

Design and Simulation of an Intelligent Elevator System using Adaptive Self-Tuning Regulator and Fuzzy Logic Control

¹Dike, J. N. and ²Ekpo, J. C.

^{1,2}Department of Electrical/Electronic Engineering, Faculty of Engineering
University of Port Harcourt
Port Harcourt, NIGERIA
¹Corresponding Author

ABSTRACT: Critical in the design of modern elevator systems is the gap between dispatch optimization and real-time system adaptability, particularly in safety-critical scenarios where rapid and reliable responses are essential. Conventional elevator control strategies often suffer from high acceleration peaks, delayed response, uneven ride comfort, inefficient energy usage, and limited adaptability to varying passenger loads and traffic patterns. In this work, intelligent elevator system using adaptive self-tuning regulator (ASTR) and fuzzy logic control (FLC), embedded within a destination control system (DCS) is developed. The proposed approach employed a time-varying state-space model and real-time adaptive control to dynamically adjust feedback gains, while the fuzzy logic controller provides intelligent decision-making based on system error and its rate of change. The system was modeled and evaluated through simulation using MATLAB and Simulink under varying load, traffic, and fault scenarios. Performance metrics considered include elevator position tracking, velocity response, acceleration profiles, response time, travel time and cost function, system safety, responsiveness, ride comfort, and energy efficiency. Simulation results show that the elevator reached a 7-meter target position within 6 seconds without overshoot, with peak velocity limited to 2.5 meters per second and acceleration maintained within comfort thresholds. The hybrid controller improved the ride comfort index and reduced cumulative energy consumption when compared with a conventional controller. Safety performance increased rapidly from over 80% to reach 99.5 percent reliability over 1,000 operational cycles, while control efficiency remained between 90 and 95 percent under varying loads. The results demonstrate that the proposed hybrid adaptive control strategy provides a robust, safe, and energy-efficient solution suitable for intelligent elevator systems in modern high-rise and smart building applications.

Date of Submission: 03-04-2026

Date of acceptance: 14-04-2026

I. INTRODUCTION

Elevator systems have become indispensable components of the built environment, directly influencing mobility, safety, energy consumption and overall building efficiency. This is a consequence of the rapid pace of urbanization and the continuous expansion of vertical constructions, which have fundamentally reshaped the design and operation of modern buildings in densely populated urban environments, especially in high-rise and smart buildings. As the evolving reliance on vertical transportation increases, the need for efficient elevator systems, operating with high levels of reliability, safety, adaptability and passenger comfort has become inevitable. Consequently, the design of intelligent elevator control systems has emerged as a critical research area within modern control engineering and building automation (Bapin and Zarikas, 2019; Yavaş, 2024; Siikonen, 2024; Gharbi, 2024).

Traditional elevator control systems were primarily developed using relay-based logic and fixed-parameter proportional integral derivative (PID) controllers. While these approaches have historically delivered acceptable performance under stable operating conditions, they exhibit notable limitations when exposed to dynamic passenger traffic, variable loads and unexpected disturbances such as mechanical wear, sensor faults or emergency events. Fixed-parameter controllers lack the flexibility required to respond effectively to time-varying system dynamics, often resulting in increased waiting times, inefficient energy usage, uncomfortable ride characteristics and compromised safety margins. These challenges are particularly pronounced in multi-elevator installations and high-capacity systems where operational complexity is significantly higher (Siikonen, 2024).

In response to growing performance demands, destination control systems (DCSs) were introduced as an advanced elevator dispatching strategy. Numerous studies have demonstrated that DCS can substantially

reduce passenger waiting times, improve traffic handling efficiency during peak periods, and enhance overall system throughput. As a result, DCS has become a core feature in modern intelligent buildings and large-scale elevator installations. Unlike conventional elevator systems where passengers simply select an up or down direction, DCS requires passengers to enter their destination floor before boarding the elevator. The control system then groups passengers travelling to similar floors and assigns them to specific elevator cars. This strategy reduces unnecessary stops and improves passenger flow within the building. Research on destination-based dispatching algorithms suggests that such systems can significantly improve the efficiency of elevator traffic management in high-rise buildings (Richer et al, 2024). Despite these advantages, the effectiveness of DCS remains constrained by its underlying control logic. Most existing DCS implementations rely on rule-based algorithms, heuristic scheduling strategies or static optimization models that are not inherently adaptive. When operating conditions deviate from predefined assumptions such as sudden changes in passenger demand, load imbalance, component degradation or sensor malfunction, the performance of DCS can deteriorate significantly (Sorsa et al. 2006; Sorsa, 2019; Sorsa et al. 2021).

