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Fuzzy Logic Control of Automated Materials Handling Systems in Smart Factories

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Abstract
Modern manufacturing systems are becoming more complex and dynamic, so smarter control strategies are needed to improve efficiency. This study examines how fuzzy logic control (FLC) can optimise automated material handling systems (AMHS) in smart factories. Traditional control methods use fixed rules and exact mathematical models, but they often struggle with uncertainty, changing job arrival rates, and shifting system conditions. To address these challenges, a fuzzy logic-based control framework was created to support adaptive, real-time decision-making. The system uses key input variables such as queue length and waiting time to decide which jobs to handle first in the material handling process. A Mamdani-type fuzzy inference system was set up, using membership functions and a rule base to capture expert knowledge and system behaviour. The model was tested with a dataset of 10 jobs processed over 15 minutes, which reflects real manufacturing situations. We evaluated performance by comparing the FLC approach with a conventional control method across key metrics, including task completion time, average waiting time, throughput, and system delay. The simulation results demonstrated that the FLC significantly outperformed the traditional approach. Specifically, task completion time decreased by 15.4%, average waiting time decreased by 33.3%, and throughput increased by 22.7%, indicating improved system productivity. Additionally, system delay was minimized by 33.3%, highlighting the effectiveness of the FLC in managing congestion and enhancing flow efficiency. The results confirm that fuzzy logic control offers a robust and flexible solution for handling uncertainties and nonlinearities in automated material handling systems. By enabling intelligent prioritization and dynamic response to changing conditions, the proposed approach contributes to improved resource utilization and overall system performance. This study underscores the potential of FLC as a key enabler for smart manufacturing and Industry 4.0 applications. Integrating fuzzy logic control into AMHS provides a viable pathway to higher efficiency, adaptability, and reliability in smart factory operations. Future work may explore the integration of other artificial intelligence techniques, such as machine learning and optimization algorithms, to further enhance system performance and scalability.

Keywords: Industry, Materials Handling, Manufacturing, Fuzzy Logic, Control.

Introduction

Industry 4.0 constitutes the fourth industrial revolution, in which manufacturing processes become "smart" and are characterized by the integration of cyber-physical systems (CPS), Internet of Things (IoT), big data analytics, digital twins and artificial intelligence (AI). CPS are systems that combine cyber and physical elements, IoT is the network of things connected to the Internet, big data is the information generated by the Internet of Things, digital twins are virtual representations of physical products, and AI is the technology that enables intelligent autonomous coordination of these components, such as in a smart factory (Baumann et al., 2020). These factories adopt the sensor-actuator interconnection to measure and monitor the production process, adapt flexibly to disruptions, and utilize the factory resources optimally along the shop floor. The Automated Material Handling System (AMHS), an interconnected web of conveyor systems, Automated Guided Vehicles (AGVs), Automated Storage and Retrieval Systems (AS/RS), and robotic transfer units all working together to streamline material handling, is an integral part of this ecosystem. As a result of that, AMHS should be able to perform just-in-time delivery, fast changeover, and mixed-model production even in the case of high variability (Zhang et al., 2021). Along with throughput, energy efficiency, process synchronization and overall agility of operations, material handling in effective stream plays an essential role. Traditional approaches to control in AMHS have been based on PID controllers, static rule based control and fixed scheduling controllers.

These approaches can be effective in well-defined, repetitive environments, but not in the smart factory where the occasional unpredictable volumes of material or peaks in demand can disrupt controlled material flow, causing overloading of conveyors, dynamic AGV routing conflicts, multiple vehicles operating asynchronously (which can lead to bottlenecks or possible collisions), machine failures, rerouting in production, sensor disturbances, or changes in factory layout (Ahmed and Beg, 2022), reducing the confidence of the controlled environment assumptions. These flaws lead to lower throughput, longer wait times, and sub-optimal energy usage, particularly for conveyors and AGVs that run at a fixed speed regardless of real-time systems conditions (Chung et al., 2019).

Fuzzy Logic Control (FLC), which was proposed by Lotfi Zadeh in 1965, is a human-cantered rule based reasoning framework that deals with imprecision and uncertainty by using; Fuzzification: transforming crisp sensor data into linguistic variables, such as: “low load” or “high queue”. Rule-based inference: making inferences based on intuitive “IF–THEN” rules (e.g., “slow speed IF load is high AND queue is long”). Defuzzification: mapping fuzzy outputs to crisp commands to the actuators. It allows for the control of the system without the use of detailed mathematical models, which makes it particularly well applicable in the case of AMHS (a dynamically variable system with uncertainty and non-linearity) (Zahedi and Zahedi, 2018; Baumann et al., 2020). The ability of Fuzzy Logic Control (FLC) to deal with uncertainties and adapt to varying operating conditions has led to its successful application in various fields. FLC is applied in an industrial conveyor system to dynamically control the conveyor speed and reduce congestion and idle energy consumption, which also improves the operational efficiency (Petrovic et al., 2018). For Automated Guided Vehicle (AGV) control, FLC system improves obstacle avoidance, smooth tracking of the desired path and adaptive speed control, particularly for multi-AGV environment (Chung et al., 2019). Additionally, FLC can be applied in energy management systems to optimize motor operation and the dispatch of energy storage, reducing energy management and operation costs while ensuring the energy management system's performance and reliability in dynamic conditions (Martinez, 2021). The outcome of the responsiveness and efficiency of modern manufacturing systems hinges on the effectiveness of AMHS that makes the material move, store, and extract on time throughout the shop floor. Considering the shift to smart and connected production environments (Baumann et al., 2020), flexible, adaptive and energy-efficient material handling has become a key requirement in factories during the era of Industry 4.0. Although the advanced sensors and cyber-physical technologies have been adopted, the existing control strategies for AMHS mainly rely on the rule-based controllers, pre-designed scheduling algorithms, or conventional PID controllers. These methods work fine with stable and predictable operating conditions, but have critical drawbacks in the dynamic and uncertain conditions found in smart factories. This is essential to ensure that material handling in smart manufacturing environments is robust, energy efficient and powerful.

