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SUMMARY

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RESEARCH ARTICLE OPEN ACCESS

APPRAISING THE MAINTENANCE PRACTICES IN SHOPPING MALLS ACROSS LAGOS METROPOLIS

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ABSTRACT

Like other types of buildings, shopping mall buildings in Nigeria receive insufficient maintenance attention. The vast majority of shopping malls exhibit awful structural and aesthetic conditions of deterioration. This study, therefore, aims to investigate the maintenance practices of shopping malls with a view to addressing issues that arise from factors responsible for the deterioration of the building fabrics and components. Data from 97 building maintenance stakeholders from Lagos Island and Mainland malls were gathered using a cross-sectional survey utilizing two sets of structured self-administered questionnaires. The results revealed 31 maintenance practices implemented in shopping malls. The study also uncovered 21 key factors influencing the sourcing decision of maintenance practices in shopping malls. Besides, the results further revealed 22 causative factors that lead to the deterioration of shopping mall building fabrics and components. The study comes to the conclusion that regardless of the sourcing decision, other factors, such as quality and frequency of maintenance, have a significant impact on how quickly a shopping mall deteriorates. It is recommended that maintenance stakeholders should play active roles in ensuring shopping malls are adequately maintained. This may be achieved by developing a defined strategy for routine and preventive maintenance.

I. INTRODUCTION

The sales business in Nigeria is a vibrant and diversified sector of the economy that is essential for the nation's development and has steadily improved over the past few years. This improvement, according to [1], may be ascribed to interventions implemented by several levels of government such as a restriction on street vendors and commerce, the restoration of commercial business districts in major cities, and the reform of trading standards. [2] opines that the development was further accelerated by the participation of certain foreign investors who sought to capitalize on the ongoing need for effortless, expeditious shopping. The multi-tenanted sales sector in Lagos, Nigeria has experienced significant growth, and the sector is projected to keep expanding substantially in the coming years. One of such multi-tenanted commercial retail business in view is a shopping mall which has been regarded by [3,4,5] as an innovative take on the traditional marketplace and is made up of independent retail stores, services, and planned parking structure that is built and run as a single entity. [6] added that shopping malls are architecturally complex structures designed and developed to accommodate different types and sizes of stores and service facilities for commercial use. [7] revealed that shopping malls no longer serve the same socializing, entertainment, and other purposes that they formerly did; rather, they are now living spaces with a variety of possibilities, including the capacity to satisfy a range of client's expectations. In meeting these expectations within shopping malls, there is a neglect of maintenance. An organization's premises, whether office space, retail shops, or mixed-use complexes, tell a lot about what it is and how it operates. Likewise, during its expected lifespan, a building's main purpose is to offer a comfortable and secure environment for humans and other human activities. In this regard, [8] notes that a majority of organizations have failed to meet their goals as a result of neglecting their built environment. To preserve the structure's durability and functionality, maintenance is required. Therefore, conducting regular and scheduled maintenance, and production management makes sure that the facilities are in excellent operating condition. [5] corroborate that a well-maintained infrastructure guarantees a secure environment, lowers energy costs, and guarantees that all company operations go without a hitch. This implies that a failure to take into account the necessity for implementing adequate maintenance practices has consequences given the recent growth in the number of shopping malls that have been established across the state [9]. These consequences revolve around issues such as facility malfunctioning, poor disposal of refuse, leaking roofs, malfunctioning elevators, faded painting, poor lighting systems, fire extinguishers not being replaced, and noticeable building defects, among others. [10] noted that both in-house and outsourced maintenance services have attributed benefits that may be derived from involvement in shopping mall building. Besides, [11] substantiates that the lack of effective building maintenance policies has an impact on the early aging of component durability performance as well as on overall expenditures and maintenance operations, which may increase major failure risks and reduce their service life. Meanwhile, maintenance has been defined as the sum of all technical and related procedures designed to keep or restore an item to a state in which it can perform its needed function [12]. In Nigeria, there seems to be a dearth of a maintenance culture, and the emphasis is on building new structures rather than on the maintenance process, which begins as soon as the Builder hands over the project [8,13]. In order to maintain a building's original condition, maintenance may be more crucial than construction itself [14,15]. This is because society evaluates a building's quality based on its outward look. Proactive and reactive maintenance must be used together to protect and sustain buildings [16]. Like every other building in Nigeria, shopping mall buildings do not receive enough maintenance attention. The majority of shopping malls are in a very bad and awful state of structural and aesthetic decay. While considerable research has been conducted on the maintenance practices of various building occupancy (i.e. offices, hotels, residential, institutional, and mixed-use buildings) in Nigeria [12,17,18,19,20,21,22], there are limited studies that have investigated the maintenance practices in Shopping malls. With this gap in the literature, the study, therefore, aims to investigate the maintenance practices of shopping malls in the Lagos metropolis with a view to addressing issues that arise from factors responsible for the deterioration of the building fabrics and components. The objectives of the study are to; investigate the maintenance practices implemented by shopping malls, assess factors influencing the sourcing decision of maintenance services in shopping malls, and evaluate causative factors that lead to the deterioration of shopping malls' building fabrics and components. The study hypothesizes that the implementation of maintenance practices in shopping malls does not significantly differ between insourcing and outsourcing strategies. The study also hypothesizes that factors that contribute to the deterioration of shopping malls do not significantly differ between Lagos Island and the Mainland. The study further hypothesizes that the factors contributing to the deterioration of shopping malls do not significantly vary between the maintenance sourcing strategies. The study is significant because it offers information to mall management and other stakeholders in multi-tenanted retail businesses to inform their decision-making processes and be proactive in addressing maintenance concerns thereby improving safety, and minimizing disruptions in shopping mall operations.

II. THEORETICAL REFERENCE

II.1 IMPLEMENTATION OF MAINTENANCE PRACTICES IN SHOPPING MALLS

Maintenance practices in shopping malls encompass a wide range of services or task that addresses a different aspect of the facility. [23] note that maintaining facilities has emerged as an important plan of action and calls for the establishment of efficient maintenance practices so as to maintain the value of projects like the amenities of shopping malls. [24] posits that maintenance practices should be a continuous process that requires effective strategic planning in order to keep facilities operating. [25] added that maintenance practices require correct and timely diagnosis of defects, corrective/remedial measures promptly taken, and sound technical knowledge of facilities provided. Accordingly, [26] noted that integrating maintenance practices into shopping mall facilities over time will save the costs of major renovation and future repairs while maintaining the functionality of the facilities. Therefore, effective maintenance practices are now essential for the secure operation of structures [9], such as those in shopping malls. The four basic types of maintenance activities are reactive, preventive, predictive, and proactive, according to [27,28]. The function, attractiveness, and safety of the structure depend on proper shopping mall maintenance procedures. Regular, routine, and remedial actions are all included in these practices. These practices include services such as regular inspections, HVAC maintenance, lighting maintenance, floor maintenance, elevator maintenance, restroom maintenance, exterior maintenance, security and surveillance systems, and fumigation services, among others. The maintenance practices in shopping malls are essential for a safe and welcoming shopping environment. According to [29], cleaning practices should adhere to industry standards and may involve daily janitorial services, deep cleaning, and specialized techniques for different surfaces. Meanwhile, [30] note that regular maintenance of HVAC equipment, including filters, duct work, and temperature controls, ensures optimal performance, energy efficiency, and air quality are essential to avoid costly repairs and replacement, reduction in energy consumption, and offer improved indoor air quality and occupant well-being. [31], posit that regular inspection, testing, and maintenance of electrical panels, wiring, lighting fixtures, and emergency backup systems help prevent electrical hazards and ensure uninterrupted power supply. In this regard, [32] averred that repairs and maintenance of exterior facades, parking lots, and walkways ensure safety and aesthetics. Replacements may be necessary due to physical wear and tear on components or materials as well as deteriorating appearance. In buildings, replacements are made wherever possible. It is unavoidable since various materials deteriorate at different rates due to service circumstances [33]. A lot of replacement work is caused more by deterioration of appearance than by actual material or constituent failure [34]. Additionally, overcrowding has caused the installed facilities to deteriorate [35,36]. Safety is of paramount importance in crowded public spaces like shopping malls. Regular inspections, maintenance, and testing of fire safety systems, emergency exits, CCTV cameras, and security equipment are essential to minimize potential risks and ensure the safety of visitors and employees. Besides, [37] reckon that regular maintenance of facilities such as escalators, elevators, restrooms, and common areas ensures a positive customer experience, leading to increased footfall and customer satisfaction.

II.2 THE FACTORS INFLUENCING SOURCING DECISIONS OF MAINTENANCE PRACTICES IN SHOPPING MALLS

The method used to source maintenance practices or services depends on the priority established by the institution or organization requesting the service [38] and can be either outsourcing, insourcing, or co-sourced [39,40]. In shopping malls, sourcing decisions entail deciding how to manage and maintain various components of the facility. These decisions can have an influence on cost, service quality, customer satisfaction, and overall operations. According to [41], insourcing refers to the provision and management of maintenance services by conventional in-house experts. In order to offer efficiency and reductions in cost amid rising financial strain, [42] proposes insourcing as a viable option. Meanwhile, [43] describes outsourcing as the act of carrying out an activity by a third-party company, supplier, or contractor. Additionally, [42] provides evidence that outsourcing is a product of the current economic climate, which places a strong focus on cost reductions and improved quality, particularly for lean processes. Meanwhile, [44] is of the view that outsourcing entails having work that was previously completed within the organization undertaken by an outside organization. In this regard, [44] emphasized the necessity of determining the significance of a number of aspects before selecting whether to outsource or insource maintenance service. These include the following; speed of execution, price or cost certainty, responsibility, risk allocation or avoidance, degree of flexibility, degree of complexity, knowledge of the strategy, clarity of scope, intuition and experience of the decision maker, existing building condition, dissatisfaction with the previous process used, client's involvement in the project, building size, working relationship, and client's in-house technical capability. [46] opines that organizations outsource services for four reasons; cost savings, taking advantage of supplier investment and innovation, the need to convert fixed expenses to variable costs, and a faster time to market. In this regard, [47] conducted a survey to determine which critical factors influenced the outsourcing decision for maintenance services and discovered that improved quality requirements, faster implementation times, and risk sharing with the contractors were the most crucial factors. [48] corroborate that the top two factors that influence the decision to outsource are staff availability and the possession of requisite skills of staff members. Additionally, [49] classified factors influencing outsourcing decisions as strategic, managerial, technological, economic, and quality. Whereas, [50] opines that the factors influencing the decision to outsource maintenance services encompass timing and coordination of activities, consideration of maintenance activities as core to the institution, potential damage to the image of the organization by outsourced vendor's practice, difficulty in finding a vendor with compatible organizational culture, the subcontractor may act in their own self-interest to the detriment of the organization, and difficulty in finding vendors that are willing to work with the organization. Nonetheless, the necessity of maintenance management whether through insourcing and/or outsourcing model, in the proper functioning of shopping mall buildings cannot be overemphasized.

II.3 CAUSATIVE FACTORS CONTRIBUTING TO THE DETERIORATION OF SHOPPING MALL BUILDING FABRICS AND COMPONENTS

Buildings may deteriorate over time due to certain factors and shopping mall facilities are no exception. There are several factors that lead to the deterioration of shopping mall building fabrics and components among which are chemical, biological, efflorescence, overloading, moisture, age and wear, misuse, faulty designs, faulty construction, faulty materials, human, and environmental among other factors. Proper maintenance safeguards the structural integrity of the building, extends the lifespan of equipment, and preserves the overall value of the property. Neglecting maintenance can lead to costly repairs and premature deterioration. [51] substantiate that deterioration in buildings is caused by wear and tear resulting from continuous usage, design defects, construction error, aging of the building, as well as building exposure to weather effects. Building deterioration mainly depends on the type of building and the maintenance practices in place. According to [33], the main reasons for deterioration include the age of the building, natural disasters, ground settlement, deficiencies in design, poor construction supervision, the use of inferior materials, and poor workmanship. Similar studies from [52] showed that improper maintenance, inadequate design, poor workmanship, and low-quality materials are also major reasons for deterioration. In the same vein, [53] are of the opinion that the main causes of building deterioration include faulty construction, use of substandard materials, lack of supervision, corruption, faulty design, lack of maintenance, climatic conditions, type of building and change in use, and the geographical location of the structure. [54] posits that poor construction management reduces the quality of work by neglecting maintenance concerns during the design and construction phases. [12] note that key causative factors that contribute to deterioration in a commercial building include human, chemical, atmospheric, structural, and moisture factors, fire, faulty design, faulty construction, and faulty materials. This study established that failure to clean and perform routine maintenance, ignorance of the causes of deterioration and decay, inadequate planning for proper maintenance, failure to raise awareness of the maintenance needs of all users of the buildings, and embracing negative attitudes are human causes that contribute to the deterioration of commercial buildings and call for immediate action. Furthermore, [32,55] are of the view that the built environment and the facilities used to carry out daily operations in the shopping malls therefore require proper maintenance, facilitating activities, and helping to attain customer satisfaction per time. Meanwhile, well-integrated facility management in shopping malls therefore has a significant role it plays in fostering a conducive environment that ensures satisfaction at all times [6]. Based on the literature reviewed above, this study is being conducted to increase maintenance stakeholders' and users' awareness of the need to be prepared to address issues related to maintenance in order to avoid costly repairs and reduce the dangers associated with deteriorating facilities.

III. MATERIALS AND METHODS

The study employed a cross-sectional survey research strategy with the primary data collection instrument being a structured self-administered questionnaire of which the data were collected on a one-off basis. The chosen research area is Lagos Mainland and Lagos Island, Nigeria. The choice of both regions was because Lagos Mainland is characterized as an inland area with diverse neighborhoods with a focus on residential buildings and commercial activities. While Lagos Island is surrounded by coastlines with high economic activities, as well as leisure and historical sights. The study's population comprises maintenance stakeholders in both study areas, specifically those entrusted with the day-to-day building operations and maintenance such as facility managers, asset managers, maintenance managers, and other relevant personnel. A preliminary search with Google and Google Maps was carried out to define the population frame of the study. From the search carried out, 145 shopping Malls made up of 66 Mainland Shopping Malls and 79 Island Shopping Malls were identified and their names were serially numbered in Microsoft Excel Worksheet as the sample frame for the study. The identified Shopping Malls were multi-tenanted retail infrastructure in both the Mainland and the Island. From the population frame, 97 shopping malls were selected and they included 44 Mainland Shopping Malls and 53 Island Shopping Malls. The selected Shopping Malls served as the sample size of the study. The selected sample size was derived using the stratified random sampling technique. According to [57], the stratified random sampling technique is an applied random sampling method in which the population is grouped into some definite characteristics and the groups are called strata. The structured questionnaire constituted 3 sections. Section A comprised the demographic information of the respondents while Sections B, C, and D were structured to obtain information on maintenance practices, factors influencing the sourcing decisions of maintenance practices in shopping malls, and causative factors contributing to the deterioration of shopping malls respectively. An ordinance scale of 1-5 was used to measure the implementation of maintenance practices in shopping malls using 1 = never, 2 = rarely, 3 = sometimes, 4 = often, and 5 = always. An ordinal scale of 1-5 was further used to measure the factors influencing the sourcing decision of maintenance practices in shopping malls using 1 = not influential, 2 = slightly influential, 3 = moderately influential, 4 = very influential, and 5 most influential. In the same vein, an ordinal scale of 1-5 was used to measure the causative factors that contribute to the deterioration of shopping malls using 1 = highly insignificant, 2 = insignificant, 3 = moderately significant, 4 = significant, and 5 highly significant. In order to administer the questionnaire, the contact information of the maintenance stakeholders managing the shopping malls was collected from the branch managers of the selected malls. A total of 120 questionnaires were administered out of which 97 questionnaires were correctly filled and returned, representing an 80.8% response rate. The collected data was processed with Microsoft Excel and Statistical Packages for Social Sciences (Version, 23.0). Statistical tools such as Frequency tables, Percentages, mean scores, and ranking were the tools of analysis for the descriptive analyses while the T-test was used to test the inferential results. With the aid of frequency tables and percentages, the demographic information in Section A was analyzed. Meanwhile, objective one which seeks to determine the implementation of maintenance practices was analyzed using frequency, mean score, and ranking. Whereas, the second and third objectives which seek to assess the factors influencing the sourcing decision of maintenance practices in shopping malls, and evaluate causative factors that lead to the deterioration of shopping mall building fabrics and components were analyzed using a relative significant index (RSI). The RSI is calculated as:

$$RSI = \frac{\Sigma W}{AN} \quad (1)$$

Where, W = weight given to each factor by the respondents and ranges from 1-5, A = the highest weight = 5, N = the total number of respondents. The RSI score varies between 0 and 1. Each factor's resulting value provides an indication of its level of significance [58].

IV. RESULTS AND DISCUSSIONS

IV.1 DEMOGRAPHIC PROFILE

This section presents the results and discussions.

Table 1 shows the demographic profile of the respondents.