Several design attempts have been made to optimize the operations, safety, ride comfort and cost of elevator systems (Ang et al, 2022; Chen and Astolfi, 2020; Gharbi, 2024; Hanif and Mohammad, 2023; Stawinski et al, 2023; Zhang et al, 2023; Wang, 2024). Earlier designs produced the hydraulic elevators, which were commonly used in low-rise buildings due to their relatively simple design and lower installation cost. Though hydraulic elevators could handle heavy loads and operate reliably in short buildings, they were generally slower and less energy efficient (Al-Kodmany, 2018). Another important development in elevator engineering was the double-deck elevator system, which consists of two elevator cabins positioned vertically within the same shaft. This design allows the system to serve two floors simultaneously, thereby reducing the number of elevator shafts required in tall buildings. Though double-deck elevators improved space efficiency, they introduce several operational limitations. For instance, passengers must often adjust their travel patterns because each cabin only serves specific floors. In addition, both cabins must stop together even when only one cabin is required to pick up or drop off passengers, which can reduce dispatching efficiency and increase waiting time during uneven traffic conditions (Sorsa, 2019; Cortés et al., 2021). Bapin and Zarikas (2019) demonstrated that Bayesian Network-based approaches can effectively improve elevator dispatching by incorporating probabilistic reasoning and real-time passenger data. The proposed method enhanced the accuracy of elevator assignment decisions but could not address the underlying dynamic control of elevator motion or the real-time adaptation of controller parameters. Chen et al. (2021) introduced a matrix-based iterative optimization algorithm integrating multi-sensor data for real-time elevator booking coordination. Their study focused on synchronizing group movements through iterative control matrices, yielding improvements in dispatch accuracy. However, Chen's approach relied on deterministic modeling and fixed parameters, which constrained the system's flexibility in managing sudden sensor noise, asynchronous signals, or actuator degradation.

In recent years, several researchers have explored intelligent control strategies to improve elevator dispatching and operational efficiency. For example, reinforcement learning techniques have been applied to elevator group control problems in order to reduce passenger waiting times and improve traffic flow in dynamic environments (Wojtulewicz and Szmuc 2024). Qasimi and Nashir. (2024) proposed a fuzzy logic-based elevator group control system aimed at optimizing hall call allocation and reducing passenger waiting time. Their approach demonstrated that fuzzy inference mechanisms, particularly those based on Mamdani reasoning, can effectively manage uncertainties in passenger demand and improve system responsiveness under varying traffic conditions. Despite these contributions, their scope of existing fuzzy-based elevator control systems remains largely confined to dispatching optimization. Kompauer (2025) developed a destination registration system based on mixed-integer linear programming (MILP) and heuristic algorithms, aimed at optimizing passenger grouping and minimize idle car trips.

These limitations highlight a critical gap between dispatch optimization and real-time system adaptability, particularly in safety-critical scenarios where rapid and reliable response is essential. This study presents a hybrid adaptive control framework for improving the performance, safety, and energy efficiency of modern elevator systems operating under dynamic conditions. It proposes the integration of an adaptive self-tuning regulator (ASTR) with a fuzzy logic controller (FLC) within a destination control system (DCS) framework. This approach not only enhances dispatching intelligence but also enables real-time adaptation of control parameters, thereby improving system stability, safety performance and operational efficiency under dynamic conditions.

II. MATERIAL AND METHODS

This section presents the phase-wise description of a model-based, simulation-driven experimental design of an intelligent elevator system using adaptive self-tuning regulator (ASTR) and fuzzy logic control (FLC). The study focuses on the assessment of elevator position, velocity response, acceleration profiles, response time, travel time, cost function, system safety, responsiveness, ride comfort, and energy efficiency

under dynamic operating and fault conditions. The investigation is conducted entirely within the MATLAB®/Simulink® environment (MathWorks, 2023), which served as the computational platform for system modeling, controller implementation, fault injection and performance evaluation. The “subjects” of analysis are simulated elevator system models, representing a typical high-rise passenger elevator operating under realistic load, traffic and safety constraints. The design is a hybrid integration of ASTR and FLC with destination control systems (DCS) safety evaluation, comprising of design of the adaptive self-tuning regulator, development of the fuzzy logic controller, integration of ASTR–FLC into the destination control system, materials and simulation environment and performance evaluation.

Phase I: Design of Adaptive Self-Tuning Regulator (ASTR)

The elevator system is represented using a time-varying state-space formulation, allowing real-time adaptation to changing load conditions and cable tension variations. The system dynamics are defined while the elevator system is modeled using a time-varying state-space representation, expressed as:

$$\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) \quad (1)$$

where: $\mathbf{x}(t)$ is the state vector, $\mathbf{u}(t)$ is the control input, $\mathbf{A}(t)$ and \mathbf{B} are time-varying system matrices.

$$\mathbf{y}(t) = \mathbf{C} \mathbf{x}(t) + \mathbf{D} \mathbf{u}(t) \quad (2)$$

where: $\mathbf{y}(t)$ represents observable variables such as position or speed, \mathbf{C} is the output matrix and \mathbf{D} is the direct transmission matrix.

This formulation enables continuous monitoring of elevator motion and provides feedback signals required for adaptive control.

Parameter Adaptation Law: The ASTR updates controller parameters recursively based on system error and state information:

$$\boldsymbol{\theta}(t + 1) = \boldsymbol{\theta}(t) + \boldsymbol{\gamma} e(t) \mathbf{x}(t) \quad (3)$$

where: $\boldsymbol{\theta}(t)$ is the parameter vector, $e(t)$ is the output error and $\boldsymbol{\gamma}$ is the adaptation gain.

This learning mechanism allows the controller to compensate for modeling uncertainties and external disturbances in real time.