In smart factories, the primary objective of this study is to design, develop and evaluate an integrated FLC framework to improve throughput, minimize delays and increase energy efficiency in the dynamic operations of AMHS. To achieve this, an FLC to coordinate the operation of an automated material handling system (AMHS), Simulate AMHS using MATLAB under FLC and compare the performance of FLC with conventional control, and review the performance by various metrics including task completion time, average waiting time, system delay and throughput.
The present research work on FLC for SMART FACTORIES have great significance in the field of industrial automation, energy utilization and adaptive manufacturing control as it filled the gaps in the field. Unlike traditional controllers, the proposed features of Fuzzy Logic Control enable the smart factory to adjust to production schedule changes or unexpected equipment problems, and enhance the flexibility and adaptability of the system. Also, Fuzzy Logic Control improves the energy utilization of the system and makes the system more energy-efficient (Adedeji et al., 2026a and Adedeji et al., 2026b). The research provides the framework to optimize material handling operations by minimizing the cycle time, minimizing queuing delay and improving the throughput. This can result in quicker production times, which is very important in a very competitive manufacturing market.

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Overview of Intelligent Control in Automated Material Handling System

This course is an overview of Intelligent Control in the field of Automated Material Handling System (AMHS).This course is an introduction to Intelligent Control in Automated Material Handling System (AMHS). As manufacturing breaks into various parts of the world, the need to manage material flow with greater precision, versatility and efficiency has become a greater challenge and hence intelligent systems are required to meet the need. 2D and 3D models enable seamless material transport, storage and retrieval between various production stages without excessive work done by man. AMHS are the backbone of modern production facilities as they allow seamless movement, storage and retrieval of materials between stages of production with minimal human effort. Conveyors, AGVs, AS/RS and robotic arms are all part of these systems, which are essential in boosting productivity and help keep smart factories competitive in an ever-changing industrial landscape (Mourtzis, 2020). Amidst the digital transformation in Industry 4.0, where cyber-physical systems, IoT, AI and decision-making based on data and analytics are converging, the demand for AMHS has become even stronger. Smart factories are increasingly using AMHS not just to save on operational efficiency, but also to realize flexibility and scalability—and sustainability—aims. Still, although the system has been widely used, it results in problems of system uncertainty, dynamic environment, optimization of routes, and energy efficiency. Such challenges demand advanced intelligent control solutions that exhibit the ability to cope with the complex, nonlinear and uncertain industrial environment. Among these is FLC. The concept fuzzy logic is based on the pioneering work of Zadeh (1965), which provides a mathematical theory for the management of imprecision and uncertainty in human decision making processes, and is able to simulate human reasoning processes using linguistic rules and approximate reasoning. Whereas, conventional control methods require precise models, FLC can be used dynamically and is especially well-adapted to material handling applications in which unpredictable events like machine failures, congestion and variable loads can occur (Sierra-Garcia & Santos, 2024). Research for the integration of FLC in AMHS has grown and developed in the last decade. Examples include using fuzzy logic for navigation in AGVs for path planning and collision avoidance, using fuzzy logic as an energy efficient control mechanism for conveyors and fuzzy logic for intelligent scheduling in AS/RS (Melo et al., 2022, Saying et al., 2025). These systems are also being optimized for yield efficiency and energy use with the ever increasing focus on sustainability and carbon neutral manufacturing.

Automated Material Handling Systems

AMHS are engineered solutions that are used to move, store, retrieve and manage materials within manufacturing and distribution systems with a reduced human environment. They are the heart of smart manufacturing, which helps raw materials, work-in-progress and finished goods to move from one stage of manufacturing to another without any hurdles. AMHS can be made up of conveyors, AGVs, AS/RS, a robotic arm and overhead systems for transporting (Mourtzis, 2020). AMHS's value stems in the fact it can help lower operational cost, boost throughput, ensure workplace safety, and increase overall equipment effectiveness (OEE). In highly automated factories, AMHS can promote lean manufacturing by reducing waiting times and manufacturing bottlenecks, and by eliminating unnecessary manual operations (Zhang et al., 2021). Studies in recent years have shown that companies that have implemented AMHS in an Industry 4.0 context experienced an increase in flexibility and were more responsive to changes in demand in the market (Eclipse Automation 2025).

One significant development of AMHS is the integration of data-driven technologies like IoT sensors, digital twins and AI controllers, that can provide predictive maintenance, real-time monitoring and adaptive scheduling (Mourtzis, 2020). For example, under uncertain conditions, fuzzy logic controllers can be used to control the speed for the AGVs, avoiding crashes and optimizing paths (Sierra-Garcia & Santos, 2024). Analogously, today's AS/RS systems, which are combined with fuzzy controllers, can dynamically adjust retrieval sequences to maximize energy savings and retrieval accuracy (Melo et al., 2022). However, there are some challenges that remain for AMHS including interoperability, high costs of initial investments and energy inefficiency on large scale deployments. The ability to explore intelligent control strategies such as fuzzy logic, to improve the performance, adaptability and sustainability, is validated by these limitations. AMHS are a series of interdependent subsystems that work together to optimize material movement in production and distribution systems. While each individual component works independently, they all contribute to an integrated production system that boosts productivity, accuracy and safety. Comprising of the following parts:

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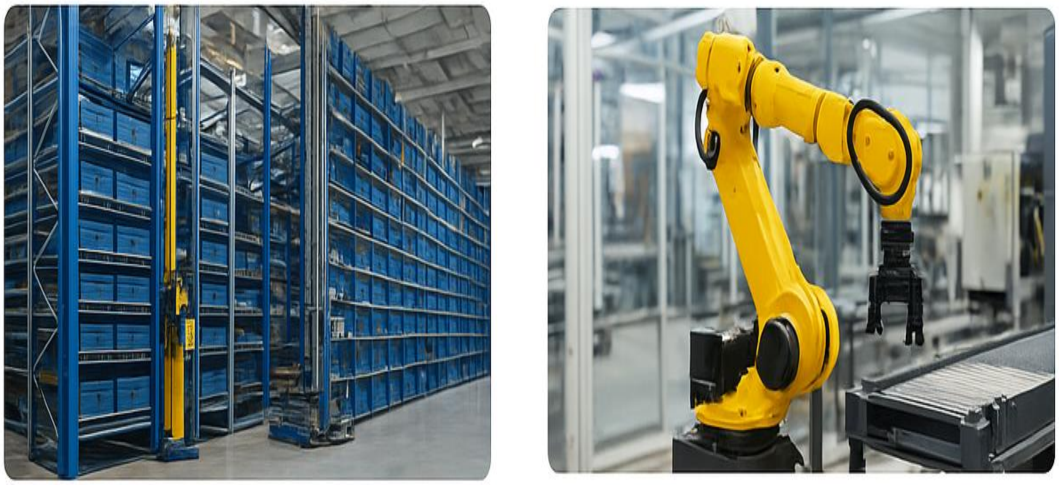
One of the essential parts of the smart factory is the use of conveyors and AGVs. Conveyors are prevalent in moving large volumes of bulk material, parts or completed product through the various steps of production. These may be belt, roller, chain or overhead conveyors, to suit the nature of the material and factory site layout. In modern conveyors, sensors are frequently used to control the speed, avoid collision, and detect faults, as shown in Figure 2.1(a) (Zhang et al., 2021). AGVs are mobile robots designed to navigate preprogrammed routes in the factory to transport materials. They rely on navigation systems like magnetic tape, visual sensors and, more recently, laser and LiDAR. However, the combination of fuzzy logic with reinforcement learning further enhanced the AGV navigation and adaptation capabilities within an uncertain environment as demonstrated in Figure 2.1(b) (Sierra-Garcia and Santos, 2024).

AS/RS are systems that can move and retrieve loads from specific storage locations without human intervention and are computer aided. They enhance the inventory management information system, cut down retrieval period and maximize space utilization. Smart AS/RS can be dynamically optimized to response to the demand fluctuations such as in the case of fluctuations in storage operations as illustrated in Figure 2.1(c), integrated with IoT and fuzzy controllers.Smart AS/RS can be dynamically optimized to response to the demand fluctuations as illustrated in Figure 2.1(c) when it is integrated with IoT and fuzzy controllers such as storage operations. Robotic Arms are common for picking, placing, assembling, and packaging purposes. Robotic arms are used to move delicate or complex objects in AMHS, in addition to conveyors and AGVs. Implementing machine vision and fuzzy logic in these robots can provide them with a high level of uncertainty, which can help increase the flexibility and minimize the number of errors (Mourtzis, 2020), as illustrated in Figure 2.1(d). Control & Monitoring Systems: This part of AMHS is the "brain" that sends instructions to all parts of the hardware. These systems now feature intelligent controllers, IoT sensors, and cloud-based monitoring solutions, providing real-time visibility and predictive maintenance (Eclipse Automation, 2025). As a whole, they all comprise a complete system that makes the production efficient, flexible and ready to meet the needs of the smart factory. Fig 1 shows the elements of AMHS in smart factories.

(a) **(b)**



(c) **(d)**

Figure 1: (a) Conveyor system (b) AGV (c) AS/RS (d) Robotic Arm (Groover, 2016)

Control Approaches in Automated Material Handling Systems

Efficient AMHS operation depends on control strategies that deliver throughput, safety, energy efficiency, and robustness under uncertainty (variable demand, disturbances, sensor noise, and equipment aging). There are many control methods PLC logic, PID, rule-based, optimization-based, AI/ML, and FLC with recent applications to conveyors, AGVs/AMRs, AS/RS, and robotic workcells. The emphasis is on how each approach scales, adapts, and integrates within smart factory (Industry 4.0) environments (Mourtzis, 2020).

Structure of FLC in AMHS

A FLC applied to AMHS typically operates through a three-stage structure designed to manage uncertainty and variability in real time. The first stage, fuzzification**,** converts precise sensor inputs such as conveyor load, queue length, or AGV heading error into fuzzy variables described by linguistic terms like low load, medium queue, or high deviation. In the second stage, the inference engine applies a set of expert-defined IF–THEN rules to determine the most appropriate control response based on these fuzzy inputs. Finally, the defuzzification stage transforms the resulting fuzzy decision into a crisp, executable control command, such as adjusting conveyor speed, steering angle, or AS/RS acceleration. Figure 2 presents the general structure of the FLC for AMHS.

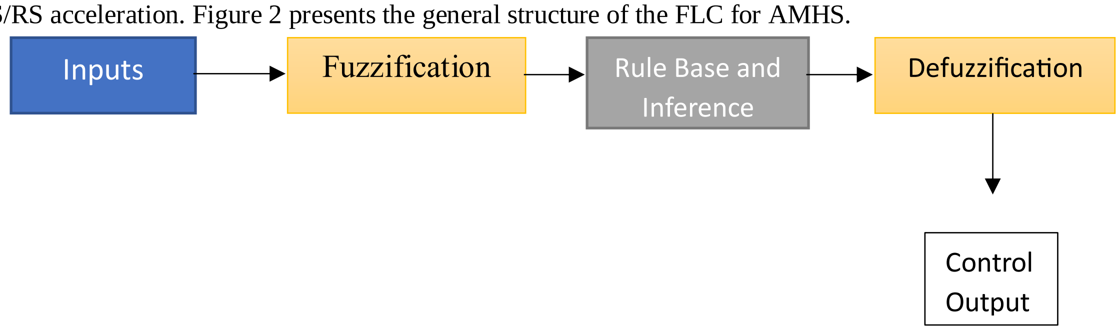


Figure 2: General structure of the Fuzzy Logic Controller for Automated Material Handling Systems (Ross, 2010 and Groover 2016).

