AI-Based Fuzzy Logic Approach for Load Shedding Scheme for Enhanced Power System Stability in the Barishal, Bangladesh

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ABSTRACT

One of Bangladesh's most urgent problems is still load-shedding, especially in the Barishal region, where frequent outages are frequently caused by an imbalance between the supply and demand for electricity. The majority of traditional load shedding techniques are reactive, manual, and unable to adjust to changing operating conditions. In order to optimize load shedding decisions, this paper suggests an Artificial Intelligence (AI) method based on fuzzy logic. The approach incorporates a number of variables into a fuzzy inference engine, such as the supply-demand ratio, system frequency, and meteorological conditions. A MATLAB/Simulink model was created and evaluated in a variety of real-world situations, including weather disruptions, supply shortages, and generator failure. According to the results, the AI-controlled method outperforms classical methods in terms of frequency and voltage stability, outage duration, and response time to disturbances. The suggested plan has a great deal of potential to improve Barishal's power system dependability and can be expanded to other parts of Bangladesh.

Keywords: hybrid Load shedding, fuzzy logic, artificial intelligence, power system stability, Barishal, Bangladesh.

INTRODUCTION

Over the past decade, significant blackouts have occurred globally, causing financial losses and disruptions in customer services[1]. These events highlight the need for effective control strategies to mitigate system blackouts. One key approach is implementing robust contingency analysis procedures to maintain a delicate equilibrium between power supply and demand. The power grid is complex and interconnected, and even minor disruptions can trigger a cascade of events, leading to system instability[1][2]. In such critical situations, power system operators must resort to emergency operation control strategies, including load shedding, to regain stability and prevent system-wide disasters[3].

In Bangladesh, the lack of generation capacity has led to a shortage of electricity, affecting industrial and agricultural growth and the country's economy. Load shedding is done to balance power demand and supply, forcing industries and businesses to close or relocate. To address this shortage, several options are under consideration, such as increasing generation capacity, developing renewable energy technologies, and power system optimization[4].

Fig. 1 illustrates the map of Barishal Upazila, the main administrative and commercial sub-district of Barishal, which occupies an area of roughly 324.41 square kilometers. It is located between latitudes 22°39′ and 22°50′ north and longitudes 90°15′ and 90°23′ east. The Kirtankhola River forms the upazila's boundary, and it is distinguished by a dense network of both urban and rural communities. Barishal Upazila, the district's commercial center, has a high demand for electricity from small businesses, markets, and households. Regular load shedding and power outages have a direct impact on daily life, education, and business operations. Furthermore, the availability of crop residues from nearby agricultural regions points to the potential for the production of electricity using biomass. Barishal Upazila is a good candidate for the implementation of localized renewable energy solutions and intelligent load management strategies due to its unique geographic and resource characteristics.

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Fig. 1. The map of Barishal Upazila[5]

The Barishal upazila of Bangladesh faces a significant challenge in maintaining an uninterrupted power distribution network. Load shedding, a practice where power is intentionally cut off due to fluctuations in demand and supply, continues to be a persistent issue, causing disruptions and inconveniences for residents and adversely impacting local businesses. Traditional methods for load shedding management often fail to adapt swiftly to the dynamically changing energy landscape, resulting in suboptimal outcomes[6].

In the contemporary era of technological innovation and data-driven decision-making, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools with the potential to revolutionize load shedding management[7][8]. This paper explores the innovative application of AI techniques to control and mitigate load shedding in Barishal, aiming to create a smarter, more responsive, and efficient power distribution system that minimizes disruptions and enhances the city's energy infrastructure.

LITERATURE REVIEW

Conventional load shedding relies on predetermined thresholds or operator intervention[9]. While effective in preventing total blackouts, these methods are reactive, rigid, and often lead to unnecessary outages.

Studies in Pakistan and Libya have explored AI-based control systems, employing neural networks, particle swarm optimization, and fuzzy logic for load management. For example, Alarbi (2019) used AI to reduce customer inconvenience during shedding, while Alamri (2020) focused on ANN-based load optimization in Pakistan’s grid[1][2]. In microgrids, fuzzy logic has been successfully applied to integrate renewables and balance fluctuating demand[8][10][11].