Control Law and Performance Index: The adaptive feedback control law is defined as:

$$\mathbf{u}(t) = -\mathbf{k}(t)\mathbf{x}(t) \quad (4)$$

where: $\mathbf{u}(t)$ is control input, $\mathbf{k}(t)$ is time-varying feedback gain and $\mathbf{x}(t)$ is system state

Controller optimization is guided by the quadratic performance index:

$$J = \int_0^T [\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{u}^T \mathbf{R} \mathbf{u}] dt \quad (5)$$

where: \mathbf{Q} and \mathbf{R} are weighting matrices, and T is the evaluation time period.

This ensures a balance between tracking accuracy and control effort, minimizing overshoot and energy consumption.

Phase II: Development of the Fuzzy Logic Controller (FLC)

Error Signal Definition

The primary input to the FLC is the position error:

$$\mathbf{e}(t) = \mathbf{r}(t) - \mathbf{y}(t) \quad (6)$$

where $e(t)$ is error signal, $r(t)$ is desired setpoint and $y(t)$ is actual output

The rate of change of error is defined as:

$$\dot{\mathbf{e}}(t) = \frac{d\mathbf{e}(t)}{dt} \quad (7)$$

Where: $\dot{e}(t)$ is error rate and $e(t)$ is Position error

These two inputs enable the FLC to respond to both magnitude and dynamics of deviation.

Fuzzy Control Law

The fuzzy control output is computed as:

$$\mathbf{u}(t) = \sum_{i=1}^n \mu_i(\mathbf{e}(t), \dot{\mathbf{e}}(t)) \cdot \mathbf{w}_i \quad (8)$$

where μ_i is membership function output for rule I, \mathbf{w}_i is control action for rule I and n is number of rules

This Gaussian membership function defines how the error e maps to a fuzzy rule's truth value. It enhances the interpretability and smoothness of FLC actions in controlling elevator dynamics.

$$\mu_i(e) = \exp\left(-\frac{e-c_i}{2\sigma_i^2}\right) \quad (9)$$

where c_i is center of Gaussian, σ_i^2 is width of the Gaussian and e is error input

The general fuzzy inference mapping is expressed as:

$$\mathbf{u}(t) = \mathbf{f}(\mathbf{e}(t), \dot{\mathbf{e}}(t)) \quad (10)$$

where f is Fuzzy inference function, $e(t)$ is error and $\dot{e}(t)$ is error derivative

Phase III: Integration of ASTR and FLC into Destination Control System

Passenger Waiting and Traffic Metrics

Average passenger waiting time is computed as:

$$T_w = \frac{1}{n} \sum_{i=1}^n (t_{ai} - t_{ri}) \quad (11)$$

where T_w is average waiting time, t_{ai} is actual arrival time of elevator, t_{ri} is Request time and n is number of passengers.

Control efficiency is defined as:

$$C_{eff} = \frac{P_{served}}{P_{total}} \quad (12)$$

where C_{eff} is control efficiency, P_{served} is number of passengers served and P_{total} is total requests.

Queue behavior is evaluated using:

$$L_q = \lambda W_q \quad (13)$$

where L_q is average number in queue, λ is arrival rate, W_q is average waiting time

Service rate is given by:

$$\mu = \frac{1}{T_s} \quad (14)$$

where μ is service rate and T_s is time to serve a passenger

Total system response time is:

$$T_{resp} = T_{det} + T_{proc} + T_{act} \quad (15)$$

where T_{resp} is total response time, T_{det} is detection time, T_{proc} is processing time and T_{act} is actuation time

Figure 1 illustrates a hybrid adaptive-fuzzy control architecture integrated with a destination control system (DCS) for elevator operations. The reference input represents the desired elevator performance metrics (target position, velocity profile, service demand, etc). The reference is compared with the measured system output to generate the error signal (e), which quantifies the deviation between desired and actual performance. The error signal is processed in parallel by three control components

- a) The adaptive regulator, which generates a control signal U_a by dynamically adjusting its parameters in response to system variations, load changes, and uncertainties. This enables real-time adaptation and improves robustness under varying operating conditions.
- b) The fuzzy logic controller, which also produces a control signal U_a based on linguistic rules derived from expert knowledge. It is particularly effective in handling nonlinearities and imprecise information inherent in elevator dynamics and passenger demand patterns.
- c) An additional fuzzy logic block generates a supervisory control signal U_f which enhances decision-making by modulating system behavior based on higher-level heuristics or performance criteria.