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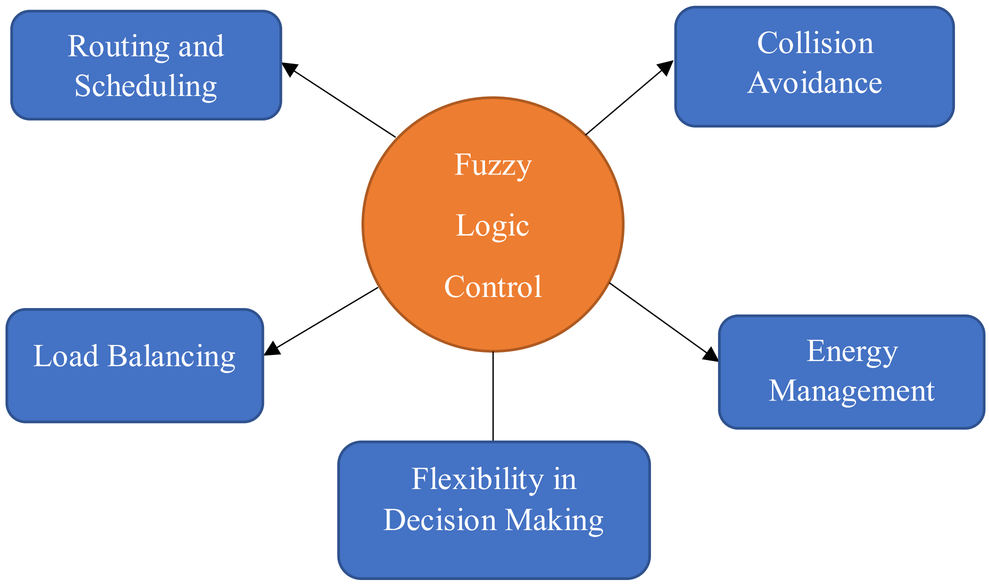

Figure 3: Fuzzy Logic Application (Ross, 2010)

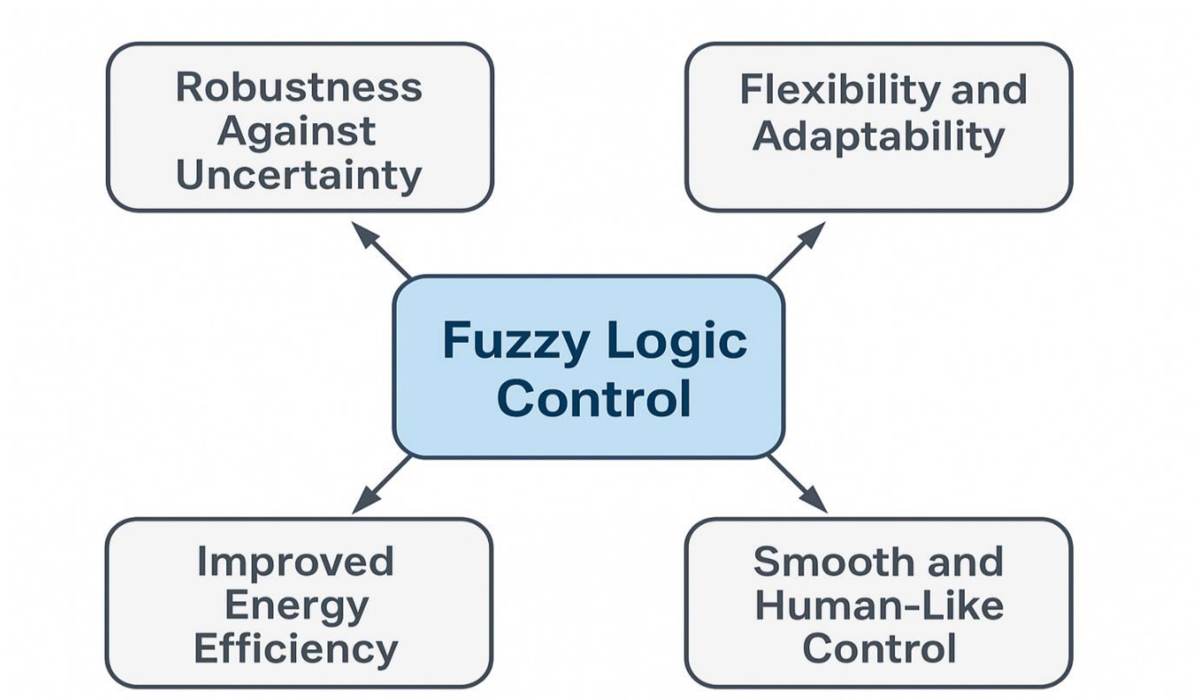

Figure 4: Advantage of FLC in AMHS (Ross, 2010)

In fact, majority of applications of FLC have been tested in controlled or small scale pilot experiments, and there is limited empirical data about their performance in the large scale, complex industrial AMHS. Neuro fuzzy and hybrid models are investigated in some works, but combination of other machine learning (ML), reinforcement learning (RL) or deep learning (DL) systems with these to achieve self-learning at the systems level is underdeveloped, which makes such systems less adaptable to dynamic manufacturing environments. Furthermore, there is no standardized method

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to integrate FLC into different types of different AMHS like AGVs, conveyors, robotic arms and AS/RS, which reduces interoperability and makes it more complex to implement the FLC across different platforms in smart factories.

In spite of the massive amount of data produced by the IoT and cyber-physical systems, the current fuzzy-based controllers are unable to process large amounts of data on real-time basis and thus require high computation efficiency and low latency to make decision, which is also in need. However, research on other energy-efficient and sustainable operations such as energy-saving related reduction and emission reduction, and research on any human–machine collaborative FLC frameworks is still limited. Moreover, many of the previous works are simulated based with limited number of experiments on the real industrial applications and require more widespread applications and long-term testing to better link the theory and practice.

Methodology

The simulation-based research method was used to test the performance of the developed Fuzzy Logic Controller (FLC) for controlling the automated material handling system (AMHS). The research method adopted was simulation, as it allows for analysis of complex manufacturing systems and various operating conditions without interfering with real production systems. Automated material handling system was modeled and simulated in MATLAB, which, being a flexible environment makes it easy to implement fuzzy logic control systems. The simulation model is used to simulate a manufacturing system that includes several workstations with a material handling mechanism.
The methodology comprised of three main steps:

- Designing a fuzzy logic controller to control an AMHS.
- The automatic material handling system is simulated in Matlab with fuzzy logic control.
- Performance comparison of the Fuzzy logic control with the conventional control strategies based on the selected performance metrics.