Despite these advances, minimal research has focused on regional applications within Bangladesh. Barishal, with its chronic electricity shortfall, presents a critical case where intelligent load shedding can enhance system reliability and minimize consumer disruption[12][13]. This study addresses that gap.

METHODOLOGY

In this study, we explore the most efficient use of AI technologies for controlling load shedding over a region. We go into the intricate process used to create the load-shedding control system, which depends on undervoltage, overvoltage, frequency deviation, and weather conditions. We will look at the structure of the system, the data collection process, and how the AI algorithm uses the fuzzy logic method.

System Architecture

The proposed AI-based load shedding system consists of three major modules. Here, Fig. 2 illustrates the flowchart of the proposed system architecture. System block diagram of the AI-based load-shedding controller showing measurement inputs, fuzzy inference block, and feeder CB outputs

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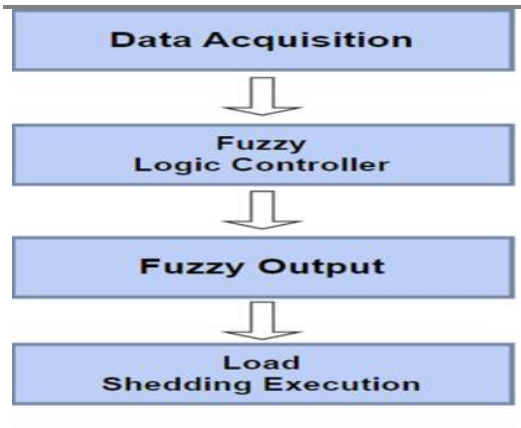

Fig. 2. The flowchart of the system architecture

1) Data Acquisition: Real-time inputs such as supply-demand ratio, system frequency, and weather conditions[8][14].

2) Fuzzy Logic Controller: Fig. 3 presents the flow chart of the fuzzy logic controller, which serves as the Main decision-making unit that processes inputs using fuzzy membership functions and rule bases[14][15].

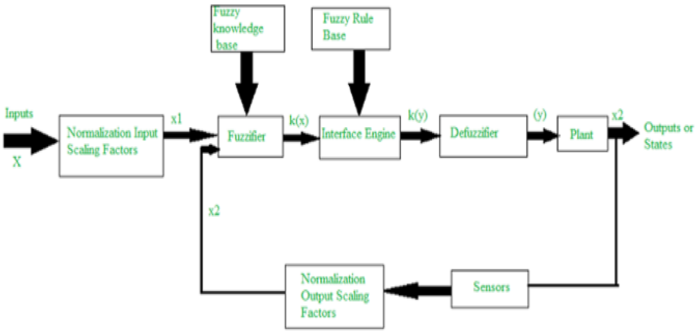

Fig. 3. Flowchart of fuzzy logic controller

3) Execution Module: Implements load shedding commands in affected areas based on fuzzy output.

Fuzzy Logic Design

The fuzzy logic design depends on two variables- Input variables and Output variables.

We selected Supply–Load Ratio, Frequency, and Weather as input variables because they collectively reflect the grid's short-term stress and the external conditions that influence demand and generation stability. The Supply–Load Ratio captures instantaneous supply adequacy, Frequency indicates system stability and imbalance, and Weather accounts for demand surges and renewable generation variability. Together, these variables enable the controller to make context-aware, priority-based load-shedding decisions.

1) Input variables:

- Supply-load ratio (0.5 — 2.0). Fig. 4 is a graph showing the fuzzy membership functions of the supply-load ratio. It defines three linguistic variables- (Poor, Average, Good) — triangular/trapezoidal shapes and universes of discourse. {Poor: trapezoid left (0.5, 0.5, 0.8, 1.0), Average: triangle (0.9, 1.15, 1.4), and Good: trapezoid right (1.3, 1.6, 2.0, 2.0)}