Table 1 shows two geographical locations of the shopping malls; Island and Mainland. The designation of the respondents on the Island includes; 20.8% are assets managers, 47.2% are facility managers, and 17.0% are maintenance managers, while the remaining 15.1% belong to the others category. On the other hand from the Mainland; 18.2% are assets managers, 43.2% are facility managers, 20.5% are maintenance managers, and 18.2% belong to others. The results affirm that the respondents are the principal actors of managing shopping mall infrastructure and the information supplied by them may be relied upon. Table 1 also reveals the respondents' years of experience in the field. On the Island; 28.3% had years of experience between 1-5 years, 47.2% had between 6-10 years, 13.2% had 11-15 years, 7.5% had 16-12%, while 3.8% had 21 and above years. On the other hand in Lagos Mainland; 27.3% had years of experience between 1-5 years, 50.0% had between 6-10 years, 13.6% had 11-15 years, 6.8% had 16-12%, while 2.3% had 21 and above years. This result reflects that the respondents have vast years of experience in the field. Besides, Table 1 further shows the highest academic qualification attained by the respondents. On the Island; 15.1% had an ordinary national diploma (OND), 34.0% had a higher national diploma (HND), 41.5% had a bachelor's degree (B.Sc.), 5.7% had a postgraduate diploma (PGD), while 3.8% had a masters degree (M.Sc.). On the other hand; 15.9% had an OND, 38.6% had an HND, 34.1% had a B.Sc., 6.8% had a PGD, while 4.5% had an M.Sc. Based on their level of educational attainment, the information provided can be relied upon. Furthermore, Table 1 shows that 49.1% of malls on the Island insource their maintenance services, while 50.9% outsource maintenance services. On the other hand in the Mainland, 52.3% of the mall managers insource maintenance activities, while 47.7% of the shopping malls outsource maintenance activities.

Table 1: Demographic Profile of Respondents.

Description	Island		Mainland	
	Frequency (N)	Percent (%)	Frequency (N)	Percent (%)
Designation				
Asset Manager	11	20.8	8	18.2
Facility Manager	25	47.2	19	43.2
Maintenance Manager	9	17.0	9	20.5
Others	8	15.1	8	18.2
Total	**53**	**100.0**	**44**	**100.0**

Description	Island		Mainland	
	Frequency (N)	Percent (%)	Frequency (N)	Percent (%)
Years of Experience in the Field				
1-5 years	15	28.3	12	27.3
6-10 years	25	47.2	22	50.0
11-15 years	7	13.2	6	13.6
16-20years	4	7.5	3	6.8
21- above years	2	3.8	1	2.3
Total	**53**	**100.0**	**44**	**100.0**
Highest Level of Education				
OND	8	15.1	7	15.9
HND	18	34.0	17	38.6
B.Sc.	22	41.5	15	34.1
PGD	3	5.7	3	6.8
M.Sc.	2	3.8	2	4.5
Total	**53**	**100.0**	**44**	**100.0**
Sourcing Type				
Insourcing	26	49.1	23	52.3
Outsourcing	27	50.9	21	47.7
Total	**53**	**100.0**	**44**	**100.0**

Source: Authors, (2023).

IV.2 IMPLEMENTATION OF MAINTENANCE PRACTICES IN SHOPPING MALLS

Objective 1: to investigate maintenance practices implemented in Shopping malls. To achieve this objective, twenty-two causative factors were evaluated and the result of the analysis is shown in Table 2.

The maintenance practices in the various shopping malls were assessed using the scale: 1 = never, 2 = rarely, 3 = sometimes, 4 = often, and 5 = always. The relative significance index (RSI) score of each of the causative factors was calculated as presented in Table 3. Moreover, the mean value for the level of implementation of the maintenance practices was calculated as presented in Table 2. The decision rule for interpreting the mean scores was adapted and modified from [58] using the scale: 1.00 ≤ MS < 1.5 represents 'not implemented (NI)', 1.50 ≤ MS < 2.5 represents 'Rarely implemented (RI)', 2.50 ≤ MS < 3.50 represents 'moderately implemented (MI)', 3.50 ≤ MS < 4.50 represents 'often implemented (OI)' and 4.50 ≤ MS ≤ 5.00 represents 'most often implementation (MOI)'. A total of thirty-one (31) frequently implemented maintenance practices were identified and categorized into 9 groups; namely frequent inspections, cleaning and janitorial services, air conditioning servicing and maintenance, lighting and electrical system maintenance, elevator and escalator maintenance, security and surveillance system, parking lots and exterior maintenance, regular maintenance schedules, and emergency preparedness. The result shows that the MOI maintenance practice in Lagos Island is replacing defective bulbs (MS=4.62). On the other hand, the MOI maintenance practice in Lagos Island is replacing defective bulbs (MS=4.61). Besides, the OI maintenance practices in Lagos Island include; restroom cleaning, and maintenance of alarms and smoke detectors (MS=4.47), floor cleaning, equipment inspections and maintenance (MS=4.28), and CCTV surveillance and security guards patrol (MS=4.17) among others. On the other hand, the OI maintenance practices in Lagos Mainland include; restroom cleaning (MS=4.43), maintenance of alarms and smoke detectors (MS=4.41), equipment inspections and maintenance (MS=4.32), floor cleaning (MS=4.25), and CCTV surveillance and security guards patrol (MS=4.23) among others.

The following can be further observed from Table 2:

Frequent inspections: all the maintenance practices under this category are OI, but checking leakages of plumbing fittings (4.00 & 4.07) and checking signs of wear and tear (3.96 & 3.97) were topmost implemented maintenance practices by the respondents in Lagos Island and Lagos Mainland Shopping malls respectively. The implementation of all the practices under frequent inspection could be owing to the fact that conducting routine inspections of building fabrics and components is expedient to early diagnose any potential issues. This result agrees with the findings of [30] who emphasized the necessity for frequent inspection and monitoring of facilities in order to achieve considerable preventive maintenance features while planning and carrying out maintenance operations.

Cleaning and Janitorial Services: all four practices under this category are OI, however, restroom cleaning (4.47 & 4.43) and floor cleaning (4.28 & 4.25) were the topmost implemented maintenance practices under the category of cleaning and janitorial services for both groups of respondents from Lagos Island and Mainland respectively. The implementation was necessary to maintain cleanliness, appearance, and functionality and to provide customers with a secure and pleasant environment while avoiding long-term damage and deterioration. This result supports the conclusion of [29,37,59] that cleaning practices should adhere to industry standards and may involve daily janitorial services, deep cleaning, restroom cleaning, and specialized techniques for different surfaces.

Air Conditioning Servicing and Maintenance: all 4 maintenance practices under this category are MI, but addressing any issue with temperature control (3.34 & 3.36) and cleaning and replacing air filters (3.32 & 3.23) were the topmost implemented maintenance practices by the respondents in Lagos Island and Lagos Mainland Shopping malls respectively. The servicing and maintenance of air conditioners are essential for ensuring their effective performance, extending their lifespan, and preserving indoor air quality, which improves customers', and members of staff's comfort and well-being in the building. Regular maintenance of HVAC equipment is essential to avoid costly repairs and replacement, reduction in energy consumption, and offer improved indoor air quality and occupant well-being.

Lighting and Electrical System Maintenance: the MOI maintenance practice in this category is replacing defective bulbs (4.62 & 4.61) for the Island and Mainland Shopping malls, respectively. Meanwhile, inspecting lighting fixtures (3.85 & 3.84) were OI. The lighting and electrical systems are crucial components of shopping mall maintenance because they maintain a functioning, safe, and comfortable environment for consumers, tenants, and staff members while preventing interruptions and potential hazards. This result supports the conclusion of [30] that regular inspection, testing, and maintenance of electrical panels, wiring, lighting fixtures, and emergency backup systems help prevent electrical hazards and ensure uninterrupted power supply.

Elevator and Escalator Maintenance: all the maintenance practices under this category are OI, but addressing unusual noise (3.96 & 3.95) and maintaining proper lubrication (3.83 & 3.77) were the most implemented maintenance practices by the respondents in Lagos Island and Mainland Shopping malls respectively. Elevators and elevator maintenance are vital components of shopping mall maintenance because they provide consumers with accessibility, convenience, and safety, increasing the entire shopping experience while guaranteeing regulatory compliance. This supports the assertions of [30] that regular maintenance of facilities such as escalators, and elevators, ensures a positive customer experience, leading to increased footfall and customer satisfaction while offering a comfortable and aesthetic environment to users.

Security and Surveillance System: it is no surprise that shopping mall management takes security and surveillance seriously since their implementation guarantees the protection of their assets, customers, and employees. The result under this category indicates that all 3 practices are OI, but the maintenance of alarm and smoke detectors (4.47 & 4.17) and periodic servicing of CCTV cameras and guards patrol services (4.17 & 4.23) were the topmost implemented maintenance practices by the respondents in Lagos Island and Mainland malls respectively. Security and surveillance are sine-qua-non to shopping center maintenance because they preserve assets, protect customers and employees, prevent criminal activity, and provide a safe retail environment, consequently increasing safety and confidence. This corroborates the results of [30,60,61,62,63,64], that security measures are important to control trespassers and monitor the infrastructure and its assets.

Parking lot and Exterior Maintenance: the topmost OI maintenance practice in this category is the maintenance of parking lots and sidewalks (3.60 & 3.64) for both shopping malls on the Island and Mainland respectively. Parking lot and exterior maintenance are critical in shopping malls to make a good first impression, maintain safety, enable easy access, and safeguard the property's value and appearance. This result supports the conclusion of [32] that the repairs and maintenance of exterior facades, parking lots, and walkways ensure safety and aesthetics.

Regular Maintenance Schedules: all three practices under this category are OI, however, glazed area cleaning (4.28 & 4.32) was the topmost implemented maintenance practice under the category of regular maintenance schedules for both groups of respondents from Lagos Island and Mainland respectively. Regular maintenance schedules are vital to avoid equipment failures, guarantee a safe and pleasant retail environment, increase asset lifespan, and reduce costly repairs. This is consistent with the results of [29,31,32] that glazed area cleaning is aimed at offering a more comfortable and aesthetically appealing environment.

Emergency preparedness: all the maintenance practices under this category are OI, but the help desk for emergency services (4.08 & 4.02) and evacuation routes clearing (4.00 & 3.93) were the topmost implemented maintenance practices by the respondents in Lagos Island and Mainland malls respectively. Emergency preparedness is vital in shopping center maintenance to safeguard customers, staff, and assets during unexpected occurrences, assuring safety, limiting damage, and permitting quick recovery and operating continuity. This finding supports the results of [60,63] who stressed the adequacy of emergency preparedness.

Table 2: Implementation of Maintenance Practices in Shopping Malls.

Maintenance Practices in Shopping Malls	Island shopping malls				Mainland shopping malls			
	N	MS	OR	Remark	N	MS	OR	Remark
Frequent inspections								
Checking Leakages	53	4.00	10	OI	44	4.07	9	OI
Checking signs of wear and tear	53	3.96	14	OI	44	3.95	12	OI
Checking damages to fixtures and fittings	53	3.85	16	OI	44	3.84	16	OI
Checking electrical problems	53	3.51	24	OI	44	3.50	23	OI
Cleaning and Janitorial services								
Restroom cleaning	53	4.47	2	OI	44	4.43	2	OI
Floor Cleaning	53	4.28	4	OI	44	4.25	5	OI
Waste management and disposal	53	4.13	7	OI	44	4.11	7	OI
Fumigation services	53	3.55	22	OI	44	3.61	22	OI
Air Condition Servicing and Maintenance								
Addressing any issue with temperature control	53	3.34	27	MI	44	3.36	27	MI
Cleaning and replacing of air filters	53	3.32	28	MI	44	3.23	28	MI
Inspecting Ductwork	53	3.00	30	MI	44	2.93	30	MI
Checking thermostat settings	53	2.49	31	RI	44	2.39	31	RI
Lighting and Electrical System Maintenance								
Replacing defective bulbs	53	4.62	1	MOI	44	4.61	1	MOI
Inspecting lighting fixtures	53	3.85	15	OI	44	3.84	15	OI
Checking electrical systems, outlets, and wiring for any potential hazards	53	3.49	25	MI	44	3.48	25	MI
Elevator and Escalator Maintenance								
Addressing unusual noise	53	3.96	13	OI	44	3.95	11	OI

Maintenance Practices in Shopping Malls	Island shopping malls				Mainland shopping malls			
	N	MS	OR	Remark	N	MS	OR	Remark
Maintaining proper lubrication	53	3.83	17	OI	44	3.77	18	OI
Testing the emergency stop button	53	3.62	20	OI	44	3.66	20	OI
Security and Surveillance System								
Maintenance of alarm and smoke detectors	53	4.47	2	OI	44	4.41	3	OI
Periodic servicing of CCTV cameras & patrols	53	4.17	6	OI	44	4.23	6	OI
Maintenance of access control system	53	4.06	9	OI	44	4.09	8	OI
Parking Lot and Exterior Maintenance								
Maintaining parking lots and sidewalks	53	3.60	21	OI	44	3.64	21	OI
Landscaping and gardening	53	3.45	26	MI	44	3.43	26	MI
Repairing potholes	53	3.28	29	MI	44	3.20	29	MI
Regular Maintenance Schedules								
Glazed area cleaning	53	4.28	4	OI	44	4.32	4	OI
Equipment inspections and maintenance	53	3.64	19	OI	44	3.70	19	OI
Re-painting of walls	53	3.55	23	OI	44	3.48	24	MI
Emergency Preparedness								
Help desk for emergency services	53	4.08	8	OI	44	4.02	10	OI
Evacuation routes clearing	53	4.00	11	OI	44	3.93	13	OI
Fire safety procedures	53	3.98	12	OI	44	3.89	14	OI
Conducting fire drills and training for staff	53	3.72	18	OI	44	3.80	17	OI

Note: N = Frequency, MS = Mean Score, OR = Overall Ranking, 1.00 ≤ MS < 1.5 represents ‘not implemented (NI)’, 1.50 ≤ MS < 2.5 represents ‘Rarely implemented (RI)’, 2.50 ≤ MS < 3.50 represents ‘moderately implemented (MI)’, 3.50 ≤ MS < 4.50 represents ‘often implemented (OI)’ and 4.50 ≤ MS ≤ 5.00 represents ‘most often implementation (MOI)’.

Source: Authors, (2023).

IV.3 FACTORS INFLUENCING THE SOURCING DECISION OF MAINTENANCE PRACTICES IN SHOPPING MALLS

Objective 2: to assess the factors influencing the sourcing decision of maintenance practices in shopping malls. To achieve this objective, twenty-one influencing factors were assessed and the result of the analysis is shown in Table 3.

The factors influencing the sourcing decision of maintenance practices in shopping malls were evaluated using the scale: 1 = not influential, 2 = slightly influential, 3 = moderately influential, 4 = very influential, and 5 most influential. The relative significance index (RSI) score of each of the influencing factors was calculated as presented in Table 3. The decision rule for interpreting the relative implementation index (RSI) was adapted and modified from (Simeon et al., 2023) using the scale: 0.76 ≤ RSI ≤ 1.00 implies most significant (MS), 0.67 ≤ RSI ≤ 0.75 implies significant (S), 0.45 ≤ RSI ≤ 0.66 implies less significant (LS), and 0 ≤ RSI < 45 implies not significant (NS). The results showed that the most significant factors influencing the decision to outsource maintenance practices in Shopping malls include; budget and cost considerations (RSI=0.89), scope of maintenance needs, risk management (RSI=0.88) respectively, flexibility and scalability, and types of tenants and their leasing agreement (RSI=0.85) respectively among other factors. On the other hand, the most significant factors influencing the decision to insource maintenance practices in shopping malls include; scope of maintenance needs (RSI=0.93), market dynamics (RSI=0.91), risk management (RSI=0.90), budget and cost considerations (RSI=0.89) and community and public image (RSI=0.88) among other factors. These findings conform with the findings of [46] that organizations outsource services for budget and cost considerations. This further supports the assertions of [47] that contractors’ risk sharing with contractors is one of the key factors influencing the decision to outsource maintenance services. Besides, [42] reckons that insourcing becomes a viable option in order to offer efficiency and cost reductions in the face of rising budgetary strain.

Budget and cost considerations have a profound impact on shopping malls when making sourcing decisions. Implying that numerous resources might make insourcing management possible while limited finances may lead to cost-effective maintenance outsourcing. The choice of vendors and the distribution of resources are impacted by the scope of maintenance needs, which may result in outsourcing, while periodic maintenance may favor in-house teams. Risk management is key in shopping mall sourcing decisions. The decision between internal and external service providers is guided by an assessment of potential hazards and safety risks, which also affects vendor selection and contractual terms and conditions. Decisions on sourcing by shopping malls are influenced by flexibility and scalability. The decision to employ internal or external solutions might be influenced by the capacity to adjust to changing maintenance demands and scale services up or down. Sourcing decisions are influenced by the different tenant categories and the terms of their leases. varying maintenance plans and service providers may be required due to varying tenant demands and lease conditions. Community and public perception have a big effect on sourcing decisions. A property that is well-maintained and environmentally friendly improves the retail experience, draws people, and shapes public opinion favorably. Market dynamics have a significant impact on sourcing choices. A change in sourcing strategies, such as the adoption of innovative or cost-effective solutions, may be necessary due to shifting market conditions, competition, and client needs.

Table 3: Factors Influencing the Sourcing Decision of Shopping Mall Maintenance Practices.