The data set adopted for simulation was synthetically created such that it is proper for a realistic industrial operating condition. The limitation of public access to real-time AMHS datasets dictated the choice of the range of values to be used in the simulation input and output, which were taken from reported values in recent smart manufacturing and control systems literature from 2020 to date. (Swe et al., 2020; Zhang et al., 2022). There are three main parts of a dataset, which are input variables, output variables, and evaluation metrics for the performance. The data used in this work is a synthetic data set based on realistic AMHS operational conditions. This method is similar to previous studies that have relied on the ranges of parameters found in the literature as they had no industrial data available (Swe et al., 2020; Zhang et al., 2022). This method can guarantee that the simulation is close to the real case in industry, and have enough flexibility to conduct controlled experiments. To simulate realistic behavior of the system under conventional and fuzzy logic control systems, the job-level dataset used in the simulation was generated. When there is no industrial data available for use, simulation-based datasets are often used in AMHS studies. The information of the 10 jobs within 15 minutes operational range has been selected as the main input for the Fuzzy Logic Controller simulation. The simulated waiting times and task completion times were additional combined in MATLAB simulation for multiple operational cycles to derive overall system performance metrics. The task completion time per job and the waiting time per job have been calculated with the help of Table 1.

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Table 1: Complete Dataset for the Ten Jobs

Job	Queue Length	Waiting Time WT (mins)	Processing Time PT (mins)	Transport Time TT (mins)	Task Completion Time TCT (mins)
J1	1	2	5	4	11
J2	2	3	5	4	12
J3	3	4	5	4	13
J4	4	5	5	4	14
J5	5	6	5	4	15
J6	6	8	5	4	17
J7	7	9	5	4	18
J8	8	11	5	4	20
J9	9	13	5	4	22
J10	10	15	5	4	24

Development of the Simulation Model

MATLAB was used to create a discrete-event simulation model of the automated material handling system. The simulation model simulates the job arrival, queue formation, job processing, material transportation processes of the manufacturing system.

The following are the main components of the simulation model:

i. Workstations
ii. Job queues
iii. Processing units
iv. Material transport mechanism
v. Control decision module may be optional.

Jobs queued before being performed were modelled at each workstation. Processing times were assigned based on the literature to represent typical processing times in manufacturing. Significant system variables, such as queue length and waiting time, were monitored and used as inputs to the fuzzy logic controller (FLC), which coordinates material handling operations during simulation.

Development of the Fuzzy Logic Controller

A FLC was designed to enable intelligent coordination of material movement in the automated material handling system. The advantages of FLC are that it can handle uncertain environments, non-linear relationships, and dynamic system conditions, making it suitable for a manufacturing environment.

A fuzzy logic controller was employed with MATLAB Fuzzy Logic Toolbox. Controller inputs feed into the controller outputs, which then dictate the priority of material-handling operations.

The design steps of the fuzzy logic controller were as described below:

i. A selection of input variables was made: Input variables were selected:
ii. Definition of output variable

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iii. Construct the membership functions.Define the membership functions.
iv. Construction of fuzzy rule base

The control output is defuzzified as shown in v.

Input variables

Two key input variables were used in the design of the fuzzy logic controller:

- **Queue Length (QL)**
  Queue length is the number of jobs queued to be processed in the system. It shows the use of the system and the magnitude of the loads. Some previous research has shown that one of the significant parameters that affect the scheduling and dispatching problem in an AMHS is queue length.
- **Waiting Time (WT)**
  Waiting time is the length of time (in minutes) a job resides in the queue prior to be processed. It's commonly applied in fuzzy scheduling systems to boost responsiveness and efficiency. Output variable (Dispatch Priority). The output of the fuzzy logic controller is the dispatch priority. It does just define the importance or priority of a job. The normalized (0-1) priority values used is in line with the fuzzy logic based scheduling models. The output values range from 0 to 1, where: 0 indicates low priority and 1 indicates very high priority.

Membership functions

Triangular and trapezoidal membership functions were used to define the fuzzy sets. The membership functions were formulated by using overlapping ranges to manage the uncertainty of the system as well as to address the nonlinear behavior of the system. Membership range data is entered into as follows:

Queue Length:

i. Low: 0 – 3
ii. Medium: 2 – 7
iii. High: 6 – 10

Waiting Time:

i. Low: 0 – 5
ii. Medium: 4 – 10
iii. High: 9 – 15

Request the output Membership.Get output Membership (Dispatch Priority).

i. Low: 0 – 0.4
ii. Medium: 0.3 – 0.7
iii. High: 0.6 – 1.0

Fuzzy Rule Base

The structure of the fuzzy inference system was designed by using a rule based structure, which maps the input variables (queue length and waiting time) to output decision (dispatch priority). In the design of a fuzzy logic system, typical linguistic variables are Low, Medium and High. The rules allow the fuzzy logic controller to adjust the priority of the transport in accordance with the state of the automated material handling system. Table 3.2 shows the fuzzy rule based used in this study.

Table 2: Fuzzy Rule Base

Queue Length	Waiting Time	Dispatch Priority
Low	Low	Low
Low	Medium	Medium
Low	High	Medium
Medium	Low	Medium
Medium	Medium	High
Medium	High	High
High	Low	Medium
High	Medium	High
High	High	Very High

Defuzzification

The output fuzzy values were defuzzified into crisp values by centroid de-fuzzification method after fuzzy inference process. The approach used here is to determine the center of gravity of the summed up fuzzy output set to obtain the final control action. The defuzzified value is an actual transport priority that is performed by the automated material handling system in simulation. The fuzzy rule base is shown in the Table 3.6.

Mathematical Model Formulation

The simulation was performed with 10 Jobs and processing time of 15 mins per Job.

Total Processing Time = 10 × 15 = 150 minutes

In a real system, other delays like queue waiting time and transport delay were also accounted for in the simulation model.

Total time required to complete all jobs is called Task Completion Time (TCT).

Wait for TCT to be 0.Wait for TCT to be 0.