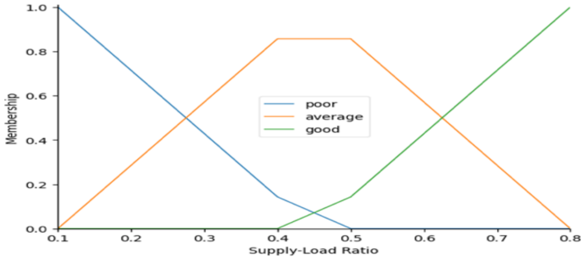

Fig. 4. The graph of the supply load ratio vs membership

- Frequency (49–51 Hz). Fig. 5 shows the fuzzy membership functions of frequency for three categories: poor, average, and good. Poor: trapezoid (0.0, 0.0, 49.2, 49.6), Average: triangle (49.4, 50.0, 50.6), Good: trapezoid (50.4, 50.8, 51.0, 51.0)}

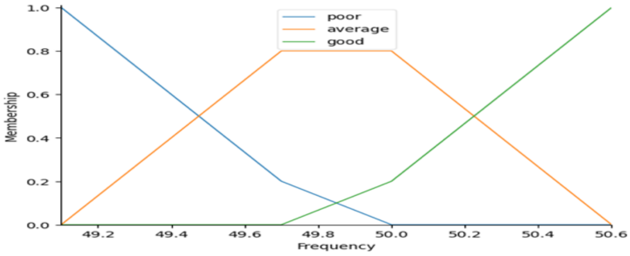

Fig. 5. The graph of frequency vs membership

- Weather condition (0–1 index). Fig. 6 presents the fuzzy membership functions of weather conditions as poor (Rainy), average (stormy), and good (clear) { Poor (bad): (0.0, 0.0, 0.3, 0.5), Average: (0.4, 0.55, 0.7) and Good: (0.65, 0.85, 1.0, 1.0)}

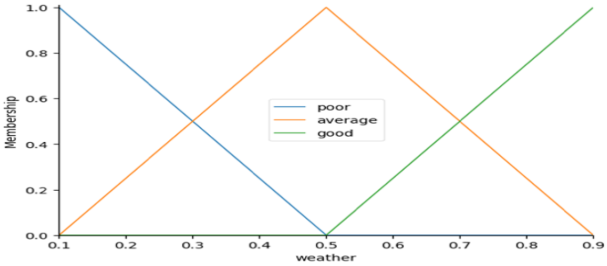

Fig. 6. The graph of weather vs membership

2) Output Variables:

- Load shedding level (None, Low, Medium, High). Fig. 7 illustrates the fuzzy membership functions of load shedding levels

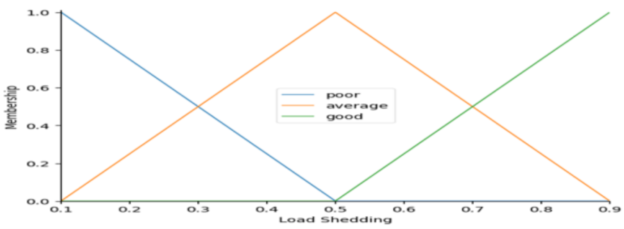

Fig. 7. The graph of load shedding vs membership

Membership functions were defined for each variable, and a rule base was constructed (e.g., *if frequency is low and demand is high, Then apply high load shedding*)[15].

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The fuzzy rules were designed using domain knowledge of power systems and by mapping typical operational scenarios to appropriate control actions. We defined linguistic terms (Poor, Average, Good) for each input and examined combinations that represent critical states. For example, when the supply–load ratio is Poor, Frequency is Average, and Weather is Good, the rule triggers a moderate shedding action because supply is insufficient even though frequency is not yet critical. Rules were validated against historical disturbance scenarios and refined iteratively to avoid conflicting outputs and ensure smooth transitions between shedding levels.

Simulation Setup

The fuzzy logic controller was implemented in MATLAB/Simulink. To facilitate the integration of our Fuzzy Logic-based load shedding system with the power grid infrastructure, we create interfaces and connectors that enable seamless data exchange and communication between the AI system and grid components. This includes:

- Developing APIs and data connectors to enable real-time data flow between the Fuzzy Logic system and grid monitoring devices.
- Establishing protocols for bidirectional communication, allowing the system to receive real-time grid status updates and send load shedding commands when necessary.