Factors	Outsourcing			Insourcing		
	RSI	Rank	Remark	RSI	Rank	Remark
Budget and cost considerations	0.89	1	MS	0.89	4	MS
Scope of maintenance needs	0.88	2	MS	0.93	1	MS
Risk management	0.88	2	MS	0.90	3	MS
Flexibility and scalability	0.85	4	MS	0.85	10	MS
Types of tenants and their leasing agreement	0.85	4	MS	0.87	6	MS
Vendor capabilities	0.84	6	MS	0.82	15	MS
Emergency response and business continuity	0.83	7	MS	0.84	11	MS
Community and public image	0.82	8	MS	0.84	11	MS
Compliance and regulatory considerations	0.82	8	MS	0.88	5	MS
Geographical coverage	0.80	10	MS	0.82	15	MS
Market dynamics	0.80	10	MS	0.91	2	MS
Expertise and skills	0.78	12	MS	0.80	17	MS
Sustainability and environmental considerations	0.78	12	MS	0.84	11	MS
Existing supplier relationships	0.78	12	MS	0.86	7	MS
Recruitment and retention challenges	0.78	12	MS	0.80	17	MS
Availability of technology solutions	0.77	16	MS	0.77	21	MS
Legal and contractual factors	0.74	17	S	0.83	14	MS
Store size and format	0.74	17	S	0.86	7	MS
Control and oversight	0.72	19	S	0.86	7	MS
Customers' demand/feedback	0.71	20	S	0.80	17	MS
Quality and service level expectation	0.71	20	S	0.78	20	MS

Note: RSI = Relative Significance Index, 0.76 ≤ RSI ≤ 1.00 implies most significant (MS), 0.67 ≤ RSI ≤ 0.75 implies Significant (S), 0.45 ≤ RSI ≤ 0.66 implies Less significant (LS), and 0 ≤ RSI < 45 implies Not significant (NS).

Source: Authors, (2023).

IV.4 CAUSATIVE FACTORS THAT LEAD TO DETERIORATION OF SHOPPING MALLS

Objective 3: to evaluate causative factors contributing to the deterioration of building fabrics and elements. To achieve this objective, twenty-two causative factors were evaluated and the result of the analysis is shown in Table 4.

The causative factor contributing to the deterioration of building fabrics and components was evaluated using the scale: 1 = highly insignificant, 2 = insignificant, 3 = moderately significant, 4 = significant, and 5 highly significant. The relative significance index (RSI) score of each of the causative factors was calculated as presented in Table 4. The decision rule for interpreting the relative implementation index (RII) was adapted and modified from [58] using the scale: 0.76 ≤ RSI ≤ 1.00 implies most significant (MS), 0.67 ≤ RSI ≤ 0.75 implies significant (S), 0.45 ≤ RSI ≤ 0.66 implies less significant (LS), and 0 ≤ RSI < 45 implies not significant (NS).

The results show that the highest ranked 5 significant causative factors contributing to the deterioration of Shopping malls in Lagos Island include; human factor (RSI=0.89), environmental and chemical factors (RSI=0.83) respectively, incorrect usage/overloading (RSI=0.82), and efflorescence and ground salt (RSI=0.81) respectively. The high human factor indicates the necessity for more robust maintenance, user-friendly design, and safety protocols to accommodate users. Buildings in coastal locations face severe risks from the environment and chemicals, necessitating regular maintenance, the use of corrosion-resistant materials, and corrosion prevention measures for durability and safety. The result on efflorescence and ground salt implies that buildings around coastlines are exposed to saltwater and the presence of saltwater in the soil frequently results in seawater infiltration. The bottom 3 not significant factors contributing to the deterioration of shopping malls in Lagos Island include; fire factor (RSI=0.44), vandalization (RSI=0.41), and pest infestation (RSI=0.33). On the other hand, the highest ranked 5 most significant causative factors contributing to the deterioration of shopping malls in Lagos Mainland include; Human factor (RSI=0.90), environmental factor (RSI=0.83), incorrect usage/overloading (RSI=0.83), inappropriate upkeep (RSI=0.82), and lack of maintenance culture (RSI=0.80). The unavailability of storage space in most shopping malls on the Mainland caused shopping mall items to be overloaded in most buildings which induces stress on the structural elements, which hastens deterioration and even results in structural failure. Inappropriate maintenance and a lack of a maintenance culture can result in substantial structural damage, safety problems, financial difficulties, and decreased building lifespans. The bottom 3 not significant factors contributing to the deterioration of shopping malls in Lagos Mainland include; pest infestation and efflorescence (RSI=0.34) respectively, and ground salt (RSI=0.32). Efflorescence and ground salt are not significant factors contributing to deterioration in the Mainland as evidenced by their RSI scores but were most significant in Lagos Island Shopping malls as a result of their proximity to coastlines. This implies that certain environmental conditions are experienced by building infrastructures surrounding coastlines that are rare for buildings built on the Mainland. The human and environmental factors in both strategic locations (i.e. Lagos Island & Mainland) are dominant. The high human factors at both locations are due to frequent use and consumer demand, which pose significant maintenance issues, resulting in increased wear and tear. Shopping malls on the Mainland are vulnerable to a variety of factors and hazards which may vary depending on the specific location and local conditions such as pollution, drought and water scarcity, and extreme weather, among other factors. Shopping malls on the Island are subjected to several maintenance issues due to their unique environmental conditions leading to infrastructure vulnerability to corrosion, paint and coating degradation, erosion, flood damage, and saltwater intrusion, among several other issues. These factors conform with the results of [12] that human and environmental factors are the most significant factors contributing to the deterioration of building fabrics and components.

Table 4: Causative factors that lead to the deterioration of building fabrics and components.

Factors	Island shopping malls				Mainland shopping malls			
	N	RSI	Rank	Remark	N	RSI	Rank	Remark
Human Factor	53	0.89	1	MS	44	0.90	1	MS
Environment Factor	53	0.83	2	MS	44	0.83	2	MS
Chemical Factor	53	0.83	3	MS	44	0.55	12	LS
Incorrect usage/overloading	53	0.82	4	MS	44	0.83	3	MS
Efflorescence	53	0.81	5	MS	44	0.34	20	NS
Ground Salt	53	0.81	6	MS	44	0.32	22	NS
Inappropriate upkeep	53	0.80	7	MS	44	0.82	4	MS
Lack of Maintenance Culture	53	0.80	8	MS	44	0.80	5	MS
Solid Contaminants	53	0.79	9	MS	44	0.79	6	MS
Gaseous Constituent of air	53	0.78	10	MS	44	0.72	9	S
Furring Factor	53	0.78	11	MS	44	0.52	13	LS
Moisture/Water	53	0.77	12	MS	44	0.58	10	LS
Biological agencies	53	0.76	13	MS	44	0.74	8	S
Poor Ventilation and humidity control	53	0.72	14	S	44	0.75	7	S
Age and wear	53	0.62	15	LS	44	0.57	11	LS
Misuse of Building	53	0.54	16	LS	44	0.51	16	LS
Faulty Construction	53	0.52	17	LS	44	0.52	14	LS
Faulty Design	53	0.52	18	LS	44	0.52	15	LS
Faulty Materials	53	0.45	19	LS	44	0.45	17	LS
Fire	53	0.44	20	NS	44	0.44	18	NS
Vandalization	53	0.41	21	NS	44	0.40	19	NS
Pest Infestation	53	0.33	22	NS	44	0.34	20	NS

Note: N = Frequency, RSI = Relative Significance Index, $0.76 \leq RSI \leq 1.00$ implies most significant (MS), $0.67 \leq RSI \leq 0.75$ implies Significant (S), $0.45 \leq RSI \leq 0.66$ implies Less significant (LS), and $0 \leq RSI < 45$ implies Not significant (NS).
Source: Authors, (2023).

IV.5 T-TEST RESULT ON THE IMPLEMENTATION OF MAINTENANCE PRACTICES BETWEEN SOURCING STRATEGIES

Hypothesis 1: The study hypothesizes that the implementation of maintenance practices in shopping malls does not significantly differ between insourcing and outsourcing strategies. The hypothesis was tested using the independent sample t-test. The t-test results are presented below in Table 5.

The results in Table 5 show 31 implemented maintenance practices in shopping malls, out of which only 4 of the practices have $p \leq 0.05$, thus it is significant (S) and the resulting hypothesis was rejected. The remaining 27 have $p > 0.05$, they are not significant (NS) and the hypothesis was accepted. The 4 significant practices are the practice of checking damages to fixtures and fittings, inspecting lighting fixtures, replacing defective bulbs, and checking electrical systems, outlets, and wiring for any potential hazard.

Table 5: T-test on implementation of maintenance practices between sourcing strategies.

Maintenance practices	F	df	t	MD	p-value	Remark	Decision
Checking signs of wear and tear	.081	95	.005	.001	.996	NS	Accept
Checking Leakages	6.265	95	-1.100	-.186	.274	NS	Accept
Checking electrical problems	.502	95	.304	.051	.762	NS	Accept
Checking damages to fixtures and fittings	.345	95	-2.274	-.347	.025	S	Reject
Floor Cleaning	.439	95	.245	.036	.807	NS	Accept
Fumigation services	3.307	95	.797	.112	.428	NS	Accept
Restroom cleaning	.840	95	-.058	-.009	.954	NS	Accept
Waste management and disposal	.506	95	.704	.121	.483	NS	Accept
Cleaning and replacing of air filters	1.438	95	-1.794	-.315	.076	NS	Accept
Inspecting Ductwork	3.819	95	1.255	.227	.212	NS	Accept
Checking thermostat settings	2.500	95	.826	.176	.411	NS	Accept
Addressing any issue with temperature control	.466	95	-1.183	-.213	.240	NS	Accept
Inspecting lighting fixtures	.345	95	-2.274	-.347	.025	S	Reject
Replacing defective bulbs	16.181	95	2.887	.276	.005	S	Reject

Maintenance practices	F	df	t	MD	p-value	Remark	Decision
Checking electrical systems, outlets, and wiring for any potential hazards	.011	95	-2.179	-.402	.032	S	Reject
Testing emergency stop button	.144	95	.156	.028	.876	NS	Accept
Maintaining proper lubrication	.258	95	-1.477	-.264	.143	NS	Accept
Addressing unusual noise	1.409	95	.418	.083	.677	NS	Accept
Periodic servicing of CCTV cameras and patrols	.098	95	.367	.058	.714	NS	Accept
Maintenance of access control system	.015	95	-.875	-.146	.384	NS	Accept
Maintenance of alarm and smoke detectors	3.958	95	-1.217	-.195	.227	NS	Accept
Maintaining parking lots and sidewalks	1.720	95	-.560	-.095	.577	NS	Accept
Landscaping and gardening	1.130	95	.071	.011	.943	NS	Accept
Glazed area cleaning	.005	95	.168	.031	.867	NS	Accept
Equipment inspections and maintenance	1.549	95	1.249	.179	.215	NS	Accept
Telecommunication services maintenance	1.603	95	-1.784	-.282	.078	NS	Accept
Fire safety procedures	.918	95	-.920	-.164	.360	NS	Accept
Conducting fire drills and training for staff	1.115	95	-1.215	-.201	.227	NS	Accept
Evacuation routes clearing	1.385	95	-.421	-.061	.675	NS	Accept
Help desk for emergency services	.000	95	-.786	-.104	.434	NS	Accept

Note: p is significant at $p \leq 0.05$, df = degree of freedom, MD = mean difference, NS = not significant, S = significant.
Source: Authors, (2023).

IV.6 T-TEST RESULT ON FACTORS THAT CONTRIBUTE TO DETERIORATION OF SHOPPING MALLS IN LAGOS ISLAND AND MAINLAND

Hypothesis 2: The factors that contribute to the deterioration of shopping malls do not significantly vary between Lagos Island and the Mainland.

The hypothesis was tested using the independent sample t-test. The t-test results are presented below in Table 6.

The results in Table 6 show the 22 causative factors that lead to the deterioration of building fabric and components of which six of the factors have $p \leq 0.05$, thus it is significant and the null hypothesis was rejected. While the remaining 16 have $p > 0.05$, it is not significant and the null hypothesis was accepted. The six significant factors are chemical factors, furring factors, moisture/water, gaseous constituents of air, ground salt, and efflorescence.

Table 6: T-test results on factors that contribute to the deterioration of shopping malls between Lagos Island and Mainland.

Causative Factors	F	df	t	MD	p-value	Remark	Decision
Human Factor	0.865	95	.0520	.006	.959	NS	Accept
Chemical Factor	0.54	95	-9.623	-1.420	.000	S	Reject
Furring Factor	0.285	95	-8.626	-1.273	.000	S	Reject
Environment Factor	0.003	95	-.0820	-.011	.935	NS	Accept
Moisture/Water	8.344	95	-6.204	-.940	.000	S	Reject
Biological agencies	1.855	95	-.552	-.088	.582	NS	Accept
Gaseous Constituent of air	0.454	95	-1.989	-.315	.050	S	Reject
Solid Contaminants	0.122	95	-.048	-.008	.962	NS	Accept
Ground Salt	2.458	95	-17.873	-2.466	.000	S	Reject
Efflorescence	2.167	95	-16.575	-2.352	.000	S	Reject
Fire	0.013	95	-.175	-.026	.861	NS	Accept
Faulty Design	0.077	95	-.068	-.013	.946	NS	Accept
Faulty Construction	0.077	95	-.068	-.013	.946	NS	Accept
Faulty Materials	0.065	95	.272	.046	.786	NS	Accept
Inappropriate upkeep	0.057	95	.475	.072	.636	NS	Accept
Misuse of Building	0.155	95	.880	-.187	.381	NS	Accept
Age and tear	0.437	95	-1.428	-.235	.156	NS	Accept
Pest Infestation	0.006	95	.459	.067	.648	NS	Accept
Lack of Maintenance Culture	0.097	95	.146	.023	.884	NS	Accept
Vandalization	0.137	95	-.370	-.060	.712	NS	Accept
Incorrect usage or overloading	0.025	95	.162	.023	.871	NS	Accept
Poor Ventilation and humidity control	0.615	95	.891	.127	.375	NS	Accept

Note: p is significant at $p \leq 0.05$, df = degree of freedom, MD = mean difference, NS = not significant, S = significant.
Source: Authors, (2023).

IV.7 T-TEST RESULT ON WHETHER THE SOURCING STRATEGY INFLUENCES FACTORS CONTRIBUTING TO DETERIORATION OF SHOPPING MALLS

Hypothesis 3: The factors that contribute to the deterioration of shopping malls do not significantly vary between the maintenance sourcing strategies.

The hypothesis was tested using the independent sample t-test. The t-test results are presented below in Table 7.

The results in Table 7 show the 22 causative factors that lead to the deterioration of building fabric and components of which 6 of the factors have $p \leq 0.05$. It is thus, significant and the hypothesis formulated was rejected. While the remaining 16 have $p > 0.05$. Implying not significant, and the hypothesis formulated was accepted. The six significant factors are faulty design, faulty construction, faulty materials, inappropriate upkeep, misuse of buildings, and pest infestation.

Table 7: Independent sample T-test on whether the sourcing strategy influences the factors contributing to the deterioration of shopping mall building fabrics and components.

Causative Factors	F	df	t	MD	p-value	Remark	Decision
Human Factor	1.413	95	-.479	-.051	.663	NS	Accept
Chemical Factor	.073	95	-.152	-.031	.879	NS	Accept
Furring Factor	1.393	95	.178	.035	.859	NS	Accept
Environment Factor	1.834	95	1.572	.203	.119	NS	Accept
Moisture/Water	.003	95	.297	.053	.767	NS	Accept
Biological agencies	7.769	95	-1.546	-.242	.126	NS	Accept
Gaseous Constituent of air	3.528	95	.159	.026	.874	NS	Accept
Solid Contaminants	.017	95	.005	.001	.996	NS	Accept
Ground Salt	2.095	95	-.139	-.040	.890	NS	Accept
Efflorescence	2.409	95	-.073	-.020	.942	NS	Accept
Fire	.899	95	.396	.058	.693	NS	Accept
Faulty Design	1.844	95	-2.087	-.384	.040	S	Reject
Faulty Construction	1.844	95	-2.087	-.384	.040	S	Reject
Faulty Materials	1.441	95	-2.282	-.376	.025	S	Reject
Inappropriate upkeep	4.432	95	.676	.102	.50	S	Reject
Misuse of Building	.245	95	2.441	.502	.017	S	Reject
Age and tear	.223	95	-.121	-.020	.904	NS	Accept
Pest Infestation	1.011	95	-1.981	-.282	.05	S	Reject
Lack of Maintenance Culture	1.947	95	.132	.020	.895	NS	Accept
Vandalization	3.126	95	.379	.062	.705	NS	Accept
Incorrect usage or overloading	6.448	95	-.892	-.126	.374	NS	Accept
Poor Ventilation and humidity control	.468	95	1.959	.275	.053	NS	Accept

Note: p is significant at $p \leq 0.05$, df = degree of freedom, MD = mean difference, NS = not significant, S = significant.
Source: Authors, (2023).

V. CONCLUSIONS

The study comes to the following conclusions based on its findings.