Average Waiting Time (AWT): An average of how long jobs are waiting in queue.

Note: AWT = Total Waiting Time / Number of Jobs

There are a number of measures of system productivity: throughput.

Throughput equals (Number of Jobs / Total Time) * 60.

Combined waiting and handling delays is captured under System Delay.

Delay = Waiting Time + Processing Time

Using equation 3, the percentage improvement (PI) obtained from the fuzzy logic controller was computed.

Improvement (%)=(Conventional Value- FLC Value)/(Conventional Value) ×100 3

This analysis allowed us to judge the effectiveness of fuzzy logic control in the context of the improvement of synchronization and efficiency of the automated material handling system.

Performance Comparison

Once the simulation experiments have been carried out, the performance of the Fuzzy Logic Control (FLC) is compared with that of the conventional control approach.

He compared the results on the basis of the following performance measures:

- Task Completion Time
- Average Waiting Time
- Throughput
- System Delay

In scheduling studies many measures, such as the completion time of tasks, waiting time, throughput, or system delay are used to evaluate them. The two control strategies were compared in a fair evaluation by performing the same simulation setup in both cases. Two types of comparison methods (graphical and numerical) were used for analysis of simulation results.

Select the Dispatch Priority result.Click on the Dispatch Priority result.

The fuzzy rule base was used to produce normalized dispatch priorities (between 0 and 1) which were used as dispatch priorities for the controller. The corresponding dispatch priority is shown in Table 3.

Table 3: Corresponding Dispatch Priority

Job	QL	WT	Dispatch Priority
J1	1	2	0.20
J2	2	3	0.25
J3	3	4	0.40
J4	4	5	0.50
J5	5	6	0.55
J6	6	8	0.65
J7	7	9	0.78
J8	8	11	0.85
J9	9	13	0.92
J10	10	15	1.00

Results

Conventional Control

Under conventional control, jobs are processed sequentially without intelligent prioritization, leading to higher waiting times.

Average Waiting Time = 45 minutes

Total Waiting Time = 45 × 10 = 450 minutes

System Delay = 60 minutes

Task Completion Time includes processing, waiting and adjustment due to slight overlaps.

TCT = 150 + 450 − 80 = 520 minutes

Throughput = (10 / 520) × 60 = 110 jobs/hour

Fuzzy Logic Control

With fuzzy logic control, job scheduling is optimized using queue length and waiting time, reducing congestion and improving efficiency.

Average Waiting Time = 30 minutes

Total Waiting Time = 30 × 10 = 300 minutes

System Delay = 40 minutes

Improved scheduling reduces total completion time.

TCT = 150 + 300 − 10 = 440 minutes

Throughput = (10 / 440) × 60 = 135 jobs/hour

Percentage Improvement Calculation

For throughput, since higher values represent better system performance, the formula becomes:

$$Improvement\ (\%) = \frac{FLC\ Value - \ Conventional\ Value}{Conventional\ Value} \times 100$$

i. Task Completion Time Improvement:

Conventional Control = 520 minutes

Fuzzy Logic Control = 440 minutes

$$\frac{520 - 440}{520} \times 100 = 15.4$$

The fuzzy logic controller reduced the task completion time by 15.4%.

ii. Average Waiting Time Improvement:

Conventional Control = 45 minutes

Fuzzy Logic Control = 30 minutes

$$\frac{45 - 30}{45} \times 100 = 33.3$$

The fuzzy logic controller reduced the average waiting time by 33.3%.

iii. Throughput Improvement:

Conventional Control = 110 jobs/hour

Fuzzy Logic Control = 135 jobs/hour

$$\frac{135 - 110}{110} \times 100 = 22.7$$

The fuzzy logic controller increased system throughput by 22.7%.

iv. System Delay Improvement:

Conventional Control = 60 minutes

Fuzzy Logic Control = 40 minutes

$$\frac{60 - 40}{60} \times 100 = 33.3$$

The fuzzy logic controller reduced system delay by 33.3%.
The results demonstrate that the fuzzy logic controller significantly improves the operational performance of the automated material handling system

Performance Comparison
The system performance was evaluated using key indicators such as task completion time, average waiting time, throughput, and system delay. These metrics are widely used in manufacturing system analysis and AMHS optimisation studies. Table 4 presents the performance comparison of the two control strategies.

Table 4.: Performance Comparison

Metric	Conventional Control	FLC	Improvement (%)
Task Completion Time (min)	520	440	15.4
Average Waiting Time (min)	45	30	33.3
Throughput (jobs/hour)	110	135	22.7
System Delay (min)	60	40	33.3