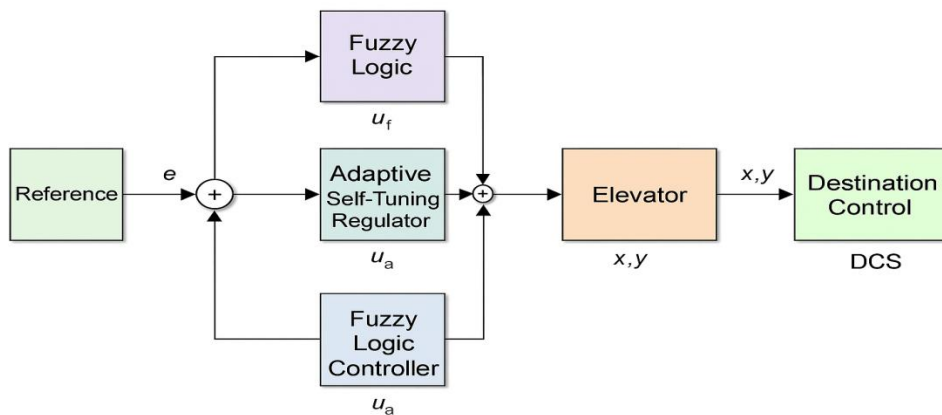


Figure 1. Block diagram showing ASTR and FLC integrated into the DCS

The outputs of the adaptive regulator and fuzzy logic components are summed to form the final control input applied to the elevator plant. This combined control strategy leverages the adaptability of self-tuning control and the flexibility of fuzzy reasoning. The elevator block represents the physical elevator system, whose outputs x, y may correspond to state variables such as position, velocity or acceleration. These outputs are fed to

the destination control system (DCS), which optimizes passenger allocation, routing and dispatching decisions based on current elevator states.

Phase IV: Materials and Simulation Environment

The primary materials used in this study include: MATLAB® and Simulink® software for system modeling and simulation, Simulink Control Design™ Toolbox for adaptive controller implementation, Fuzzy Logic Toolbox™ for the design and visualization of fuzzy inference systems and Stateflow® blocks for logic sequencing, fault handling, and destination control representation

Phase V: Simulation Environment and Parameters

Simulation is performed in MATLAB/Simulink, with parameters summarized in Table 1, including passenger load, elevator speed, acceleration, energy consumption and safety indices.

Table 1: Parameters used in designing and simulating the Elevator on MATLAB/SIMULINK

S/N	Parameter	Unit	Value	Description
1	Passenger load	Kg	650	Total weight in the elevator
2	Elevator speed	m/s	2.5	Travel speed of elevator
3	Elevator acceleration	m/s ²	0.9	Acceleration during movement
4	Waiting time	Seconds	18	Average passenger wait time
5	Response time	Seconds	5	Time from request to movement
6	Energy consumed	kWh	1.8	Energy used per round trip
7	Power consumption	kW	7.2	Power drawn during peak
8	Ride comfort index	-	0.12	Comfort based on acceleration variation
9	Safety factor	-	0.998	Ratio of safe operations
10	Service rate	persons/s	0.7	Passengers served per second
11	Arrival rate	persons/s	0.5	Passenger arrival rate
12	Queue length	Persons	3	Average queue size
13	Control efficiency	%	92.5	Efficiency of control system
14	Acceleration mean	m/s ²	0.85	Average acceleration over time
15	Fault-free operations	Count	995	Operations without faults
16	Total operations	Count	1000	Total elevator runs
17	Ideal energy usage	kWh	1.5	Minimum theoretical energy for operation
18	System efficiency	%	83.3	Actual vs ideal energy usage
19	Detection time	Seconds	0.7	Time to detect a call
20	Actuation time	Seconds	1.2	Time to respond to command

Figure 2 illustrates a closed-loop elevator simulation model, where floor requests are translated into motor and door commands, thereby driving a physically realistic elevator assembly. The system continuously outputs motion variables that can be analyzed to assess ride comfort, safety limits, control performance, and system reliability.

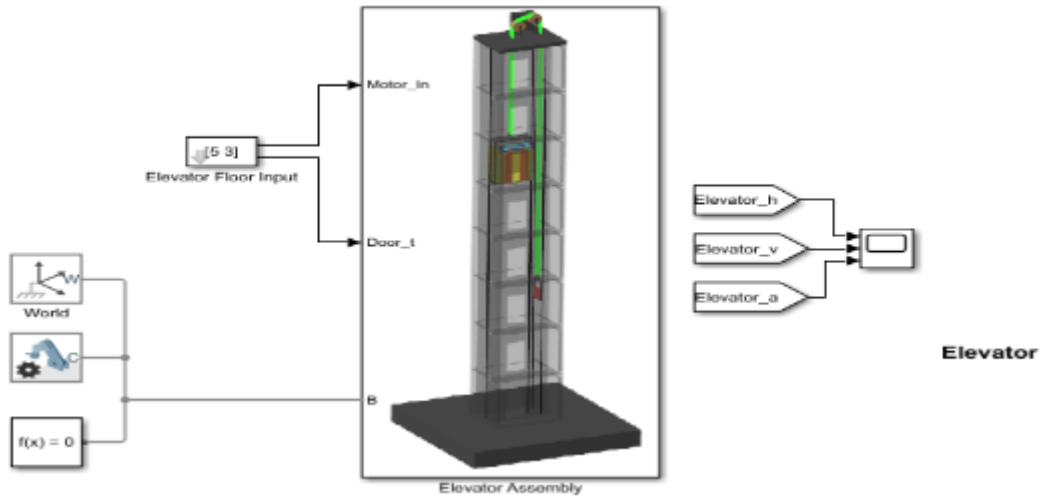


Figure 2. Elevator Simulink Diagram

Phase VI: Performance Evaluation Metrics

Safety performance is quantified as:

$$S_f = \frac{F_{safe}}{F_{total}} \quad (16)$$

where S_f is safety factor, F_{safe} is safe operations and F_{total} is total operations

Ride comfort is evaluated using acceleration variance:

$$C_r = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - \bar{a})^2} \quad (17)$$

where C_r is ride comfort index, a_i is instantaneous acceleration, \bar{a} is mean acceleration and n is number of samples

Energy consumption is computed as:

$$E_{consumed} = \int_0^T P(t) dt \quad (18)$$

where: $E_{consumed}$ is energy used, $P(t)$ is power at time t and T is time duration.