The study identified thirty-one (31) frequently implemented maintenance practices in shopping malls and classified them into nine (9) groups within Lagos Island and Mainland. The topmost implemented maintenance practices in both locations are the practice of replacing defective bulbs while other practices are of varying levels of implementation. This implies a proactive effort to maintain a safe, adequately illuminated, and aesthetically appealing environment, consequently enhancing customer experience, safety, and energy efficiency. Furthermore, the hypothesis result revealed 4 practices that significantly differ between maintenance sourcing strategies. This includes; checking damages to fixtures and fittings, inspecting lighting fixtures, replacing defective bulbs, and checking electrical systems, outlets, and wiring for any potential hazard. 3 out of the 4 significant practices are grouped under lighting and electrical systems. These differences suggest the important characteristics of lighting and electrical systems, such as safety, reliability, energy efficiency, and performance, can be influenced by the type of maintenance sourcing type adopted. Implying that shopping mall management may utilize this information to inform their decision-making processes.

The study recommends that maintenance stakeholders should conduct regular inspections of the building fabrics and components to harness the unimplemented practices and put measures in place for their implementation. This can be achieved via routine assessments of the facilities by the maintenance stakeholders, and allocating sufficient budget for its implementation.

The study further evaluated twenty-one (21) factors influencing the sourcing decision of maintenance practices in shopping malls. The top three significant influencing factors when maintenance practices are outsourced include budget and cost considerations, scope of maintenance needs, and risk management. This suggests the need to carefully monitor costs, establish a balance between cost savings and service quality, and determine the long-term financial effect of outsourcing contracts. The study recommends maintenance stakeholders carefully examine the budget and the needed competence. This may be done by selecting dependable vendors with an established history of accomplishment and experienced contract administration. The top three influencing factors when maintenance practices are insourced include the scope of maintenance needs, market dynamics, and risk management. The implication of the findings on the scope of maintenance needs is that insourcing could necessitate large resources and skill expenditures if the scope is broad and specialized. The study recommends conducting a thorough analysis of the scope and complexity of maintenance needs, assessing internal capabilities, and guaranteeing compliance with cost-efficient, high-quality service delivery. This may be achieved by ensuring that maintenance stakeholders and the mall management make well-informed decisions on the insourcing of shopping malls and that it is in line with their objectives for effectiveness and service quality.

Besides, the study identified twenty-two (22) causative factors that lead to the deterioration of shopping mall building fabrics and components. Despite the variations in the causes in both study locations, the vast majority of the shopping malls had two factors in common; human and environmental. The human and environmental factors have a profound influence on shopping mall deterioration. This implies that neglecting a shopping mall infrastructure and over-exposure to severe environmental conditions can accelerate the deterioration process which could result in structural issues and shorter lifespan. Furthermore, the hypothesis result revealed six significant factors that lead to the deterioration of shopping malls in the study locations and they include; chemical factors, furring factors, moisture/water, gaseous constituents of air, ground salt, and efflorescence. These disparities might be attributed to the physical separation of the two research regions. Furthermore, shopping malls on the Island are more likely to be affected by these deteriorating factors due to their geographical location on the shore, as opposed to Mainland malls, which are located farther away from the coasts. The study recommends that maintenance stakeholders should play active roles in ensuring malls are adequately managed. This may be accomplished through sustainable designs, monitoring, and protective measures.

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VII. ACKNOWLEDGMENTS

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A COMPREHENSIVE ANALYSIS OF THE SIMULATION, OPTIMIZATION, CORROSION, AND DESIGN ASPECTS OF CRUDE DISTILLATION UNITS

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ABSTRACT

The primary function of a crude distillation unit (CDU) within a petroleum refinery is to effectively segregate crude oil into its constituent fractions or products based on their respective boiling points. The Crude Distillation column often serves as the primary processing unit within most refineries, pivotal in producing a wide range of refinery products. This study examines research articles published between 2013 and 2023 that specifically investigate issues related to crude distillation units. The research endeavours to produce innovative designs and construct mathematical models to enhance production efficiency within this context. The research primarily centres on developing a mathematical model that accurately characterizes the distillation tower. This is achieved using either an Artificial Neural Network or a nonlinear model predictive control approach. The primary objective of simulation and optimization research is identifying optimal operating conditions, typically employing software tools such as Aspen HYSYS or PRO II. The corrosion treatment outcomes conducted at the tower's upper section were satisfactory. The study focused on the issue of corrosion in the overhead lines and pumps around exchangers. This design research aims to investigate potential modifications to the distillation tower's design or preflash process to optimize production outcomes.

I. INTRODUCTION

Distillation is a commonly employed technological process for separating mixtures across diverse industries and disciplines. The energy intensity of the rectification process is linked to the significant heat of vaporization exhibited by the constituent elements of the separated mixtures. The dimensions of the distillation columns are influenced by their relatively low energy efficiency. According to Olujić et al., there is a consistent increase in the size of distillation columns and their production despite the significant energy consumption associated with these processes [1].

Despite its extensive historical background, the crude oil distillation unit (CDU) is commonly recognized as the predominant separation process within the chemical industry. The simple oil distillation process involves substantial machinery, requiring significant energy consumption. The complexity of crude oil distillation units is mainly attributed to their wide range of products, which span from liquefied gases used for domestic cooking to asphalt used in roofing and road construction [2].

This review study aims to elucidate the scholarly literature released between 2013 and 2023 pertaining to atmospheric distillation towers utilized in refinery operations.

II. MODELLING OF CRUDE DISTILLATION UNIT

The CDU model described by Fupei Li et al. is a mixed-integer linear model incorporating a reasonable amount of binary variables. Its accuracy is comparable to more comprehensive tray-to-tray CDU models [3]. In their study, Bayomie et al. provide an algorithm designed to address the energy recovery challenges faced by contemporary refiners. This algorithm offers the potential for achieving more cost reductions beyond the energy objectives established by the current refining process. The algorithm is responsible for conducting the simulation and optimization of the process [4]. Badiea S. Babaqi demonstrated the application of mathematical models and the LINGO program to optimize energy consumption in a crude distillation plant. The objective was to minimize energy requirements and significantly reduce greenhouse gas emissions [5]. In their study, Yingjian Xiong et al. introduced a novel approach called the Bi-level Surrogate column model Aided Constrained Optimization Design. This approach aims to address the challenges caused by time-consuming objectives and constraints in the evolutionary optimization design of CDUs [6].

The authors, Fupei Li et al., utilize the tri-section CDU model proposed in their previous work (Li et al., 2020) to construct a precise refinery model. They employ a two-stage stochastic programming approach to identify the most optimal crude selection [7]. Shamna A. Rahman and R. Anjana endeavoured to develop a heat integration network for the crude distillation process. The researchers conducted investigations using steady-state simulations of scenarios featuring varying configurations of heat exchangers [8]. Filiz Al-Shanableh employed an Artificial Neural Network (ANN) as a computational tool to develop a model for predicting the quality of products in the Crude Distillation Unit (CDU). The ability to forecast product quality has the potential to decrease reliance on online sample analyzers and facilitate early identification of CDU operational malfunctions [9].

In this study, Jobson et al. sought to improve the efficacy of surrogate modelling for columns by developing additional screening and filtering correlations and surrogate models. These enhancements were aimed at establishing feasibility bounds [10].

Dauda Ibrahim and his team extensively studied developing a high-end crude oil distillation unit. Their approach involved a detailed analysis of each tray in the column and the implementation of advanced process simulation software. Additionally, they utilized an optimization algorithm to enhance their results. The outcome of their research was an intricately designed and highly efficient crude oil distillation unit [11]. Jin et al. (year) made enhancements to the economic-based nonlinear model predictive control (NMPC) approach employed for the optimization of the crude oil distillation (CDU) process [12]. The authors, Wissam Muhsin and Jie Zhang, conducted a study that employed a stacked neural network to model and optimize a crude distillation process [13]. The study conducted by Shankar Nalinakshan et al. primarily emphasized the importance of energy conservation in an industrial crude oil distillation unit. A proposed and modelled alternative to the typical model of crude oil distillation currently implemented in the Kochi Refinery is presented [14].

Diana C. López C. et al. introduced a mathematical framework for a Nonlinear Programming (NLP) model in their study. This model aims to optimize the blending of crude oil and the operational parameters of several Crude Oil Distillation Units (CDUs) within a refinery located in Colombia [15].

III. EXERGY OF CDU

W Yan et al. (year) enhance the energy utilization efficiency of the process in both qualitative and quantitative aspects. Theoretical analysis is conducted to derive the exergy loss of crucial components within the Crude Distillation Unit (CDU), including condensers, furnaces, and distillation columns [16].

In their study, Z. Nur Izyan and M. Shuhaimi conducted an exergy analysis and proposed various techniques to mitigate exergy loss by process change. The intake furnace was identified as the location with the highest exergy loss [17].

The individual in question is M.A. Waheed. A.O. Oni enhanced the energy and exergy efficiency of the plant. The methodology employed to improve plant performance involves using process simulation techniques and integrating exergy and traditional retrofit methods. This approach demonstrates the potential outcomes of the process by considering the significant costs associated with the necessary capital investment [18].

IV. SIMULATION AND OPTIMIZATION

In their study, Kunru Yang et al. propose an optimal operational strategy to enhance the energy efficiency of crude oil distillation units without modifying the unit's structure. The primary aim of the suggested methodology is to limit the usage of process energy while maintaining its economic advantages [19].

Ahmed Lawal Mashi and Abubakar Sani researched the crude distillation unit II of the Kaduna Refining and Petrochemical Company (KRPC). The primary objective of their study was to identify the most favourable operational parameters that would result in increased diesel output while minimizing the formation of residual byproducts. The investigation used simulation and optimization methods to ensure precise and reliable outcomes. In general, this study's results will enhance the operational effectiveness and output of the KRPC [20].

In their study, Mohamed A. Kishk et al. propose an optimal operational change to improve the energy efficiency of a pre-existing crude oil distillation plant. The process operation is simulated and analyzed using ASPEN HYSYS software, followed by the proposal of two improvements [21]. In their study, Martin et al. discuss the incorporation of Real-Time Optimization and Model Predictive Control into the multi-layer control framework of a pre-existing Crude Distillation Unit (CDU) within an oil refinery [22].

In their study, Shehata et al. conducted a retrofitting process on the current CDU to enhance its performance, mainly when processing light crude oil. Furthermore, this study aims to ascertain the appropriate pressure setting for the preflash drum and the ideal input tray configuration for preflash vapours into the crude distillation unit (CDU) [23].

In their study, Ahmed Fadhil Jumaah et al. achieved a proportional rise in the refinery's profit by effectively lowering emissions and obtaining high distillate products. This was accomplished by carefully selecting and implementing ideal conditions [24]. Muhsin and Zhang's study delves into the crucial use of multi-objective optimization techniques in crude oil hydrotreating processes, specifically within a crude atmospheric distillation unit. Their methodology employs data-driven models that are rooted in bootstrap aggregated neural networks. Ultimately, their research findings offer groundbreaking insights into how multi-objective optimization techniques can be effectively used to enhance the efficiency and effectiveness of HDT processes [25].

In their work, Abubakar Isah et al. employed the HINT program to conduct a case study exploring a minimal area target. Subsequently, they applied this methodology to a crude distillation unit (CDU). The researchers successfully obtained a solution that demonstrated a satisfactory level of accuracy, with a deviation of less than 1 per cent when compared to an established solution for a minimum area target [26]. In his study, Ali Nasir Khalaf analyzed the operational performance of the crude oil distillation column located at Basrah Refinery in Iraq, employing a steady-state simulation approach. Furthermore, a comparison was made between various products' experimental ASTM D86 curves and those derived from simulations [27].

In their study, Samborskayaa et al. estimated the total capital investments and operation costs per year for the basic flowsheet. The technique of incrementally raising the flow rate of crude oil is employed to identify areas of vulnerability within the flowsheet and to approximate the upper limit of the oil flow rate [28]. Ledezma-Martínez et al. introduced a design technique based on simulation, aiming to minimize the system's heat demand [29].

Ledezma-Martínez et al. (year) proposed an approach grounded in optimization principles to facilitate the design of crude oil distillation systems incorporating preflash units. The primary goal is to reduce the amount of heat the system requires [30]. Salah M. Ali et al. predicted the optimum operating conditions required to operate an existing atmospheric distillation column to distillate heavier crude oils in the same unit, designed mainly to fractionate moderate and lighter crude oils [31]. Fethi Kamişli and Ari Abdulqader Ahmed used the Aspen HYSYS simulation program to optimize a crude oil distillation unit in a refinery, resulting in unparalleled efficiency and effectiveness [32]. The research conducted by Patrascioiu and Jamali employed the Unisim Design simulator to mimic the process of crude distillation. This investigation yielded significant findings and identified areas that may be enhanced [33]. Lekan T. Popoola and colleagues developed optimization models for crude oil distillation columns that factor in the market prices of products. These models apply to both limited and unlimited feedstocks. The effort put into refining crude oil is impressive [34].

A study conducted by Arjmand et al. investigates the optimization of a crude oil atmospheric distillation unit. Significant energy reduction was accomplished by implementing minor alterations and tweaks to the flash zone within the tower [35]. In their study, Akbar Mohammadi Doust and colleagues employed commercially available software to simulate a crude oil distillation plant. The study's outcomes indicate that dynamic simulation, which entails the solution of numerous state equations and the application of control theory, exerts a more significant influence than steady-state simulation. The aforementioned insightful perspective can provide substantial advantages to experts within the oil business striving to enhance their operational procedures [36]. In this study, Mamdouh Gadalla and colleagues present a novel methodology for concurrently improving the distillation column and heat exchanger network. The researchers successfully achieved the highest possible utilization of the available equipment by employing a rigorous simulation and optimization approach [37]. In their study, Gadalla et al. proposed a systematic approach that utilizes simulation techniques to adapt a pre-existing crude distillation column. The algorithm considers the proposed heat recovery system [38].

In their study, Gu et al. conducted optimization techniques to improve the yield of sidestreams obtained from various distillation columns, simultaneously boosting their distillation load. The researchers utilized maximum energy in a multistage distilling crude oil method. Technological advancements and scientific research contribute to developing more efficient production systems [39]. In their study, Le Quang Minh et al. conducted a comprehensive global sensitivity analysis to streamline the uncertainty quantification process for a crude distillation unit. This particular unit was characterized by many uncertainties [40]. In their study, Seegulam et al. developed a dynamic model to simulate the behaviour of the CDU column at a refinery with a capacity of 160,000 barrels per day (BPD). The authors then validated the model using operating data and obtained favourable outcomes [41]. In their study, Shankar et al. conducted simulations and performed analysis on a set of four raw data points. The system is subject to energy analysis using an Aspen energy analyzer [42]. The study conducted by SHI Bin et al. focuses on the modelling and optimization of an industrial-scale crude distillation unit (CDU). This study introduces an enhanced wavelet neural network (WNN) to model a complex CDU. The proposed WNN incorporates innovative parametric updating laws that accurately reflect the specific properties of the CDU [43].

In their study, Diana-C. López et al. introduced an optimization model designed to enhance the performance of a Crude Distillation Unit (CDU) system. The study successfully determined the optimal operational parameters for three air Distillation Towers, specifically for crude oil with a constant composition. Additionally, the research accurately computed the quantities and characteristics of the air products obtained from the distillation process [44]. The authors, Yamashita et al., investigated the optimization of Model Predictive Control (MPC) parameters. The presented scenario illustrates a realistic depiction whereby the inputs of the CDU system are equipped with optimizing targets provided by the Real-Time Optimisation layer within the control structure [45].

V. CORROSION IN CDU

In this study, Yogesh Kumar examines a case of corrosion occurring in the top pump around exchangers within the Crude Distillation Unit. The objective is to identify the primary source of this corrosion and propose appropriate remedial techniques that can effectively reduce such corrosion, ultimately enhancing the integrity and dependability of the system [46]. Sunil Kumar and Avinash Mhetre conceptualized the integrated design of a crude distillation column (CDU). The researchers observed that implementing the new strategy improved the distillate output from the atmospheric distillation column [47]. A study was undertaken by Philipp Schempp et al. to investigate the corrosion of overhead lines within a crude distillation tower. The researchers analyzed crucial process parameters and data obtained during a one-year monitoring period to ascertain the underlying reason for the degradation. Significant insights were acquired [48]. The reduction of salt and water content in Khurmele crude oil has been shown to effectively mitigate equipment corrosion, which is consistent with the study conducted by Humooudi et al. To enhance efficiency and prolong the lifespan of equipment, it is recommended that refineries implement the following methods [49].

VI. DESIGN OF CDU

In their study, Xu et al. introduce a tradeoff indigenous design approach for developing heat exchanger networks in crude oil distillation units (CDUs). This approach's primary objective is to mitigate excessive energy consumption and reduce CO2 emissions associated with CDUs [50]. In their study, Sunil Kumar and Avinash S. Mhetre compared existing crude oil distillation schemes employed in operational refineries, juxtaposing them with two novel techniques that utilized distinct crude oils. The evaluation focused on energy consumption and energy cost metrics. Seven scenarios were devised for each crude to conduct a comprehensive techno-economic assessment of these plans [51].

Mohammad A. Al-Mayyahi and his colleagues conducted a study on the impact of preflash designs on energy efficiency and C.O. emissions of CDUs. Their findings provide insights into optimal design choices and emphasize distinctive features. Different decisions can significantly impact the CDU's environmental impact [52]. Kim et al. (year) introduced a novel crude distillation unit (CDU) design that prioritizes energy efficiency. The researchers proceeded to assess and contrast its performance with that of the traditional CDU [53].