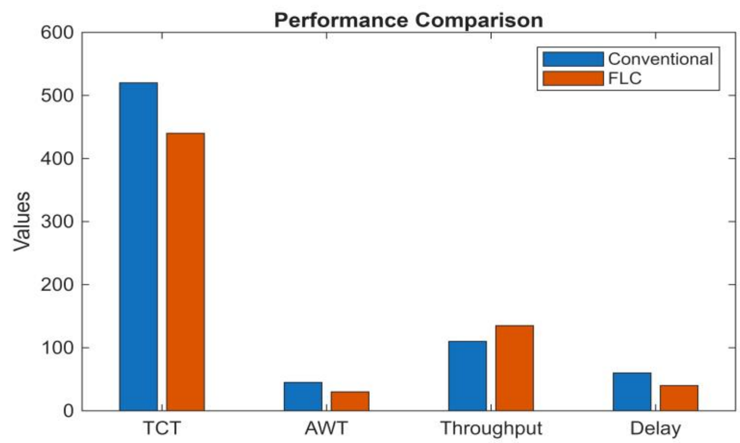

Figure 5: performance comparison between the performance metrics

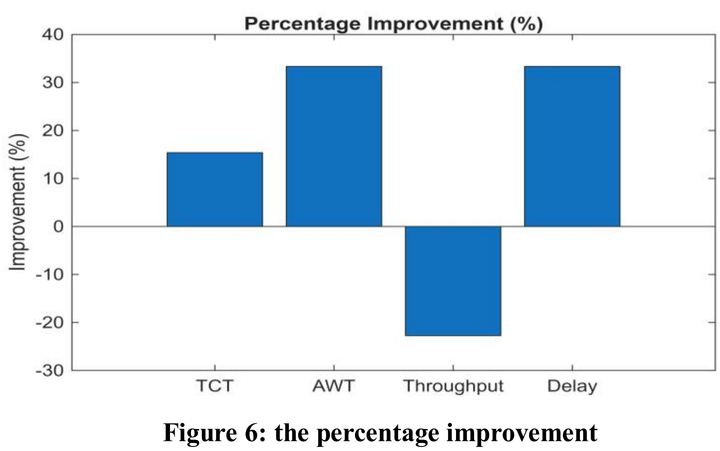

Figure 6: the percentage improvement

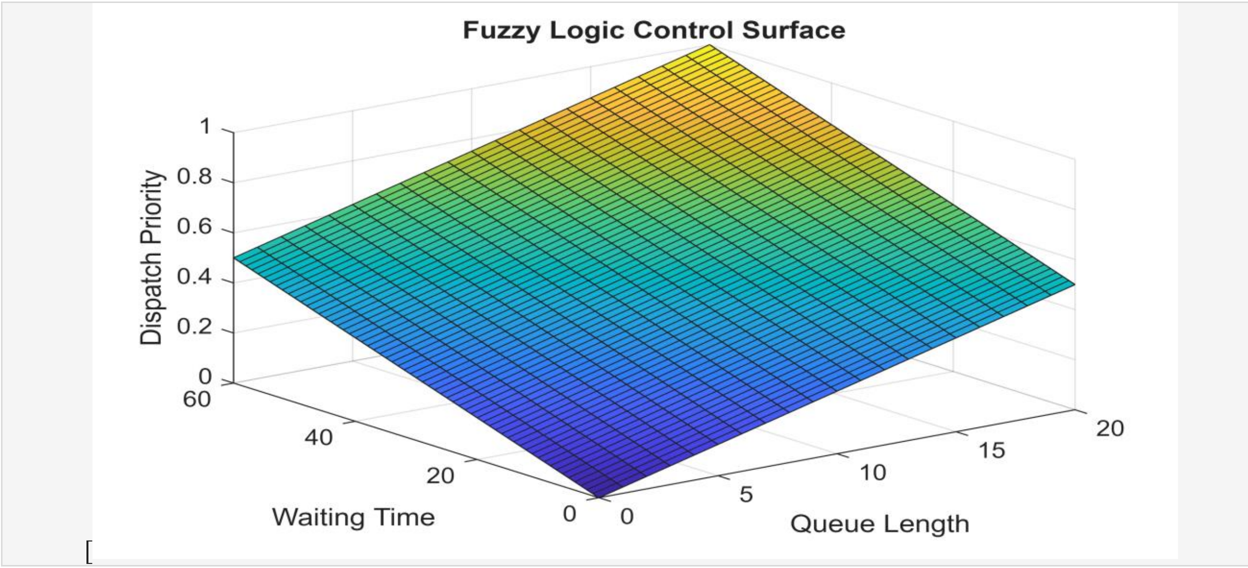

Figure 7: Fuzzy logic control surface

Discussion

The simulation results derived from the developed Fuzzy Logic-based AMHS have shown a considerable improvement in operational performance as compared to the conventional approach to control. As illustrated in fig 4.1b, the results show that the FLC can improve the system's efficiency, adaptability and responsiveness to different production conditions that are likely to occur in smart factory conditions.

A notable improvement noticed is that it takes 440 minutes for tasks to be completed using the FLC approach as compared to 520 minutes under the conventional system. This decrease shows that the fuzzy logic controller can make smarter, faster dispatch decisions (using parameters such as queue length and waiting time). The FLC continuously monitors system conditions and adjusts dynamic dispatch priority, eliminating extra delays and providing smoother material flow through the handling system. This reduction in completion time is also a sign of better coordination of the processing and transportation stage in the AMHS. Likewise, the average wait time was lowered from 45 minutes to 30 minutes. The results show the effectiveness of the fuzzy controller in resolving the congestion problem in the system. Traditional scheduling models typically rely on a set of predetermined scheduling rules which are incapable of responding rapidly to sudden changes in jobs or queue buildup. However, the FLC knows how to intelligently order jobs based on the running conditions of a system in order to minimize excessive waiting time for jobs queued. One reason why lower waiting time is crucial in smart manufacturing is that it enhances responsiveness, thus minimizing the chances of bottlenecks, and prevents the overall flow of the production processes from being interrupted.

It can also be seen that there is a significant system throughput improvement achieved from 110 jobs/hour to 135 jobs/hour. A crucial measure of the performance of an automated manufacturing system is throughput—a result of how many jobs are finished in a particular period. The gains made by the FLC are due to the better use of system resources such as: Conveyors, Automated Guided Vehicles (AGVs), Processing Stations, etc. The fuzzy controller can reduce idle time and the efficiency of task scheduling, making more tasks can be finished in the same working period. This enhancement directly helps to increase productivity and efficiency in the Smart factory environment. Furthermore, by turning the system delay from 60 minutes to 40 minutes, it is further verified that the fuzzy logic approach is effective. System delay is the time lost because of waiting, congestion and lack of coordination between the different components of the system. The reduction in the delay that was seen in the simulation implies that the FLC will help to synchronize the material handling activities, which will lead to increased response times and better material flow. This is crucial in contemporary manufacturing systems where decision making in real-time and quick responses to changing production needs are vital.