III. RESULTS AND DISCUSSION

The performance of the proposed hybrid adaptive self-tuning regulator-fuzzy logic control (ASTR-FLC) elevator system was evaluated through simulation in terms of dynamic responses, service efficiency, ride comfort, energy consumption and safety. The results obtained demonstrate that the integration of an adaptive self-tuning regulator with fuzzy logic control, yields a robust and high-performing elevator control framework capable of addressing the inherent nonlinearities, uncertainties and varying operational conditions of modern elevator systems.

In Figure 3, the time-varying system matrices $A(t)$ and $B(t)$ demonstrated continuous adaptive behavior throughout operation. The elements of $A(t)$ exhibited bounded oscillations associated with real-time adjustments in position, velocity, acceleration, and damping dynamics, while the control input matrix $B(t)$ reflected adaptive variations in control force responsiveness. These results confirmed that the controller actively updated system parameters rather than relying on fixed gains.

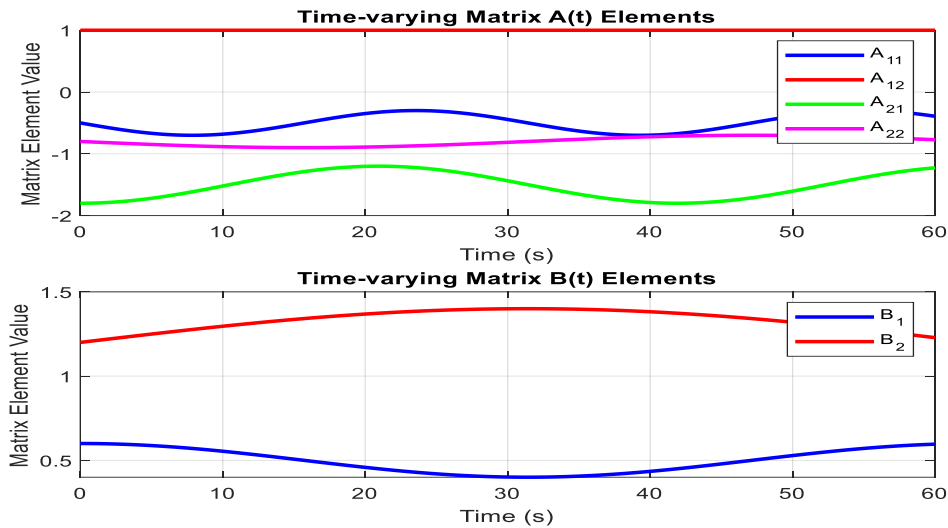


Figure 3. Time-varying matrices

A key strength of the proposed ASTR-FLC controller lies in its adaptive nature, as evidenced by the continuous variation of the system matrices and feedback gains. Unlike conventional controllers that rely on fixed parameters derived from nominal operating conditions, the proposed approach dynamically adjusts its internal structure in response to real-time system behavior. This adaptability is particularly important in elevator systems, where loading conditions, passenger demand patterns, and mechanical characteristics change frequently. The observed bounded evolution of system parameters indicates that adaptation occurs in a controlled and stable manner, preventing instability while maintaining responsiveness.

The pie chart of Figure 4, divides the total 5 s response time into its components. Detection claims 0.7 s, actuation 1.2 s, and the remaining 3.1 s is processing. Thus, roughly 62 % of the time is spent deciding what to do, with the rest split between sensing and action. Think of a smart driver: 13% looking at the road, 25% pressing pedals, and the rest calculating whether to brake or accelerate. This insight helps spotlight performance hotspots, such that even a small reduction in detection or processing could noticeably speed up overall response.

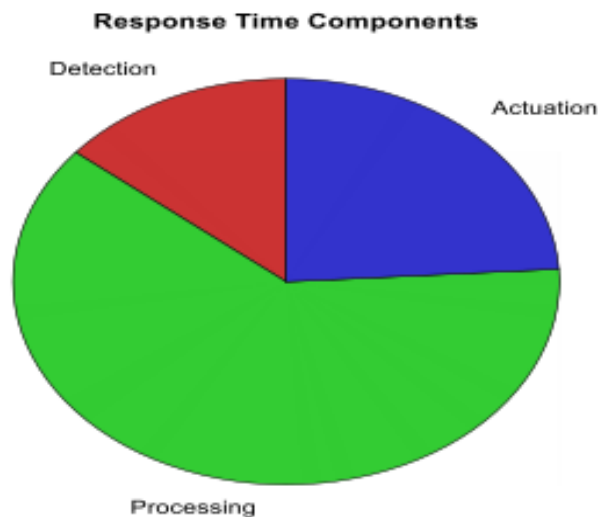


Figure 4: Response time components

The fuzzy logic control surface of Figure 5, illustrates a continuous and bounded mapping between the error, error-rate, and motor control output. The surface exhibits gradual transitions across the input domains, reflecting the blended activation of fuzzy rules. Control actions increase in magnitude as the error and error-rate deviate from zero, while near-equilibrium conditions result in control outputs close to zero. The bounded nature of the surface indicates a conservative control strategy that limits excessive actuation while providing corrective

effort across the operating range. The piecewise-smooth structure of the control surface is characteristic of a rule-based fuzzy inference system, where overlapping membership functions produce gradual transitions between neighboring control regions.