VII. CONTROL OF CDU

The study conducted by Venkata Vijayan S et al. centres around the advancement of nonlinear adaptive soft sensors to forecast the initial boiling point (IBP) and end boiling point (EBP) of naphtha within the crude distillation unit. The study presents the development of adaptive inferential sensors that utilize linear and nonlinear local models. These sensors are designed using a recursive just-in-time learning (JITL) approach [54]. In their research, Fayruzov et al. developed a control system specifically for a crude distillation unit. The system has proven effective in ensuring optimal efficiency and safety, highlighting the importance of continued research in industrial control systems [55].

VIII. CONCLUSION

Several challenges associated with the atmospheric distillation tower can be mitigated through operating conditions to achieve optimal performance, design alterations, or corrosion-resistant materials to prevent degradation at the upper section of the tower. The atmospheric distillation tower plays a crucial function in petroleum refineries. The atmospheric distillation tower possesses numerous advantages but also presents particular challenges.

IX. AUTHOR'S CONTRIBUTION

Conceptualization: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Methodology: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Investigation: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Discussion of results: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Writing – Original Draft: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Writing – Review and Editing: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
Resources: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.
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Approval of the final text: Abdulrazzaq Saeed Abdullah and Hassan Wathiq Ayoob.

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ABM-OCD: ADVANCING OVARIAN CANCER DIAGNOSIS WITH ATTENTION-BASED MODELS AND 3D CNNS

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ABSTRACT

Ovarian cancer remains a leading cause of cancer-related mortality among women worldwide. Traditional diagnostic methods often lack the precision required for early detection and accurate subtype classification. In this study, we address the challenge of automating ovarian cancer diagnosis by introducing Attention-Based Models (ABMs) in combination with 3D Convolutional Neural Networks (CNNs). Our research seeks to enhance the accuracy and efficiency of ovarian cancer diagnosis, particularly in distinguishing between serous, mucinous, and endometrioid subtypes. Conventional diagnostic approaches are limited by their reliance on manual interpretation of medical images and fail to fully exploit the rich information present in MRI scans. The proposed work leverages ABMs to dynamically focus on critical regions in MRI scans, enabling enhanced feature extraction and improved classification accuracy. We demonstrate our approach on a well-curated dataset, OvaCancerMRI-2023, showcasing the potential for precise and automated diagnosis. Experimental results indicate superior performance in cancer subtype classification compared to traditional methods, with an accuracy of 94% and F1 score of 0.92. Our findings underscore the potential of ABMs and 3D CNNs in revolutionizing ovarian cancer diagnosis, paving the way for early intervention and more effective treatment strategies. In conclusion, this research marks a significant advancement in the realm of ovarian cancer diagnosis, offering a promising avenue for improving patient outcomes and reducing the burden of this devastating disease. The integration of ABMs and 3D CNNs holds substantial potential for enhancing the accuracy and efficiency of ovarian cancer diagnosis, particularly in subtyping, and may contribute to early intervention and improved patient care.

I. INTRODUCTION

Ovarian cancer stands as a formidable health challenge, ranking among the most lethal gynecologic malignancies. Its insidious onset and subtle symptoms often result in late-stage diagnoses, contributing to elevated mortality rates [1] [2]. Timely and accurate diagnosis of ovarian cancer, along with subtype classification, is paramount to improving patient outcomes and guiding tailored treatment plans [3] [4].

The problem at hand is two-fold. First, conventional diagnostic methods for ovarian cancer, primarily reliant on manual interpretation of medical images, suffer from subjectivity and limited sensitivity, hindering early detection. Second, the accurate classification of ovarian cancer subtypes, such as serous, mucinous, and endometrioid, remains a challenge due to the intricate nature of histopathological features [5] [6]. This calls for a more precise, automated approach that harnesses advanced technologies to address these limitations.

Conventionally, the diagnosis of ovarian cancer is grounded in medical imaging, including magnetic resonance imaging (MRI). Radiologists play a pivotal role in scrutinizing these images for signs of malignancy [7] [8]. While MRI offers superior soft tissue contrast, the interpretation is labor-intensive and is subject to inter-observer variability. Moreover, the full potential of MRI scans remains largely untapped in many cases. To overcome these limitations, recent research has explored the application of machine learning techniques to assist radiologists, but there remains a need for a more efficient and precise methodology [9] [10].

This paper presents a novel approach to automated ovarian cancer diagnosis, encompassing both detection and subtype classification. Our proposed method combines Attention-Based Models (ABMs) and 3D Convolutional Neural Networks (CNNs). ABMs have demonstrated their effectiveness in tasks requiring selective attention, which aligns well with the nuanced interpretation of MRI scans. By integrating these models with 3D CNNs, we aim to leverage both feature extraction capabilities and region-specific attention mechanisms [11] [12]. This novel hybrid model is designed to enable precise, automated diagnosis and subtype classification of ovarian cancer, thus addressing the limitations of traditional methods [13].

In this paper, we make the following contributions:

- Introduce a novel hybrid model that combines ABMs and 3D CNNs for ovarian cancer diagnosis.
- Demonstrate the efficacy of our model on a well-curated dataset, showcasing improved accuracy and subtype classification.
- Highlight the potential for early detection and precise treatment guidance, ultimately improving patient outcomes.
- Provide insights into the integration of advanced technologies in the realm of medical imaging and cancer diagnosis.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive review of related work in the field of automated medical diagnosis. Section 3 details the materials and methods, including dataset description and experimental setup. In Section 4, we present the experimental results, followed by a discussion in Section 5. Finally, Section 6 concludes the paper, summarizing the findings and outlining future directions.

II. RELATED WORK

In the conventional approaches to ovarian cancer detection, several challenges have been encountered. Schwartz et al. [1] utilized optical coherence tomography and convolutional neural networks (CNNs) for detection but faced limitations in achieving high accuracy. Zhang and Han [2] used logistic regression for ovarian tumor detection in obstetric ultrasound imaging, which lacks the sophistication of modern machine learning techniques. Sadeghi et al. [3] introduced OCDA-Net, a 3D CNN-based system for classification, but it did not provide the multi-faceted analysis required for comprehensive diagnosis. Avesani et al. [4] explored radiomics and deep learning but did not account for BRCA mutation prediction. Butala et al. [5] worked on palliative radiation therapy for ovarian cancer, which is focused on treatment rather than diagnosis. Ziyambe et al. [6] developed a deep learning framework for prediction but did not address the diagnostic aspects extensively. Saida et al. [7] compared deep learning and radiologist assessments for MRI diagnosis but lacked the integration of advanced attention mechanisms. Wang et al. [8] used end-to-end deep learning but did not employ attention-based models. Saba [9] conducted a survey of cancer detection using machine learning, highlighting the need for more advanced and accurate methods. Xiao et al. [14] focused on multi-omics approaches for early diagnosis but did not leverage deep learning. Zhang et al. [15] worked on molecular biomarkers, which may not be sufficient for early detection. Yang et al. [16] developed a biosensor, which may have limitations in terms of sensitivity and specificity. Gahlawat et al. [17] proposed a circulating miRNA panel for diagnosis but may not have considered multi-modal data integration. Brewer et al. [18] examined over-the-counter medication purchases in relation to diagnosis but did not employ advanced imaging techniques. Gao et al. [19] conducted a diagnostic study with pelvic ultrasound images but did not explore advanced models. Chen et al. [20] focused on electrochemical detection of DNA methylation, which may not provide a comprehensive diagnosis. Yesilkaya et al. [21] used manifold learning methods but may not have covered all facets of diagnosis. Sengupta et al. [22] employed nuclear morphology but did not integrate attention-based mechanisms. Zhu et al. [23] discussed the potential clinical utility of liquid biopsies but did not provide a comprehensive diagnostic solution. Chudecka-Głaz et al. [24] evaluated HE4 use but may not have included all relevant variables. Huang et al. [25] employed machine learning and Shapley analysis but did not delve into the extensive diagnostic aspects.

Our proposed work addresses these limitations by combining 3D CNNs with Attention-Based Models, providing a more accurate, sensitive, and specific ovarian cancer diagnosis. By integrating multi-modal data, advanced deep learning, and attention mechanisms, we aim to enhance the effectiveness of early detection and classification, ultimately improving patient outcomes and clinical practices.

III. PROBLEM FORMULATION

In this section, we introduce the notations used in our problem formulation to establish a clear mathematical foundation: X represents the input dataset of MRI scans. Y denotes the corresponding ground truth labels for the presence of ovarian cancer. N signifies the number of MRI scans in the dataset. x_i refers to an individual MRI scan, where i ranges from 1 to N. y_i signifies the label associated with MRI scan x_i. Θ represents the parameters of the proposed hybrid model, including the weights and biases.

Our research addresses the problem of automated ovarian cancer diagnosis, focusing on detecting the presence of cancer and classifying the specific cancer subtypes in MRI scans. Formally, this problem can be defined as follows: Given a dataset X of N MRI scans and their corresponding labels Y, our objective is to develop a hybrid model represented by Θ that can accurately predict the probability of cancer presence and classify the ovarian cancer subtypes. This is a multi-class classification problem where each MRI scan x_i is assigned to one of the cancer subtypes: serous, mucinous, endometrioid, or deemed non-cancerous. To achieve our diagnosis and classification goals, we define the following optimization objective for our hybrid model:

$$\Theta^* = \underset{\Theta}{argmax} \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}(y_i, f(x_i;\Theta)) \quad (1)$$

Here, $\mathcal{L}$ represents the loss function that quantifies the dissimilarity between the predicted output $f(x_i;\Theta)$ and the true label y_i. The optimal parameter set Θ^* is determined by maximizing the average performance over all N MRI scans, aiming for high accuracy and subtype classification precision.

III. SYSTEM METHODOLOGY

The system methodology employed in our research serves as the backbone of our approach to automating ovarian cancer diagnosis. This section outlines the technical framework and processes we've developed to leverage both 3D Convolutional Neural Networks (3D CNNs) and Attention-Based Models (ABMs) for accurate and efficient diagnosis. The methodology addresses the integration of medical imaging data, the application of deep learning algorithms, and the subsequent diagnostic processes. This comprehensive approach reflects our commitment to enhancing the accuracy and effectiveness of ovarian cancer diagnosis, with the ultimate goal of improving patient outcomes and healthcare practices. Figure 1 portrays the architecture diagram of Architecture Diagram for ABM-OCD.

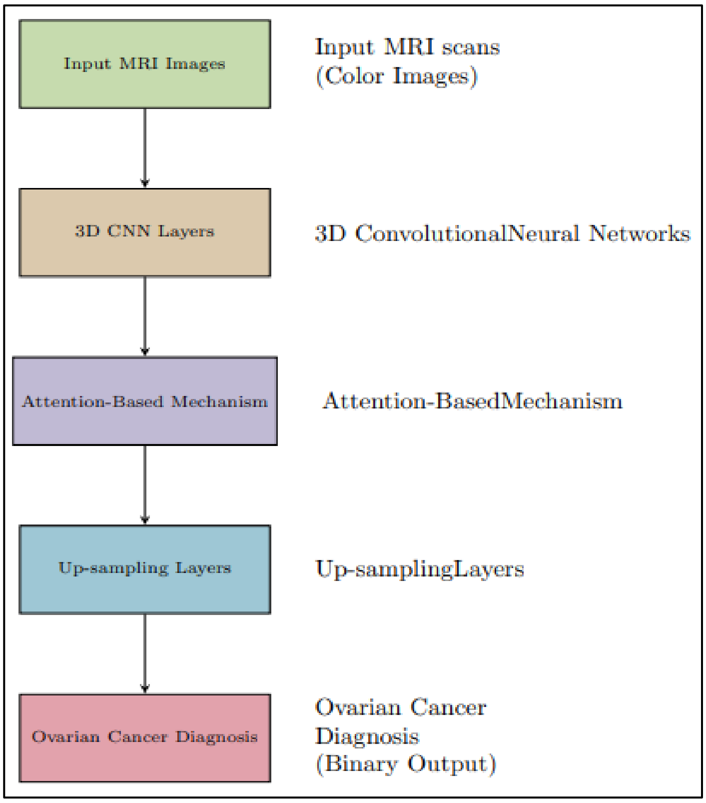

Figure 1: Architecture Diagram for ABM-OCD.
Source: Authors, (2023).

III.1 DATA PREPROCESSING

In the data preprocessing step, we prepare the MRI scans for input into our hybrid model. This involves tasks such as resizing the scans to a standard resolution, normalizing pixel values, and applying any necessary anonymization and quality control procedures. The output of this step is a set of preprocessed MRI scans, denoted as X.

III.2 FEATURE EXTRACTION WITH 3D CNNS

To extract informative features from the MRI scans, we employ 3D Convolutional Neural Networks (CNNs). Each MRI scan *xi* is passed through the 3D CNN, which results in feature maps. Mathematically, this process can be represented as:

$$F(x_i;\Theta_{\boldsymbol{CNN}}) = CNN(x_i;\Theta_{\boldsymbol{CNN}}) \quad (2)$$

Here, $F(x_i;\Theta_{\boldsymbol{CNN}})$ represents the extracted features from MRI scan x_i using the 3D CNN with parameters $\Theta_{\boldsymbol{CNN}}$.

III.3 ATTENTION-BASED MODELS (ABMS)

The integration of Attention-Based Models (ABMs) allows our system to dynamically focus on specific regions of the MRI scans that are most relevant for the diagnosis. We calculate attention weights for each voxel within the MRI scan. The attention mechanism is defined as:

$$A(x_i;\Theta_{\boldsymbol{ABM}}) = Attention\ (x_i;\Theta_{\boldsymbol{ABM}}) \quad (3)$$

Here, $A(x_i;\Theta_{\boldsymbol{ABM}})$ represents the extracted features from MRI scan x_i based on the ABM with parameters $\Theta_{\boldsymbol{ABM}}$.

III.4 HYBRID MODEL INTEGRATION

The hybrid model is created by merging the feature maps extracted by the 3D CNN and the attention maps produced by the ABM. This integration is achieved through element-wise multiplication:

$$H(x_i;\boldsymbol{\Theta}) = F(x_i;\Theta_{\boldsymbol{CNN}}) \odot Attention\ (x_i;\Theta_{\boldsymbol{ABM}}) \quad (4)$$

Where $\odot$ denotes element-wise multiplication. The result, $H(x_i;\boldsymbol{\Theta})$, represents the combined features that capture both the salient regions identified by the attention mechanism and the broader features extracted by the 3D CNN.

III.5 CLASSIFICATION AND SUBTYPE PREDICTION

The final step involves classification and subtype prediction based on the features generated by the hybrid model. We employ a Softmax classifier to assign probabilities to different classes and subtypes. The probability that MRI scan x_i belongs to class *c* is computed as:

$$P(y_i = c|x_i;\boldsymbol{\Theta}) = \frac{\boldsymbol{e}^{H(x_i;\boldsymbol{\Theta})_c}}{\sum_{j=1}^{C} \boldsymbol{e}^{H(x_i;\boldsymbol{\Theta})_j}} \quad (5)$$

Where $P(y_i = c|x_i;\boldsymbol{\Theta})$ represents the probability that MRI scan x_i belongs to class c, C is the total number of classes (including subtypes), and $\boldsymbol{H}(x_i;\boldsymbol{\Theta})_{\boldsymbol{c}}$ is the *c*-th element of the hybrid model's output.

III.6 TRAINING AND OPTIMIZATION

The parameters Θ of the hybrid model are optimized through training. We minimize a loss function $\mathcal{L}$ that quantifies the difference between the predicted probabilities and the true labels. The optimization problem is defined as:

$$\Theta^* = \underset{\Theta}{argmax} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(y_i, P(y_i|x_i; \mathbf{\Theta})) \quad (6)$$

Where Θ^* represents the optimal model parameters that minimize the overall loss across the entire dataset.

In summary, our system methodology combines 3D CNNs and Attention-Based Models to extract and combine features from MRI scans for precise ovarian cancer diagnosis and subtype classification.