Sensor data and IoT devices play a pivotal role in real-time grid monitoring and load shedding control. Our methodology involves:

- Deploying a network of sensors and IoT devices within the grid infrastructure to monitor crucial parameters, including voltage levels, current flow, frequency, and equipment health[12].
- Incorporating sensor data into the Fuzzy Logic system to enable rapid and informed decision-making in response to changing grid conditions or fault events

As shown in Fig. 8, a fuzzy logic controller that takes four RMS inputs, processes them, and distributes the resulting control signal to four separate feeders. In contrast, Fig. 9 shows a more comprehensive system block diagram. The diagrams illustrate different levels of complexity in control systems, from a basic fuzzy to an advanced AI-driven solution.

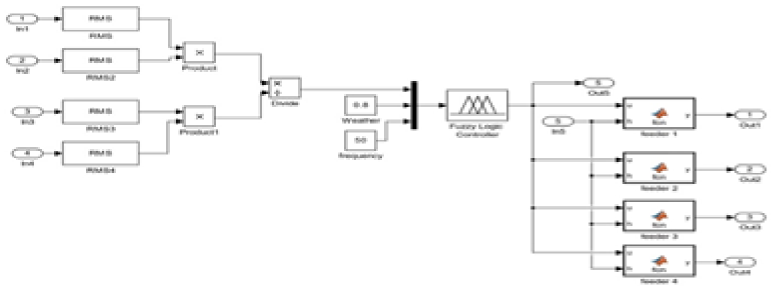

Fig. 8. Controller for the system

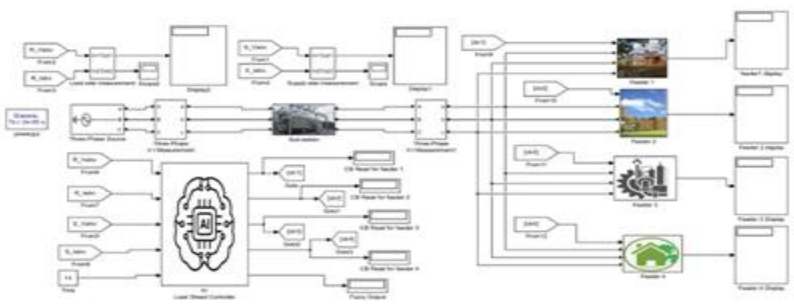

Fig. 9. AI load shead controller system and model

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A. *Code for the Load Shedding Scheme:*

```
#!/usr/bin/env python

# coding: utf-8

# # Import Library

import numpy as np

import skfuzzy as fuzz

from skfuzzy import control as ctrl

import datetime

def hour():

current_time_seconds = datetime.datetime.now()

time = str(current_time_seconds)

time = time.split(" ")[1][0:2]

time = int(time)

return time

# # Arrange Data

sl_ratio = np.arange(0.1,1.1,0.2)

weather = np.arange(0.1,1,0.1)

freq = np.arange(49.0,50.9,.3)

shed = np.arange(0.1,1,0.1)

sl_ratio

# # Assign Input

sl_ratios = ctrl.Antecedent(sl_ratio,"Supply-Load Ratio")

freqs = ctrl.Antecedent(freq,"Frequency")

weathers = ctrl.Antecedent(weather,"weather")

# # Assign Output

sheds = ctrl.Consequent(shed,'Load Shedding')

# # Define Membreship Function Automatically

sl_ratios.automf(3)

freqs.automf(3)
```

```
weathers.automf(3)

sheds.automf(3)

# # View Membership Function

sl_ratios.view()

freqs.view()

weathers.view()

sheds.view()

# # Define Rule

rule1 = ctrl.Rule(sl_ratios['poor'] & freqs['poor'] | freqs['good'] & weathers['good'], sheds['good'])

rule2 = ctrl.Rule(sl_ratios['average'] & freqs['poor'] | freqs['good'] & weathers['average'],sheds['average'])

rule3 = ctrl.Rule(sl_ratios['good'] | freqs['average'] | weathers['good'],sheds['poor'])

# # View Rule

rule1.view()

rule2.view()

rule3.view()

# # Creating The Model

sys = ctrl.ControlSystem([rule1,rule2,rule3])

sim = ctrl.ControlSystemSimulation(sys)

# # Simulation Part

load = 300

supply = 250

sl_ratio = supply/load

weather = 1

freq = 50

inst_time = hour()

sim.input['Supply-Load Ratio'] = sl_ratio

sim.input['weather'] = 1

sim.input['Frequency'] = 49.8

sim.compute()
```

```
load_shed = sim.output['Load Shedding']

sheds.view(sim=sim)

load_shed = round(load_shed, 1)-0.2

S_load = load_shed*load

S_load
```

RESULTS AND ANALYSIS

Effect of inputs on Shedding

The impact of three important input parameters—weather, system frequency, and supply-demand ratio—on load shedding results was investigated by evaluating the suggested fuzzy logic-based controller under various operating conditions.