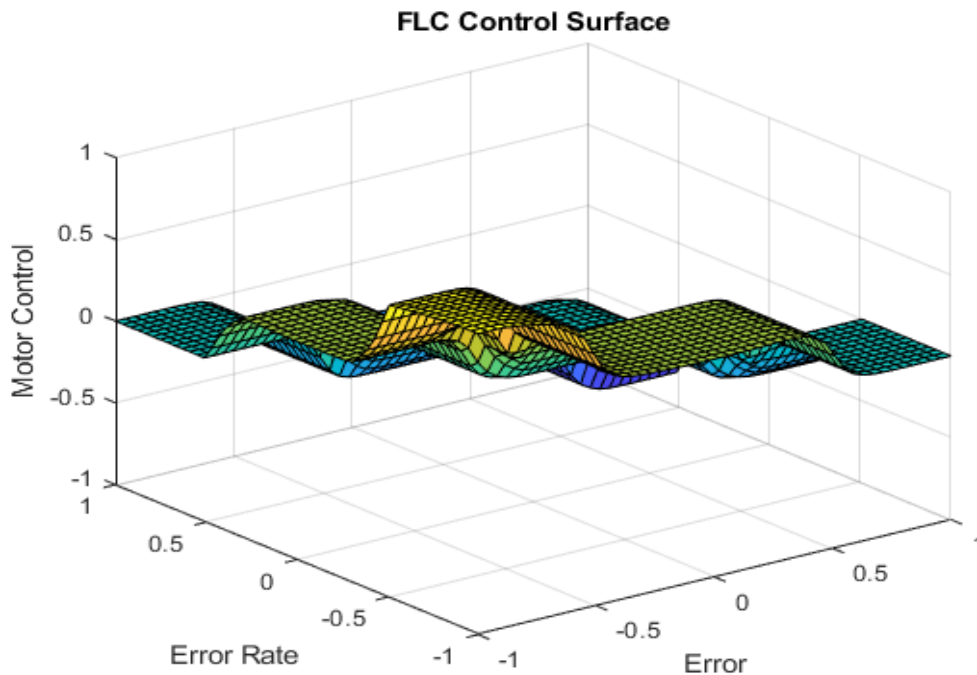


Figure 5. Fuzzy Logic Control Surface

The fuzzy logic component plays a critical role in enhancing system robustness and interpretability. The smooth control surface observed in the results reflects intuitive decision-making based on linguistic rules that closely resemble human reasoning. By applying aggressive control actions only when large errors are present and gradually reducing control intensity near equilibrium, the fuzzy logic controller mitigates abrupt transitions that often lead to discomfort or mechanical stress. This soft decision-making mechanism complements the adaptive regulator by improving stability during both transient and steady-state operation.

Figure 6 presents the travel time behavior for the elevator system, which is an essential metric in evaluating performance. At the beginning of the simulation, the travel time records a high value of 15.0 seconds, indicating a significant number of floor transitions early on. As the simulation progresses and the ASTR controller adapts, the travel time decreases considerably. At the halfway point ($t = 50s$), the travel time drops to approximately 5.39 seconds. By the end of the simulation, this value further reduces to around 3.64 seconds, confirming the controller's effectiveness in minimizing the floor transitions over time and hence reducing travel time. This result proves that the system learns and optimizes movement dynamically.