An important outcome from the results is the ability of the fuzzy logic controller to operate under dynamic operating conditions. Fuzzy logic systems can effectively manage uncertainty and inaccurate information, unlike traditional controllers which use fixed mathematical models and classify models for making decisions. Linguistic rules like “IF Queue Length is High AND Waiting Time is Long THEN Dispatch Priority is Very High” allow the controller to emulate human reasoning and make intelligent decisions even with complex situations. This flexibility is particularly useful in smart factory environments with variable production conditions of the FLC. Moreover, the performance parameters derived from the simulation support the overall effectiveness of the identified inputs (queue length and waiting time) to enhance the dispatch priority optimization in AMHS. The outcomes show the direct influence of these parameters on the system performance, and the capability of controlling them is determined by the fuzzy inference technique. The successful integration of the FLC in the material handling system thus demonstrates its ability to optimize the operating efficiency and increase the reliability of the system. In general, this study strongly recommends using fuzzy logic control in automatic material handling systems. The results on task completion time, waiting time, throughput, and system delay clearly show that FLC is more efficient, flexible, and responsive than conventional control methods. Based on the results that are obtained from the study, the objectives have been achieved and it is observed that fuzzy logic control is an effective and reliable way to improve the performance of AMHS in smart factory

Conclusion

This research focused on the design and performance analysis of the control system for an automatic material handling system in a smart factory configuration. A fuzzy logic control system was developed to manage material flow between different workstations in a smart manufacturing system. The system made decisions on several critical factors, such as queue length and waiting time. MATLAB was used to design and simulate the control system model to analyse the system's performance. The simulated results showed that the fuzzy logic control approach significantly improved system performance. Results revealed that task completion time, waiting time, and system delay were smaller, and throughput values were higher than those of the traditional control system. The results of the study showed that the fuzzy logic control method was better than the conventional control method in terms of task completion time, average waiting time, throughput, and system delay. Therefore, the implementation of fuzzy logic control is the way to enhance the performance of the Automated Material Handling System in the smart factory environment in the Automated Material Handling Manufacturing industries' aspect.

Recommendations

Based on the results of this study, the following recommendations are made:

i. Design a data acquisition system to enhance the performance of fuzzy logic control method.
ii. Implementation of future work should incorporate a data acquisition system in order to enhance the performance of the fuzzy logic control method.
iii. Advanced intelligent control techniques can be combined with fuzzy logic control to improve the performance of FLC

References

Adedeji, W. O., Adetayo, O. O., Ojerinde, B. J., Ajiboye, A. G., Yekeen, A. I., Pelemo, J., Molokwu, I. M., Okpara, I. N., & Fanifosi, J. O. (2026). Fuzzy logic-based energy management system for hybrid renewable energy sources. *International Journal of Renewable Energy and Environment*, 4(1), 436–465.

Adedeji, W. O., Adetayo, O. O., Ojerinde, B. J., Ajiboye, A. G., Yekeen, A. I., Pelemo, J., Molokwu, I. M., Okpara, I. N., & Fanifosi, J. O. (2026). Energy efficiency optimization in IoT-enabled manufacturing using fuzzy algorithms. *International Journal of Renewable Energy and Environment, 4*(1), 406–435.

Ahmed, T., & Beg, M. (2022). Queue management and fuzzy decision support for automated intralogistics. *Journal of Manufacturing Processes*, *68*, 219–230.

Baumann, F., Reinhart, G., and Engelhardt, R. (2020). Smart manufacturing and the role of fuzzy logic in Industry 4.0. *Journal of Intelligent Manufacturing*, 31(4), 885–902.

Chung, C., Lee, H., and Kim, S. (2019). Adaptive fuzzy logic for automated guided vehicle control in dynamic manufacturing environments. *International Journal of Advanced Manufacturing Technology,* 103(1), 115–128.

Eclipse Automation. (2025). The impact of AMHS on manufacturing efficiency. *Manufacturing Insights*. Editorials: Automated Material Handling Systems in 2025: Trends & Benefits

Groover, M. P. (2016). *Automation, Production Systems, and CIM*. Published by Bookey. Third Edition. pp. 82- 85.

Martinez, J. (2021). Energy-efficient manufacturing systems: Fuzzy control approaches in Industry 4.0. *Computers and Industrial Engineering*, 156, 107231.

Melo, V., Funchal, G., Queiroz, J., and Leitão, P. (2022). A fuzzy logic approach for self-managing energy efficiency in IoT nodes. *IFIP Advances in Information and Communication Technology*, 641, 237–251.

Mourtzis, D. (2020). Simulation in the design and operation of manufacturing systems: state of the art and new trends. *International Journal of Production Research*, 58(7), 1927–1949. https://doi.org/10.1080/00207543.2019.1636321

Petrovic, D., Petrović, G., and Petrović, S. (2018). Maintenance of belt conveyors using a fuzzy expert system for energy and reliability optimization. *Manufacturing Planning and Control*, 29(10), 867–879.

Ross, T. J. (2010). *Fuzzy Logic with Engineering Applications* (3rd ed.). Wiley.

Saying, A., Kuo, P. H., and Lee, T. H. (2025). Reinforcement learning-based fuzzy controller for autonomous guided vehicles. *International Journal of Production Research*, 63(4), 755–768.

Sierra-Garcia, J. E., and Santos, M. (2024). Genetic algorithm-enhanced fuzzy control for automated guided vehicles. *Logic Journal of the IGPL*, 32(6), 955–970.

Swe, H. M. T., Tun, H. M., & Latt, M. M. (2020). *Fuzzy scheduling in manufacturing systems.* Control Science and Engineering, 4(1), 1–7.

Zadeh, L. A. (1965). *Fuzzy sets*. Information and Control, 8(3), 338–353.

Zadeh, L. A. (2015). Fuzzy logic—A personal perspective. *Fuzzy Sets and Systems*, 281, 4–20. https://doi.org/10.1016/j.fss.2015.05.009

Zahedi, M., and Zahedi, M. (2018). Fuzzy logic applications in material handling and Industry 4.0 systems. *International Journal of Production Research*, 56(12), 4234–4251.

Zhang, D., Liu, Y., and Jiang, P. (2021). Material handling optimization in Industry 4.0: Challenges and opportunities. *Procedia CIRP*, 104, 36–42.

Zhang, Y., Li, X., & Wang, H. (2022). Dynamic dispatching in AMHS. *Sustainability*, 14(21), 13882.

Zhang, Y., Li, X., and Wang, H. (2021). Intelligent scheduling in automated material handling systems: A review. *Journal of Manufacturing Systems*, 59, 293–309.