- Supply-Demand Ratio: The fuzzy controller continuously generated a "No Shedding" output to guarantee continuous service when the supply of electricity exceeded the demand. The system dynamically increased the level of shedding in proportion to the gap as shortages emerged. By fine-tuning its decisions, the fuzzy system reduced needless outages, in contrast to classical methods that disconnect large blocks of consumers regardless of demand levels[16]. In Barishal, where demand varies greatly during peak hours, this adaptive response is particularly helpful.

- Weather: According to simulation results, the likelihood of medium-to-high shedding was raised by unfavourable weather conditions like storms or heavy rainfall. By incorporating weather into the decision-making process, the system was able to predict possible instability brought on by network disruptions (such as line trips or substation flooding)[17]. Compared to conventional techniques, which are oblivious to environmental influences, this capability clearly offers an advantage.

- System Frequency: The fuzzy controller showed a high degree of sensitivity to variations in frequency. In contrast to traditional shedding techniques, frequency recovery was accomplished considerably more quickly under abrupt disturbances like generator loss. This suggests that the AI-based system improves overall system stability in addition to demand-supply balancing.

System Performance

In addition to the impact of individual inputs, the system's overall performance was evaluated in terms of resilience, speed, and adaptability.

- Quick Reaction: After identifying instability, the fuzzy logic controller started load shedding in milliseconds. Classical methods, on the other hand, frequently call for manual intervention, which causes delays and increased instability[8]. One significant step toward real-time stability control is the automation of decision-making.

- Adaptability: Taking into account several factors at once, the system dynamically changed the shedding levels. For example, when demand was high but weather was stable, the shedding remained moderate; however, in cases of high demand combined with stormy weather, the system automatically shifted to higher levels of shedding to maintain grid integrity.

- Resilience: The fuzzy logic system remained stable with little disturbance even in the face of extreme unforeseen circumstances like transmission line tripping and generator outages. The fuzzy system distributed shedding more fairly across time and consumers, enhancing fairness and service continuity, while the classical method disconnected entire load blocks, resulting in sudden supply interruptions[7].

Table 1 Comparison of AI-Fuzzy vs. Classical Load Shedding[18]

Performance Criteria	Classical Method	AI-Fuzzy Method
Response Time	Slow (manual)	Fast(automatic)
Adaptability	Very Low	High
Frequency Stability	Moderate	Improved
Customer Disruption	High	Reduced
Handling Weather Conditions	Absent	Integrated

Comparative Analysis

The obvious benefits of the AI-fuzzy controller over the traditional method are demonstrated by a comparative analysis.

Predefined load blocks are disconnected by the traditional load shedding mechanism, frequently in excess of what is necessary[19]. This not only wastes the supply that is available, but it also causes needless inconveniences for customers. The fuzzy logic system, on the other hand, keeps service for as many customers as possible by only shedding the amount necessary to restore stability.

Additionally, by adding weather as a decision variable, the system was able to predict difficulties specific to Barishal, like cyclones and intense rains. An innovative advancement over conventional methods is the capacity to couple grid parameters with environmental data[8].

While the conventional system recovered slowly and rapidly, the fuzzy controller restored frequency fast and with minimal variance. This demonstrates how intelligent shedding not only lowers outages but also enhances power quality and dependability.

All things considered, the simulation results validate that the use of AI and fuzzy logic in load shedding decision-making produces more practical, effective, and user-friendly results.

CONCLUTION

The study suggests an AI approach that takes supply-demand balance, weather, and frequency deviations into account when optimizing load shedding in Bangladesh's Barishal region. According to simulation results, the fuzzy controller increases adaptability, decreases outage duration, and improves grid reliability. Future studies might focus on intelligent microgrid management using renewable energy sources, real-time field testing, and expanding to smart grids and Internet of Things-based adaptive load shedding systems [11][13].

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