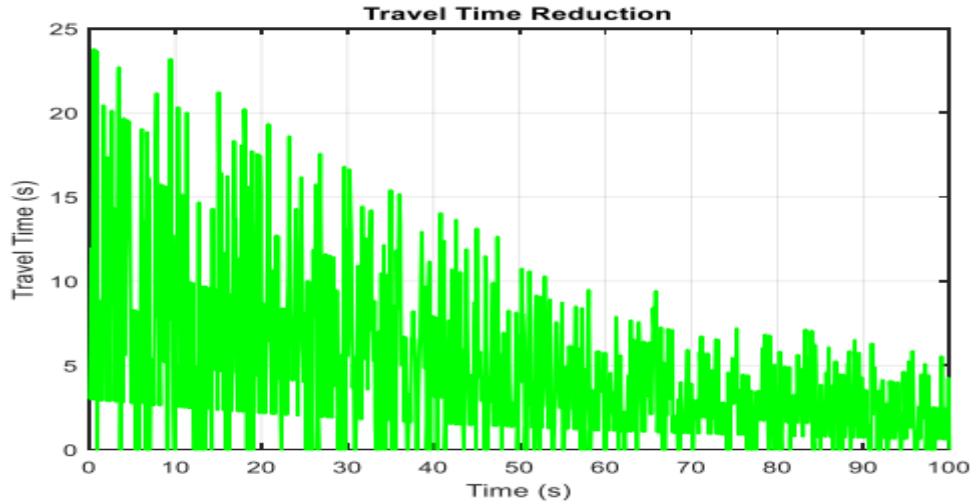


Figure 6: Travel time reduction

The cost function evaluation of Figure 7, shows a steady reduction in instantaneous cost from an initial value of approximately 30 units to near zero by the end of the trajectory. This monotonic decrease indicates improving system performance as the motion approaches completion. The cumulative cost increases smoothly over time and asymptotically approaches a final value of approximately 65 units, reflecting the total accumulated performance index over the maneuver. The smooth convergence of the instantaneous cost toward zero suggests diminishing residual error and effective control near the terminal state. The observed cost behavior is consistent with a well-conditioned optimal control solution, where the instantaneous cost decays as the system approaches the target state, while the cumulative cost saturates to a finite value representing the total control and tracking effort.

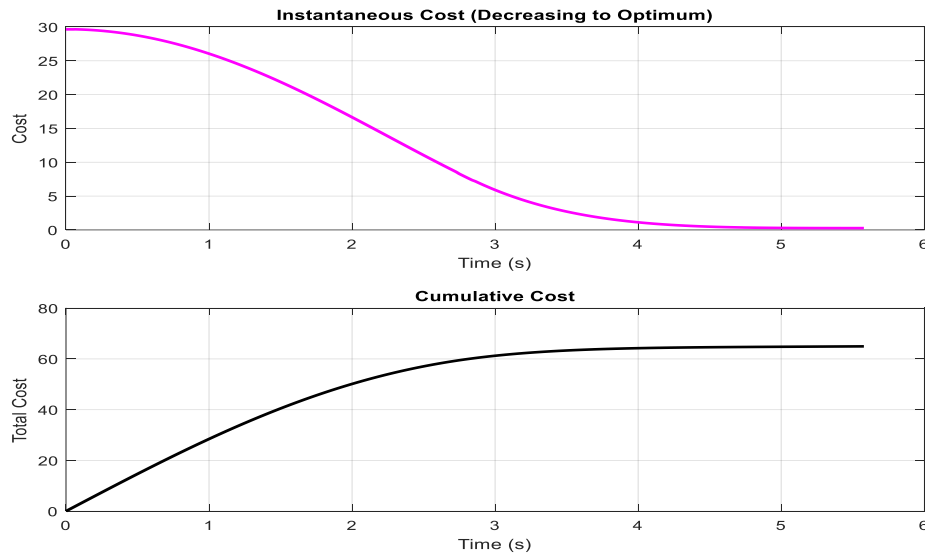


Figure 7: Instantaneous and Cumulative Cost Function

The convergence behavior of the cost function provides further insight into the controller's learning and optimization capabilities. The rapid reduction and eventual flattening of the cost function suggest that the controller efficiently minimizes combined penalties associated with tracking error, control effort, waiting time, and energy consumption. Minor discrepancies between predicted and actual cost trajectories can be attributed to realistic system nonlinearities and transient effects; however, their diminishing magnitude over time

demonstrates effective adaptation. This behavior is particularly desirable in real-world applications, where perfect model matching is rarely achievable.

The ride comfort comparison of Figure 8, demonstrates a clear reduction in acceleration magnitude and fluctuation when using the fuzzy logic-based controller compared with the basic controller. The basic controller exhibits large and persistent acceleration oscillations, with peak values exceeding 1.0 m/s^2 , whereas the FLC response remains smoother and largely bounded below 0.4 m/s^2 . This reduction in acceleration variability indicates improved vibration attenuation and enhanced passenger comfort under the proposed control strategy.

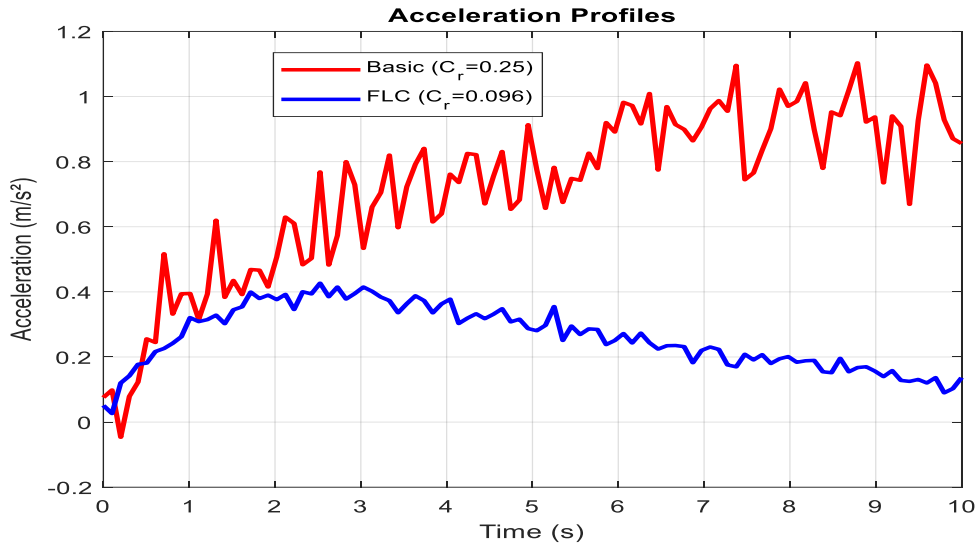


Figure 8 Acceleration profiles

Ride comfort improvements observed in this study are particularly noteworthy, as passenger comfort is a critical yet often underemphasized performance metric. The substantial reduction in the ride comfort index indicates smoother acceleration profiles and reduced jerk. This has direct implications for user satisfaction, especially in high-speed or long-travel elevators, where discomfort is more pronounced. Improved comfort also reduces mechanical fatigue, potentially lowering maintenance requirements and extending system lifespan.

