic), Valley Tools and Manufacturing, He has published in various reputable journals and conference proceedings. He is a senior member if IISE, IEOM, a member of ManufactureCT, and a former member of ASEE and POMS. He is interested in probability and simulation modelling, Job design and process improvement strategies, including six sigma and quality systems.

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