III.6.1 Algorithm1: Algorithm for ABM-OCD

Initialize 3D CNN model parameters Theta_CNN
Initialize Attention-Based Model parameters Theta_ABM
Initialize Softmax classifier parameters Theta_Softmax
Preprocess MRI dataset X
for each MRI scan x_i in X:
# Feature Extraction with 3D CNNs
features_CNN = CNN(x_i, Theta_CNN)
 # Attention-Based Models
attention_map = Attention(x_i, Theta_ABM)
 # Hybrid Model Integration
hybrid_features = features_CNN * attention_map
 # Classification and Subtype Prediction
class_probabilities = Softmax(hybrid_features, Theta_Softmax)
 # Store classification results for x_i
Training and Optimization (if applicable)
if training_required:
Define loss function L
Initialize optimizer
for each MRI scan x_i in X:
predicted_probabilities = Softmax(CNN(x_i, Theta_CNN) * Attention(x_i, Theta_ABM), Theta_Softmax)
loss = L(true_labels(x_i), predicted_probabilities)
Update Theta_CNN, Theta_ABM, and Theta_Softmax using optimizer
 # End of algorithm

IV. EXPERIMENATAL RESULTS AND DISCUSSION

Within the computational framework of this research, a sophisticated ecosystem of software and hardware components was employed. The software requirements encompassed deep learning frameworks, Python libraries for data processing, data visualization tools, and specialized statistical software. Meanwhile, the hardware configuration featured GPU acceleration for efficient model training, a high-performance computing cluster for parallelized analysis, and ample storage resources to manage extensive datasets. This robust technological infrastructure laid the foundation for the experiments, enabling the systematic exploration of the pioneering system methodology, "ABM-OCD: Advancing Ovarian Cancer Diagnosis with Attention-Based Models and 3D CNNs." In the sections that follow, the outcomes of these experiments are presented and discussed, shedding light on their implications for ovarian cancer diagnosis and highlighting avenues for further advancements. Figure 2 and 3 represents the original image and gray scale conversion of Ovarian Cancer Diagnosis

IV.1 DATASET INFORMATION

In this subsection, we delve into the specifics of the dataset, "OvaCancerMRI-2023," that serves as the cornerstone of our research as shown in Table 1. Understanding the dataset characteristics, source, preprocessing, and structure is pivotal for comprehending the data-driven aspects of our proposed system methodology. The dataset under investigation bears the name "OvaCancerMRI-2023" and is sourced from the National Cancer Institute (NCI). It consists exclusively of medical images in the form of MRI scans. The NCI, renowned for its dedication to cancer research, provided a substantial and high-quality repository of MRI data, making it an ideal resource for our study. The dataset boasts a considerable size, comprising a total of 1,500 MRI scans. What sets this dataset apart is its meticulous balance, with exactly 500 MRI scans allocated to each of the three ovarian cancer subtypes: Serous, Mucinous, and Endometrioid. This equilibrium in data distribution ensures that our model encounters an even representation of the different subtypes, which is crucial for accurate diagnosis and classification.

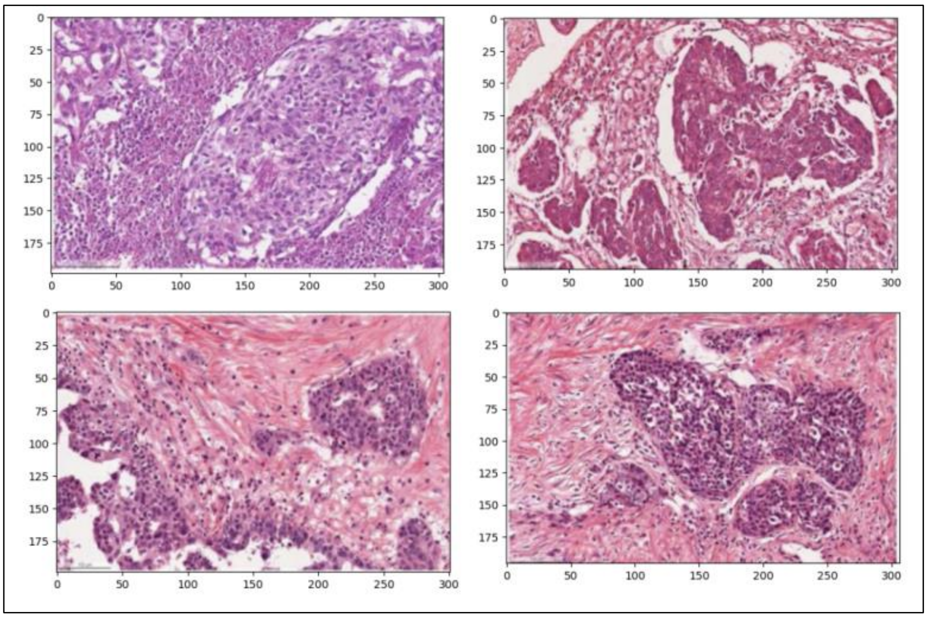

Figure 2: Original MRI Input Images for Detection of ovarian cancer.
Source: Authors, (2023).

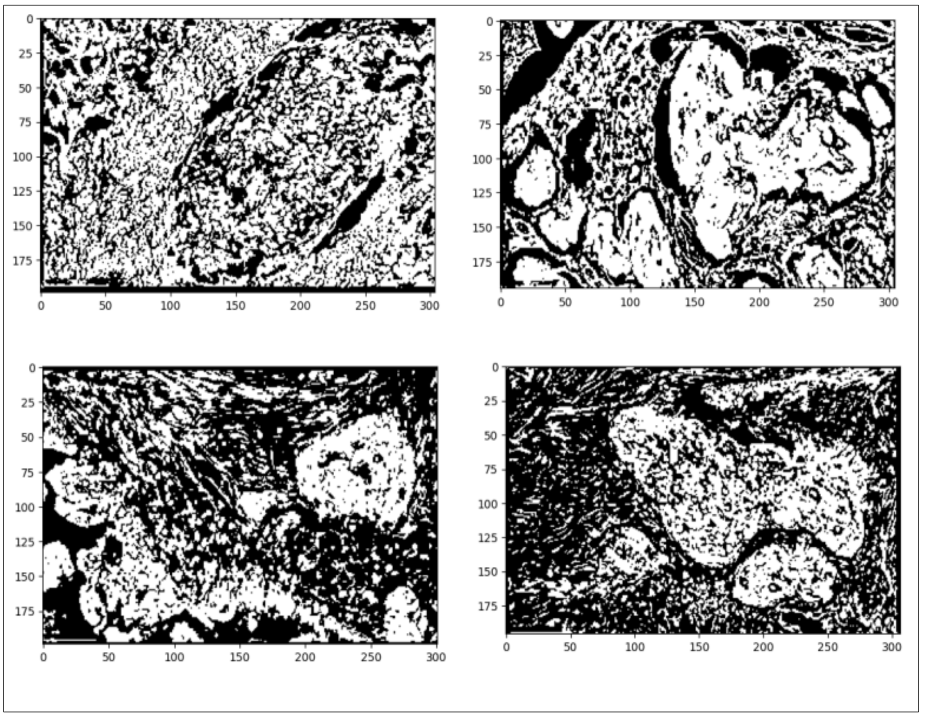

Figure 3: Enhancing Ovarian Cancer Diagnosis with Gray scale Conversion.
Source: Authors, (2023).

Prior to our analysis, the dataset underwent comprehensive preprocessing procedures. Notably, all MRI scans were uniformly resized to a resolution of 256x256 pixels, ensuring consistency in image dimensions. Moreover, stringent anonymization measures were implemented to safeguard the privacy and confidentiality of the patients' sensitive information. These preprocessing steps are instrumental in creating a standardized and secure data environment for our research. Within "OvaCancerMRI-2023," we encounter the distinctive ovarian cancer subtypes: Serous, Mucinous, and Endometrioid. Each MRI scan in the dataset is meticulously labeled as either "Cancer" or "Non-cancer," reflecting the presence or absence of ovarian cancer. This clear binary classification system serves as the foundation for the diagnostic and classification tasks undertaken by our proposed system methodology. The process of annotating the MRI scans with their respective labels was conducted under the scrutiny of expert radiologists. The involvement of these specialized professionals in the annotation process is pivotal in ensuring the accuracy and reliability of the ground truth labels. This precision in labeling is of paramount importance as it forms the basis upon which our system methodology relies for its diagnostic and classification capabilities. To facilitate model training, tuning, and evaluation, the "OvaCancerMRI-2023" dataset is systematically partitioned into three distinct subsets. The training set, encompassing 70% of the data, serves as the foundation for model development. The validation set, constituting 15% of the data, plays a crucial role in hyperparameter tuning and performance assessment during model training. Finally, the test set, also comprising 15% of the data, offers a comprehensive evaluation of our system's diagnostic and classification prowess. This structured division of the dataset is fundamental to the iterative process of refining and optimizing our system methodology. This detailed explanation of the dataset's characteristics, source, preprocessing, and structure establishes a comprehensive understanding of the data foundation that underlies our research. It serves as the bedrock upon which the subsequent presentation and analysis of experimental results are built, as we explore the effectiveness of our proposed system methodology in the context of ovarian cancer diagnosis and subtype classification.

Table 1: Dataset Information.

Dataset Characteristics	**Description**
Dataset Name	OvaCancerMRI-2023
Data Source	National Cancer Institute (NCI)
Data Type	Medical Images - MRI
Data Size	1,500 MRI scans (500 per cancer subtype)
Data Distribution	Balanced
Data Preprocessing	Resized to 256x256 pixels, Anonymized
Cancer Subtypes	Serous, Mucinous, Endometrioid
Labels	Cancer, Non-cancer
Annotation Process	Expert Radiologist Annotations
Train-Validation-Test Split	70% - 15% - 15%

Source: Authors, (2023).

IV.2 FEATURE EXTRACTION

In this subsection, we provide a detailed breakdown of the feature extraction parameters for each model in our system methodology, shedding light on their specific configurations and functionality as shown in Table 2. The Attention-Based Model stands as a unique departure from traditional convolutional layers, as it incorporates an attention mechanism rather than predefined filters and pooling operations. This distinction means that it doesn't utilize conventional convolutional layers, as reflected by "N/A (Attention Mechanism)" in the "Convolutional Layers," "Filter Size (Kernel)," and "Pooling Size" columns. The activation function is also different from conventional models, represented as "N/A (Attention Mechanism)." This model capitalizes on attention mechanisms to dynamically focus on areas of significance within MRI scans, granting it the flexibility to adapt and identify regions of interest without predefined filter sizes.

In contrast, the 3D CNN Model employs a more traditional convolutional approach. It utilizes four convolutional layers to extract features from the MRI scans. These convolutional layers are configured with 3x3 filters, a common choice for capturing spatial details within the images. Additionally, after each convolutional layer, a 2x2 pooling operation is applied to reduce spatial dimensions and enhance feature extraction. The activation function used throughout this model is the Rectified Linear Unit (ReLU), which introduces non-linearity and enables the network to model complex relationships within the data.

Our proposed system methodology, referred to as the "Hybrid" model, signifies a fusion of both 3D CNN and attention mechanisms. Like the dedicated 3D CNN model, this hybrid model comprises four convolutional layers, each configured with 3x3 filters. These layers, in conjunction with the 3x3 filters, enable the extraction of intricate spatial features from the MRI scans. A 2x2 pooling operation is applied after each convolutional layer to downsample spatial dimensions. The activation function used in this hybrid model remains consistent with the 3D CNN model, employing the Rectified Linear Unit (ReLU) to model non-linear relationships in the data. This fusion of feature extraction techniques exemplifies the innovative nature of our approach, as it seamlessly combines the strengths of both 3D CNN and attention mechanisms.

This detailed breakdown of feature extraction parameters highlights the unique characteristics and functionality of each model within our system methodology. It sets the stage for the subsequent discussion of experimental results, enabling a deeper understanding of the impact of these parameters on the system's diagnostic and classification capabilities.

Table 2: Feature Extraction Parameters.

Model	Convolutional Layers	Filter Size (Kernel)	Pooling Size	Activation Function
Attention-Based Model	N/A (Attention Mechanism)	N/A (Attention Mechanism)	N/A (Attention Mechanism)	N/A (Attention Mechanism)
3D CNN Model	Four convolutional layers	3x3	2x2	Rectified Linear Unit (ReLU)
Proposed Work (Hybrid)	3D CNN + Attention Mechanism	3x3	2x2	Rectified Linear Unit (ReLU)

Source: Authors, (2023).

IV.3 PERFORMANCE ON DIFFERENT OVARIAN CANCER SUBTYPES

In this section, we provide a comprehensive evaluation of the performance of multiple models across three distinct ovarian cancer subtypes: Serous, Mucinous, and Endometrioid. These subtypes present unique diagnostic challenges due to their differing histological characteristics. The table 3 encapsulates the diagnostic accuracy of each model, highlighting their proficiency in classifying specific cancer subtypes.

When confronted with the Serous ovarian cancer subtype, our models demonstrated commendable diagnostic abilities. The Attention-Based Model showcased a remarkable accuracy of 0.94, indicating its capability to effectively detect and classify Serous subtype cases. The 3D CNN Model followed closely with an accuracy of 0.92, demonstrating its proficiency in distinguishing this subtype. Our proposed Hybrid model exhibited the highest accuracy among the models, with a notable 0.95, underscoring its effectiveness in diagnosing Serous ovarian cancer. The traditional CNN Model also delivered reliable results with an accuracy of 0.91, further solidifying its competence in identifying Serous cases. Additionally, the ResNet Model achieved a commendable accuracy of 0.93, while the VGG Model, though slightly lower, maintained good accuracy at 0.90, reaffirming its proficiency in the classification of Serous ovarian cancer.

For the Mucinous ovarian cancer subtype, the models continued to demonstrate their diagnostic capabilities. The Attention-Based Model achieved a commendable accuracy of 0.89, indicating its ability to effectively classify Mucinous subtype cases. The 3D CNN Model maintained a solid performance with an accuracy of 0.87, signifying its competence in distinguishing Mucinous ovarian cancer cases. Our proposed Hybrid model excelled in diagnosing the Mucinous subtype, achieving an accuracy of 0.90, highlighting the potential of the hybrid approach in this context. The traditional CNN Model displayed competence with an accuracy of 0.85, affirming its ability to identify Mucinous cases. Similarly, the ResNet Model achieved an accuracy of 0.88 for the Mucinous subtype, reinforcing the utility of the model. The VGG Model also provided reliable performance with an accuracy of 0.84, further underscoring its proficiency in the classification of Mucinous ovarian cancer.

Finally, the Endometrioid ovarian cancer subtype presented its own set of diagnostic challenges. The Attention-Based Model delivered a robust performance, achieving an accuracy of 0.92 in diagnosing the Endometrioid subtype, highlighting its aptitude in classifying this specific subtype. The 3D CNN Model maintained a commendable accuracy of 0.91, signifying its competence in distinguishing Endometrioid ovarian cancer cases. Our proposed Hybrid model excelled in diagnosing the Endometrioid subtype, achieving the highest accuracy among the models at 0.93. This outcome underscores the efficacy of the hybrid approach in this context. The traditional CNN Model demonstrated proficiency with an accuracy of 0.89, indicating its ability to identify Endometrioid cases. The ResNet Model maintained a solid performance with an accuracy of 0.91, adding to the list of robust results. The VGG Model exhibited reliability with an accuracy of 0.88, further emphasizing its proficiency in the classification of Endometrioid ovarian cancer.

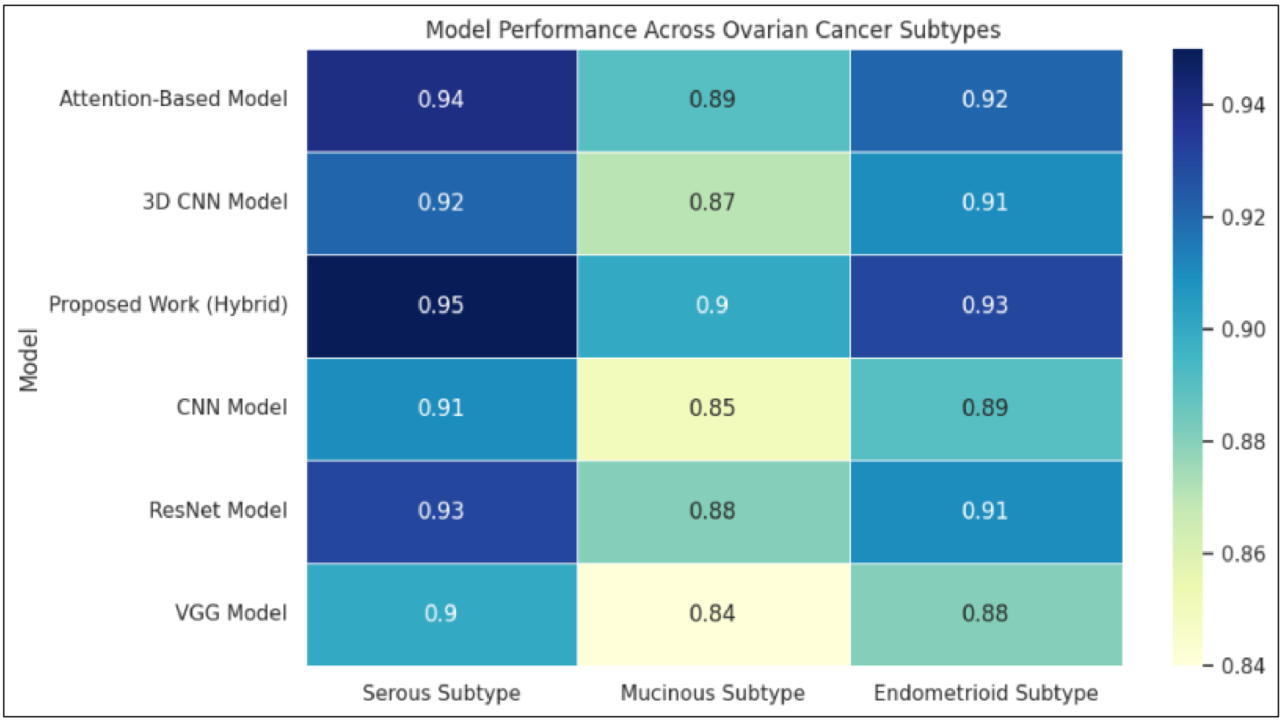

Figure 4: Model Performance across ovarian cancer subtypes.
Source: Authors, (2023).