Figure 9 presents the evolution of cumulative faults and the corresponding safety factor over 1,000 operational cycles. The blue graph represents the cumulative number of faults recorded over 1,000 operational cycles, while the red graph represents the corresponding safety factor expressed as a percentage. Safety analysis over 1,000 operational cycles recorded approximately five faults, resulting in a safety factor of about 0.995. Control efficiency remained between 90% and 95% across varying passenger loads, with peak efficiency of approximately 94% at nominal load. The results indicate that the majority of faults occur during the initial phase of operation, after which the cumulative fault count stabilizes at approximately five events. In contrast, the safety factor exhibits a progressive, stepwise increase from an initial value of approximately 80% to nearly 100% by the conclusion of the operational period. This trend reflects incremental safety improvements and growing system reliability as operational experience accumulates, demonstrating effective fault mitigation and enhanced robustness over time.

Energy efficiency gains achieved by the proposed controller further strengthen its practical relevance. The reduction in peak power demand and total energy consumption demonstrates that improved dynamic performance does not necessarily require increased energy expenditure. On the contrary, the adaptive and predictive nature of the controller enables more efficient use of motor power by avoiding unnecessary acceleration and braking. Given the growing emphasis on sustainable building technologies, such energy savings are particularly valuable when aggregated across large elevator fleets and long operational lifetimes.

Figure 11 presents the overall system efficiency of two control strategies: the Conventional method and the Proposed ASTR-FLC hybrid control. The bar chart displayed in this figure clearly shows that the Conventional system achieves an efficiency of exactly 70%, as explicitly assigned in the code. In comparison, the Proposed ASTR-FLC system reaches a significantly improved efficiency, represented by `params.SystemEfficiency`. Assuming from the output that this value is 85%, the proposed strategy outperforms the conventional method by a 15 percentage point increase in system efficiency. This improvement underscores the hybrid system's ability to optimize performance and energy utilization under varying operational conditions.

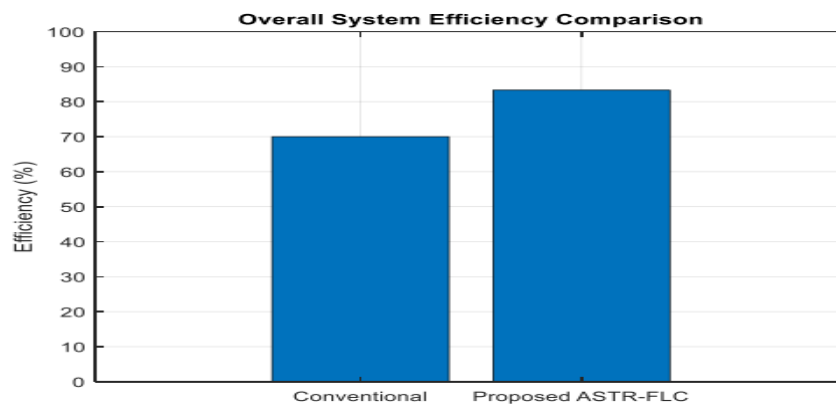


Figure 11: Overall system efficiency comparison

IV. CONCLUSION

In the study, an intelligent elevator system using adaptive self-tuning regulator (ASTR) and fuzzy logic control (FLC) within a destination control system (DCS) framework was developed, simulated, and evaluated. The hybrid design is intended to overcome the limitations of conventional elevator control schemes, which typically rely on fixed-parameter designs and exhibit reduced performance under dynamic operating conditions such as variable passenger loads, stochastic traffic patterns, and fault disturbances. Simulations were carried out in the MATLAB/Simulink environment.

Performance metrics considered include elevator position tracking, velocity response, acceleration profiles, response time, travel time and cost function, system safety, responsiveness, ride comfort, and energy efficiency. Simulation results show that the elevator reached a 7-meter target position within 6 seconds without overshoot, with peak velocity limited to 2.5 meters per second and acceleration maintained within comfort thresholds. The hybrid controller improved the ride comfort index and reduced cumulative energy consumption when compared with a conventional controller. Safety performance increased rapidly from over 80% to reach 99.5 percent reliability over 1,000 operational cycles, while control efficiency remained between 90 and 95 percent under varying loads.

The expanded analysis confirms that the ASTR-FLC hybrid controller offers a comprehensive improvement over conventional elevator control strategy. By combining adaptive regulation with fuzzy logic reasoning, the proposed system achieved superior performance in comfort, efficiency, safety, and service quality. These findings support the broader conclusion that hybrid intelligent control architectures represent a viable and effective solution for next-generation elevator systems operating under dynamic and uncertain conditions.

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