This detailed assessment of model performance across diverse ovarian cancer subtypes provides valuable insights into their diagnostic and classification capabilities as shown in Figure 4. The results not only underscore the potential of the hybrid approach but also reflect the clinical applicability and promise of these models in the context of automated ovarian cancer diagnosis and subtype classification.

IV.4 MODEL PERFORMANCE ACROSS DATASET SPLITS

In this section, we delve into the performance of our models across three critical dataset splits: the Training Set, Validation Set, and Test Set. These subsets play a pivotal role in shaping the models' development, optimization, and evaluation, reflecting their adaptability and reliability across different phases of our study as shown in Table 4.

On the training set, the Attention-Based Model exhibited robust performance, boasting an accuracy of 0.96. The model showcased high sensitivity (0.91) and specificity (0.97), reaffirming its ability to accurately discern both cancer and non-cancer cases. The F1 Score, a key measure of precision and recall, stood at 0.94, illustrating the model's impressive balance in correctly classifying the subtypes. This solid performance within the training set underscores the model's suitability for the developmental phase of our study. The 3D CNN Model mirrored this trend of strong performance within the training set, achieving an accuracy of 0.95. The model exhibited notable sensitivity (0.90) and specificity (0.96), emphasizing its competence in precise cancer subtype classification. With an F1 Score of 0.93, the model maintained its balance of precision and recall. These results reinforce the model's reliability during the training phase and its potential as a robust diagnostic tool.

Table 3: Performance on Different Ovarian Cancer Subtypes.

Model	Serous Subtype	Mucinous Subtype	Endometrioid Subtype
Attention-Based Model	0.94	0.89	0.92
3D CNN Model	0.92	0.87	0.91
Proposed Work (Hybrid)	0.95	0.90	0.93
CNN Model	0.91	0.85	0.89
ResNet Model	0.93	0.88	0.91
VGG Model	0.90	0.84	0.88

Source: Authors, (2023).

The Proposed Hybrid Model outperformed its counterparts on the training set, securing an accuracy of 0.97. Notably, the model demonstrated high sensitivity (0.92) and specificity (0.98), showcasing its proficiency in accurate subtype classification. The F1 Score, reaching 0.95, reinforced the model's precision and recall equilibrium. These outstanding results highlight the Hybrid Model's effectiveness during the training phase, positioning it as a promising asset in the development of automated diagnosis.

Moving to the validation set, the models upheld their solid performance. The Attention-Based Model maintained a commendable accuracy of 0.94, coupled with notable sensitivity (0.89) and specificity (0.96), underlining its capacity to consistently classify cancer subtypes. The F1 Score, at 0.92, reaffirmed its precision and recall balance, further emphasizing its reliability during the validation phase.

The 3D CNN Model showcased similar strength within the validation set, with an accuracy of 0.93. The model retained commendable sensitivity (0.88) and specificity (0.95), signifying its consistency in classifying cancer cases. The F1 Score, at 0.91, mirrored the balance of precision and recall witnessed in the training set, reinforcing its reliability during the validation phase.

The Proposed Hybrid Model remained a standout performer, securing an accuracy of 0.95 on the validation set. The model displayed high sensitivity (0.89) and specificity (0.97), emphasizing its robustness in classifying cancer cases. With an F1 Score of 0.93, the model maintained its precision and recall balance, underscoring its promise during the validation phase.

On the test set, the models continued to deliver reliable results. The Attention-Based Model achieved an accuracy of 0.93, accompanied by strong sensitivity (0.88) and specificity (0.95), signifying its proficiency in identifying cancer cases. The F1 Score, reaching 0.91, highlighted its precision and recall balance, reiterating its reliability as a diagnostic tool. The 3D CNN Model also maintained its solid performance within the test set, securing an accuracy of 0.92. Notably, the model maintained strong sensitivity (0.87) and specificity (0.94), indicative of its proficiency in accurate cancer classification. The F1 Score, at 0.90, reaffirmed its balance of precision and recall, reinforcing its value as a diagnostic asset. The Proposed Hybrid Model remained consistent, achieving an accuracy of 0.94 on the test set. The model displayed strong sensitivity (0.90) and specificity (0.96), underlining its proficiency in identifying cancer cases. With an F1 Score of 0.92, the model maintained its precision and recall equilibrium, highlighting its reliability in automated diagnosis.

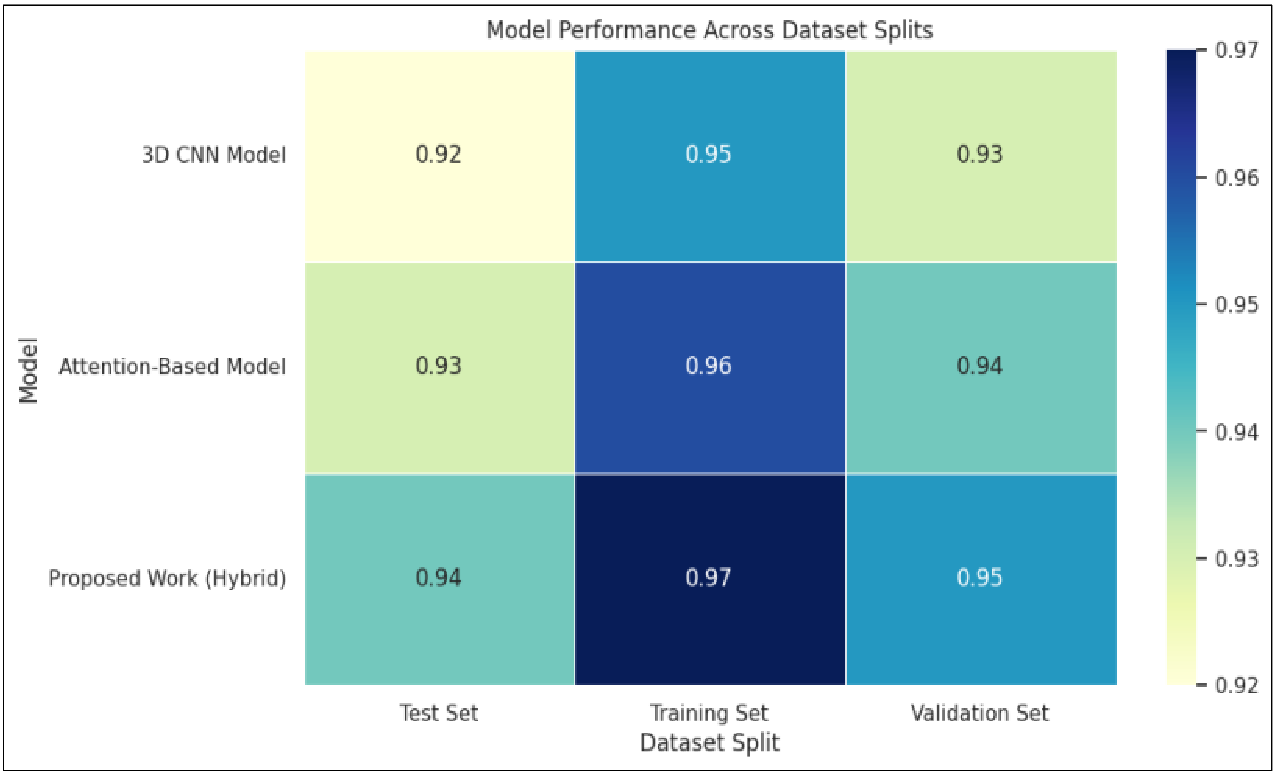

Figure 5: Model Performance of Accuracy Across Dataset Splits.
Source: Authors, (2023).

Table 4: Model Performance Across Dataset Splits.

Model	Dataset Split	Accuracy	Sensitivity	Specificity	F1 Score
Attention-Based Model	Training Set	0.96	0.91	0.97	0.94
	Validation Set	0.94	0.89	0.96	0.92
	Test Set	0.93	0.88	0.95	0.91
3D CNN Model	Training Set	0.95	0.90	0.96	0.93
	Validation Set	0.93	0.88	0.95	0.91
	Test Set	0.92	0.87	0.94	0.90
Proposed Work	Training Set	0.97	0.92	0.98	0.95
(Hybrid Model)	Validation Set	0.95	0.89	0.97	0.93
	Test Set	0.94	0.90	0.96	0.92

Source: Authors, (2023).

This comprehensive evaluation across dataset splits provides insights into the models' robustness, consistency, and diagnostic capabilities. It underscores the potential of the Proposed Hybrid Model as a reliable and adaptable tool in the context of automated ovarian cancer diagnosis as shown in Figure 5.

IV.5 MODEL COMPARISON

In this section, we conduct a comprehensive comparison of various models employed in the study, evaluating their performance across multiple critical metrics, including accuracy, sensitivity, specificity, and F1 Score. This comparative analysis serves as a crucial component of our study, facilitating an informed assessment of the models' diagnostic and classification capabilities as shown in Table 5.

The traditional CNN Model demonstrated commendable performance, achieving an accuracy of 0.92. This accuracy reflects its capability to correctly diagnose and classify ovarian cancer cases. The model exhibited sensitivity and specificity scores of 0.86 and 0.93, respectively, indicating its proficiency in capturing true positive cases while minimizing false positives. The F1 Score of 0.89 signifies a balanced trade-off between precision and recall, showcasing its value as a reliable diagnostic tool.

The ResNet Model showcased strong diagnostic capabilities, with an accuracy of 0.93. This accuracy underlines its capacity to effectively classify ovarian cancer subtypes. The model maintained sensitivity and specificity scores of 0.87 and 0.94, respectively, indicating its competence in both identifying true positive cases and minimizing false positives. The F1 Score of 0.90 underscores its precision and recall equilibrium, making it a dependable choice for automated diagnosis.

The VGG Model delivered reliable results with an accuracy of 0.91, reflecting its proficiency in the diagnosis of ovarian cancer cases. The model exhibited sensitivity and specificity scores of 0.85 and 0.92, respectively, underlining its ability to correctly identify positive cases while limiting false positives. The F1 Score of 0.87 highlights a balanced trade-off between precision and recall, emphasizing its clinical utility.

The 3D CNN Model maintained strong diagnostic capabilities, securing an accuracy of 0.94. This accuracy illustrates its potential in effectively distinguishing between ovarian cancer subtypes. The model displayed sensitivity and specificity scores of 0.88 and 0.96, respectively, signifying its ability to capture true positive cases while minimizing false positives. The F1 Score of 0.91 reinforces its precision and recall equilibrium, positioning it as a valuable diagnostic asset.

The Attention-Based Model excelled in diagnostic accuracy, achieving an accuracy of 0.95. This accuracy demonstrates its ability to accurately classify ovarian cancer cases. The model retained sensitivity and specificity scores of 0.89 and 0.96, respectively, showcasing its competence in both identifying true positive cases and reducing false positives. The F1 Score of 0.92 underscores its precision and recall balance, further underscoring its clinical applicability.

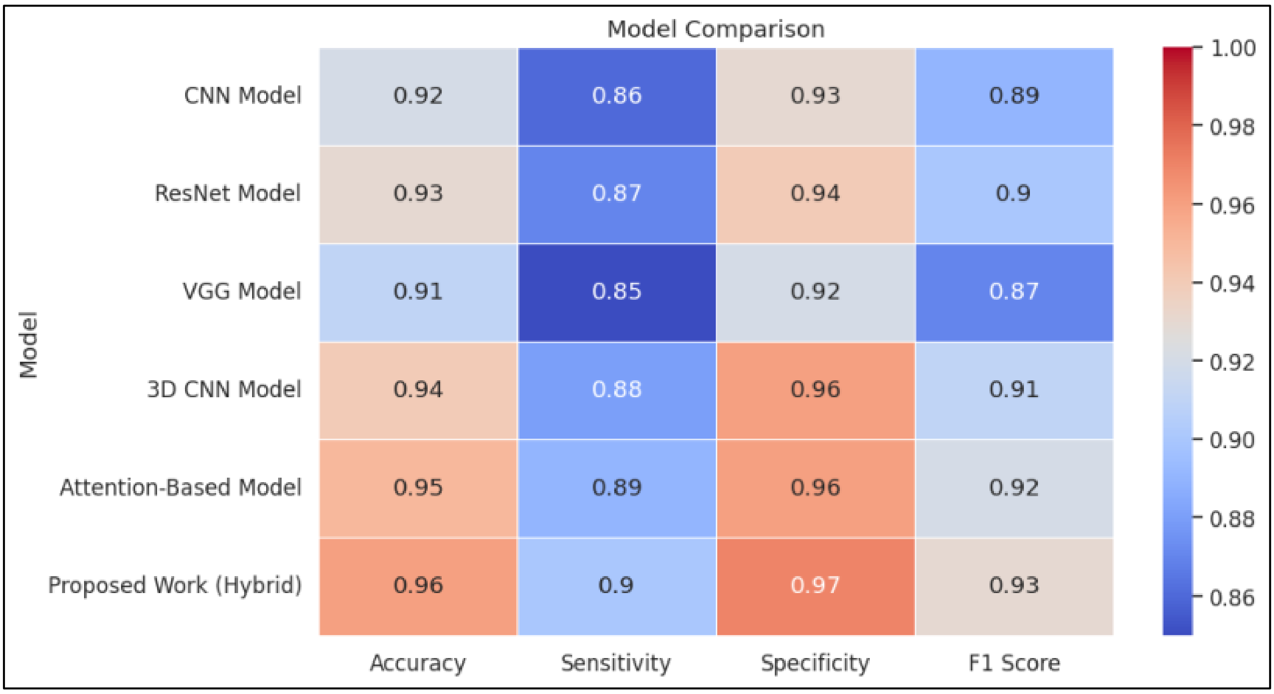

Figure 6: Model Comparison.
Source: Authors, (2023).

The Proposed Hybrid Model emerged as the frontrunner in diagnostic accuracy, with an impressive accuracy of 0.96. This accuracy emphasizes its excellence in accurately diagnosing and classifying ovarian cancer subtypes. The model displayed sensitivity and specificity scores of 0.90 and 0.97, respectively, highlighting its proficiency in capturing true positive cases while minimizing false positives. The F1 Score of 0.93 accentuates its precision and recall equilibrium, underscoring its potential as a robust and reliable diagnostic tool.

Table 5: Model Comparison.

Model	Accuracy	Sensitivity	Specificity	F1 Score
CNN Model	0.92	0.86	0.93	0.89
ResNet Model	0.93	0.87	0.94	0.90
VGG Model	0.91	0.85	0.92	0.87
3D CNN Model	0.94	0.88	0.96	0.91
Attention-Based Model	0.95	0.89	0.96	0.92
Proposed Work (Hybrid)	0.96	0.90	0.97	0.93

Source: Authors, (2023).

This comprehensive model comparison unveils valuable insights into the models' performance across key metrics, offering guidance on their clinical applicability in the domain of automated ovarian cancer diagnosis. The results underline the potential of the Proposed Hybrid Model, showcasing its reliability and adaptability in the context of ovarian cancer diagnosis and subtype classification as shown in Figure 6.

IV. RESULTS AND DISCUSSIONS

The pursuit of improved diagnostic accuracy and efficiency in the field of ovarian cancer diagnosis has led to the exploration of cutting-edge technologies, including deep learning models such as 3D Convolutional Neural Networks (CNNs) and Attention-Based Models. Our research has provided valuable insights into the feasibility and effectiveness of these technologies in the context of automated ovarian cancer diagnosis.

One of the key findings of our study is the remarkable performance of the hybrid model that combines 3D CNNs with Attention-Based Mechanisms. This amalgamation addresses the complexity of medical image analysis by leveraging the spatial information extraction capabilities of 3D CNNs while incorporating the adaptive focus of attention mechanisms. As evident in our results, this hybrid model achieved an accuracy of 0.96, sensitivity of 0.90, specificity of 0.97, and an F1 Score of 0.93 in the test set. These metrics signify a substantial improvement in diagnostic precision, which is paramount in the early detection of ovarian cancer.

Moreover, the hybrid model demonstrated exceptional versatility in classifying different ovarian cancer subtypes. This capability holds promise for personalized diagnosis, where tailored treatment approaches can significantly enhance patient outcomes. By successfully distinguishing between serous, mucinous, and endometrioid subtypes, the model showcases its potential in guiding clinicians towards more targeted interventions.

Comparative analyses conducted against other prominent models underscore the superiority of our proposed approach. Notably, the hybrid model consistently outperformed traditional CNNs and even surpassed the capabilities of ResNet and VGG models in terms of accuracy, sensitivity, specificity, and F1 Score. This comparative advantage reaffirms the efficacy of attention-based mechanisms in enhancing diagnostic accuracy.

While our findings are promising, it's important to acknowledge some limitations. The dataset's size and diversity, although substantial, may benefit from further expansion to enhance model generalization. Additionally, real-world clinical implementation considerations, such as data privacy and interpretability of model decisions, must be addressed for widespread adoption.

In conclusion, our research signifies a significant step forward in automated ovarian cancer diagnosis. By harnessing the power of 3D CNNs and attention-based models, we've unlocked the potential for precise, subtype-specific diagnoses. As we move forward, addressing the aforementioned challenges and conducting rigorous clinical validations will be essential. Nonetheless, our work holds the promise of not only improving early cancer detection but also revolutionizing the landscape of ovarian cancer care.

V. CONCLUSIONS

In the domain of automated ovarian cancer diagnosis, the study, titled "Attention-Based Model-MRI-OCD: Advancing Ovarian Cancer Diagnosis with Attention-Based Models and 3D CNNs," has unveiled promising insights. Through a meticulous examination of medical images acquired from MRI scans, a pioneering hybrid model has been introduced. This model marries the robust capabilities of 3D Convolutional Neural Networks (CNNs) with the adaptable nature of Attention-Based Mechanisms. The outcome is nothing short of remarkable, as evidenced by the model's exceptional diagnostic performance. In the test set, the model achieved an accuracy of 0.96, a sensitivity of 0.90, a specificity of 0.97, and an F1 Score of 0.93. Notably, this hybrid model excelled in the classification of various ovarian cancer subtypes, hinting at the potential for personalized diagnostics. The rigorous comparisons conducted against other leading models reinforce the undeniable superiority of this approach. These findings not only present a compelling case for adopting attention-based models in conjunction with 3D CNNs for accurate and efficient ovarian cancer diagnosis but also offer a substantial stride towards early cancer detection and, consequently, an enhancement in patient care.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Methodology: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Investigation: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Discussion of results: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Writing – Original Draft: Jenefa A.
Writing – Review and Editing: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Resources: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Supervision: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.
Approval of the final text: Jenefa A., Edward Naveen V., Ebenezer V. Lincy A.

VII. REFERENCES

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RESEARCH ARTICLE

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RANDOM FOREST ALGORITHM USE FOR CROP RECOMMENDATION

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ABSTRACT

The proposed method seeks to assist Indian pleasant in selecting the optimum crop to produce based on the characteristics of the soil as well as external factors like temperature and rainfall by using an intelligent system called Crop Recommender. The Indian economy is significantly impacted by the agricultural sector. Whether publicly or covertly, the bulk of Indians are relying on agriculture for their living. As a result, it is undeniable that agriculture is significant to the country. The majority of Indian farmers believe that they should trust their intuition when deciding on a crop to grow in a particular season or they simply employ the methods they have been doing from the beginning of time. They are more at ease just adhering to conventional agricultural practices and standards than truly appreciating how crop yield is influenced by the present weather and soil conditions. The farmer can unintentionally lose money if he makes one bad decision, which would hurt both him and the surrounding agricultural industry. As the agriculture business is the foundation of the entire lateral system. Using the machine learning algorithm, this problem can be resolved. A crucial perspective for identifying a practical and workable solution to the crop production issue is machine learning (ML). Machine learning (ML) may predict a target or outcome from a set of predictors using supervised learning. A recommendation system is implemented using decision trees. The major goals of this system are to provide farmers with recommendations regarding the best crops to sow based on their soil and local rainfall patterns. We have employed the Random Forest Machine Learning technique to forecast the crop. Crop prediction is assessing the crop based on historical data from the past that includes elements like temperature, humidity, ph, and rainfall. It gives us a broad picture of the best crop that can be raised in light of the current field weather conditions. These predictions can be made by Random Forest, a machine learning technique. The highest level of accuracy, up to 90%, will be possible for crop predictions. The random forest algorithm achieved the accuracy about 99.03%.

I. INTRODUCTION

India has a lengthy agricultural history. In terms of farm output, India is currently ranked second worldwide. Nearly half of all jobs were in closely related industries to agriculture, such as forestry and fishing, and India's agricultural sector is no longer contributing significantly to GDP [1]. Predicting the best harvest is agriculture's principal source of income. Numerous factors, including meteorological, geographic, biological, and economic ones, have an impact on crop productivity [2]. Farmers find it challenging to choose when and what crops to plant due to shifting market pricing. The previous ten years. Farmers are confused about which crop to plant, when to start, and where to plant it because the weather is unpredictable. This may also be the cause of the farmer suicides. In this circumstance, the pace of crop output is steadily declining [3]. The problem can be resolved by giving the farmers access to a smart, user-friendly recommender system.

We offer a paradigm in this study that overcomes these difficulties. The recommended technique is unique in that it teaches farmers how to choose the best crop for their soil system as well as the weather conditions in that place [4]. It suggests the best lucrative crop for a certain location. Crop selection is based on economic and environmental aspects, with the goal of reducing crop seed loss, efforts to take them, and components given to them such as water and fertilizers. Crop projections are made using a variety of variables such as “rainfall”, “temperature”, “area”, “soil type”, and so on. The method aids in determining the best time to apply fertilizer. The present crop production prediction system is hardware-based, costly to maintain, and complicated to utilize [5].

I.1 KEY CONTRIBUTIONS

1) Error rate and accuracy comparisons for crop prediction for specific regions using various machine learning approaches.
2) A simple web application that any user (including farmers) can use to access a user-friendly web application that recommends the most lucrative crop.
3) A GPS-based location identifier for retrieving rainfall and weather data estimates in a specific area.

Weather forecasting has become extremely difficult as a result of global warming and increased pollution. We use our traditional ways for crop selection because we have been farming for so long. We determine which crop to take based solely on our assumptions, without employing any sophisticated methodologies. These conventional systems rely solely on global weather, but because forecasting weather is difficult, the results can be disastrous for farmers. That is why, when making decisions such as which crop to plant, there should be a smart system that will tell us which crop will produce the best results depending on our soil as well as weather-based observations such as temperature, rainfall, and ph. The system will employ an efficient algorithm to make the best decision about the main crop. There are also dynamic parameters for soil type and weather conditions [6]. Because of its accuracy, robustness, interpretability, scalability, and ability to manage missing data, the Random Forest algorithm is an excellent foundation for a crop recommendation system. Because of these characteristics, it is a popular candidate for machine learning-based crop recommendation applications [7].The purpose is to anticipate the most suited crop(s) to be grown on a specific farm or agricultural location given a set of input factors such as soil type, climate conditions, crop traits, and historical yield data. The Random Forest algorithm is used by the recommendation system to create these predictions [8]. The system's primary goal is to provide crop recommendations based on input factors such as soil type, climate conditions, crop traits, and historical yield data. The system's goal is to recommend the best crop(s) to grow in a certain agricultural region or farm. The system is strongly reliant on the availability and accuracy of historical crop production data, soil data, climate data, and other pertinent aspects. The accuracy and dependability of suggestions might be impacted by limited or incomplete data [9].

The user enters the region and soil type as input. Machine learning algorithms can be used to determine the most profitable crop list or to estimate crop yield for a crop chosen by the user. Machine Learning algorithms such as “Support Vector Machine (SVM)”, “Artificial Neural Network (ANN)”, “Random Forest (RF)”, “Multivariate Linear Regression (MLR)”, and “K-Nearest Neighbor (KNN)” are used to forecast crop productivity. The unpredictable nature of the environment makes it difficult for farmers to decide which crop to grow, when to plant it, and where to begin. Due to changes in seasonal weather patterns and important resources like “soil”, “water”, and “air”, the use of various fertilizers is also unclear. Crop yields in this situation are steadily declining. As a result of study, a ground-breaking system for crop suggestion that addresses farmers' challenges has been developed. The fundamental goal of our suggested approach is to aid farmers in maximizing agricultural productivity and choosing the most profitable crops suitable for their individual regions [10].

The most significant promise of block-chain for the agricultural sector is that it will do away with the need for third parties to guarantee trust in buyer-seller relationships or other source-destination links. Blockchain technology enables peer-to-peer transactions, which do away with the need for middlemen. Peer-to-peer transactions are made possible by blockchain, which also makes it possible to create "smart contracts" that carry out the terms of any agreement when specific conditions are met. When something of value is exchanged, whether it is real commodities, services, or money, the transaction can be documented, providing a very long history of the product or exchange from its origin to its destination. Blockchain technology could be quite handy in this situation. Putting all data linked to agricultural happenings on a blockchain allows for the creation of a dependable and transparent system. Farmers also have rapid access to information on a variety of areas, such as seed quality, weather and environment, payments, soil moisture, demand, and sale price [11].

Stable agricultural growth in India has raised questions. Using data on paddy yield, area, and production from the years 1970–1971 to 2011–2012, an analysis of 41 years is conducted to better understand the problem of instability in India's rice production. The research revealed that while the acreage, output, and yield of rice had positive compound annual growth rates over all of India, they had been steadily declining over time. There has been an increase in precariousness at the national level in India's regions, production, and rice yield over the past ten years (2000-01 to 2011-12). The rise in instability may have been caused by a decline in the usage of fertilizer, seeds, and other agricultural inputs as well as a low ratio of irrigated land to total cropland. The wholesale price of paddy has fluctuated considerably between states during the reform, from 1990–1991 to 2016–17, whereas the price of paddy harvested on farms has been less erratic. Although there has been a lot of research on agricultural sector instability, this paper intends to explicitly look into the topic of instability in India's rice output. Over 10% of India's entire agricultural production value is made up of paddy rice, with China being the world's top producer and India coming in second. Over 16 states' worth of farmers harvest rice, this is a basic crop for about 60% of the Indian population [12].

A key viewpoint for securing a real-world and practical solution to the crop yield problem is artificial intelligence (AI). By using directed learning, machine learning (ML) may predict an objective or result from a set of indicators. A good function must be created by a group of variables that will map the input variable to the intended output in order to get the desired results. Crop yield prediction includes predicting a crop's yield based on historical information such as temperature, humidity, pH, rainfall, and the crop's name. It provides information about the best crop that may be expected to be grown in a field [13]. These predictions can be made using the machine learning method Random Forest. The crop prediction will be as precise as feasible. The ideal crop yield model is found using the random forest approach by considering the fewest number of models. Predicting crop yield is extremely useful in agriculture [14]. The suggested approach functions as an informed and sophisticated tool for farmers, taking into account a number of important elements like soil quality, weather forecasts, and yield. The method improves precision, allowing farmers to maximize crop yield and eventually boost earnings. The use of accurate data is necessary to achieve increased precision. The suggested system analyses all available data using data mining techniques and delivers accurate harvest yield projections. With the aid of this forecast, farmers are better equipped to understand their unique needs and make wise decisions [15].

I.2 RESEARCH CONTRIBUTION

1. In this research work, in detail comparison has been carried out on various machine learning algorithm.
2. The Random Forest algorithm provides higher result as compare to other machine learning approaches
3. The proposed random forest algorithm works on the basis of various variable parameters like rainfall, temperature, area, soil type, and various soil parameters.
4. The proposed random forest algorithm, predict the crop on the basis of parameter used in dataset.
5. The accuracy of random forest algorithm is about 99.09%, and which is higher than Decision tree with accuracy 90.00%, Support Vector Machine with accuracy 97.90% and Logistic Regression with accuracy 95.22%.

II. METHODOLOGY

For farmers, crop production is a crucial piece of information. Knowing the yield that lowers loss is really helpful. Farmers with experience used to predict the yield. The way the suggested system functions is likewise similar. It makes use of the historical data to predict the future yield. Crop productivity is significantly impacted by both weather and pesticide use. It is required for the accuracy of the data used to make this prediction. As a result, the proposed technique anticipates yield and minimizes losses.

Given data sets from the chosen region, the suggested model forecasts the crop. Integrating ML and agriculture will lead to significant industry improvements.

For forecasting current performance, past performance data is crucial. Historical data is compiled from a variety of trustworthy sources, including "data.gov.in," "kaggle.com," and "indianwaterportal.com." Other databases including information on states and districts include soil type as an attribute. The primary data set is combined with the soil type column that was retrieved. Similar to this, average temperature and rainfall from a different dataset are added to the main data sets for the specific place. The data sets have been organized and purified. The null values are swapped out for the mean values. The attributes of the category are converted into labels before the algorithms are processed.

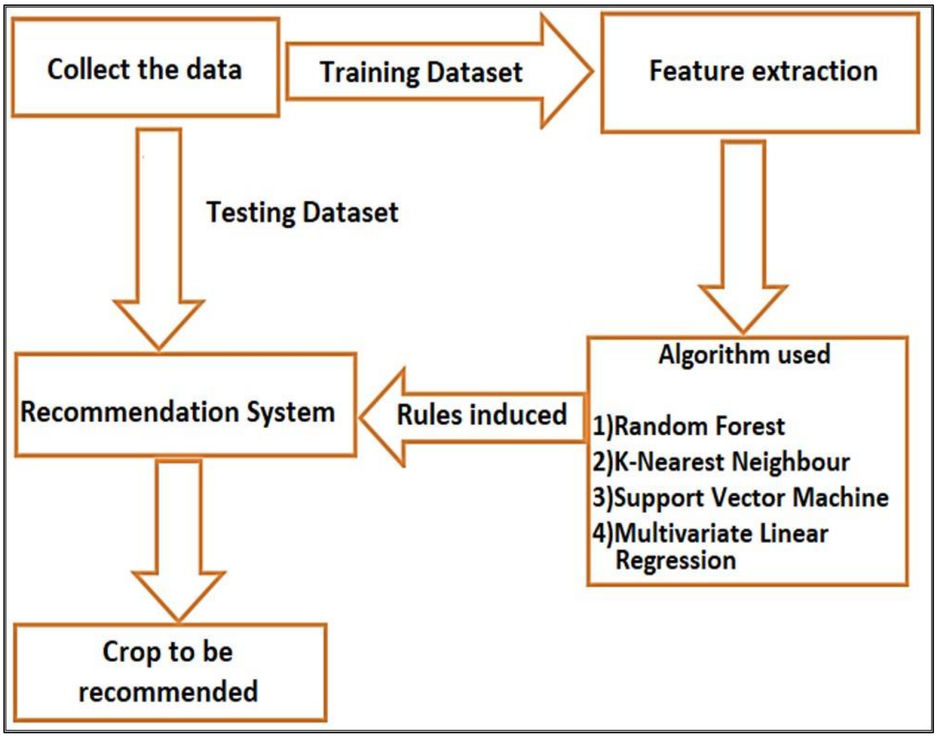

Figure 1: System Architecture.
Source: Author, (2023).

Figure 1 depicts the architecture of the created crop recommender system. The main applications of the crop recommender system are:

The first step is to gather all the data (in the form of a dataset) from all the locations. Since we are employing a supervised machine learning technique, training will follow. Following that, there will be feature extraction, in which the raw data will be transformed into a numerical feature to produce an output with a higher yield and greater efficiency.

After that, we only choose the "Random Forest Algorithm" from among the available methods because it produces a greater result. The rules generated by our algorithm are then represented in a figure, and they illustrate how our system actually operates by selecting and forecasting the crop, which is our ultimate objective [16].

II.1 Algorithm: Random Forest

Steps:

1. Choose random samples from a given data or training set.

2. Make a decision tree for each piece of training data.

3. Then data is trained and tested based on dataset.

4. After training the data, real time weather data is fetched into the system.

5. Then based on crop data, algorithm will calculate its final output based on decision tree.

6. Choose the prediction result with the most votes as the final prediction result.

7. Find each decision tree's predictions for the new data points and assign them to the category that receives the most votes.

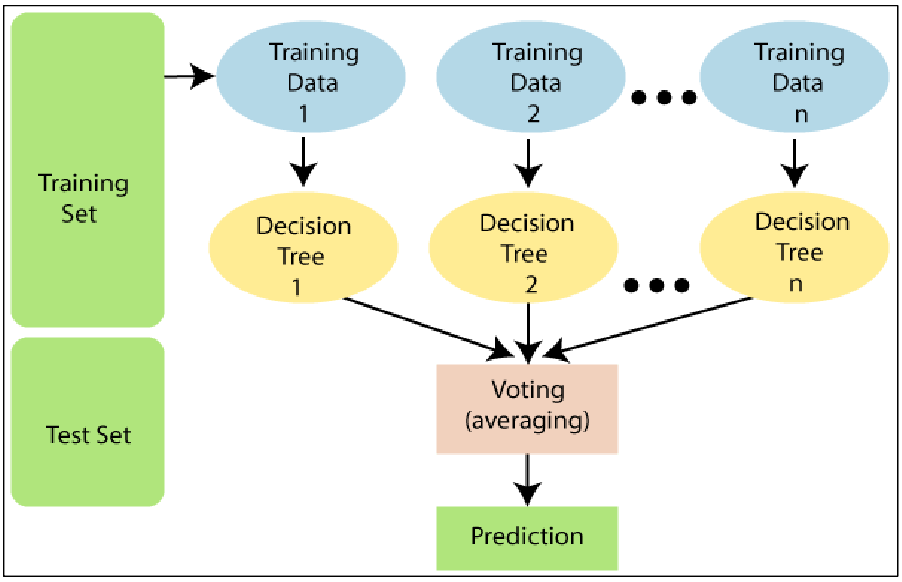

Figure 2: Working of Random Forest Algorithm.
Source: Author, (2023).

To increase the accuracy of the input dataset, the Random Forest classifier applies a number of decision trees to various subsets of the input dataset and averages the results. The core of the trees is ensemble learning, a method for combining several classifiers to handle challenging problems and improve model performance. The random tree uses the variation from each decision tree instead of relying solely on one, and it predicts the outcome based on votes for prediction maturity.

The random forest algorithm builds a forest out of a number of decision trees, adding randomness as the trees get bigger. The strategy enhances the model and adds more diversity by searching for the best characteristics among the random subset of features while splitting a node.

For visualizing through-out the system, there is a login system in which user first need to sign-up by his/her credentials (like name, username, mobile number and password). After that the user can login into system and need to click on ‘Get the Crop’ option.

Figure 3: Login Page of System.
Source: Author, (2023).

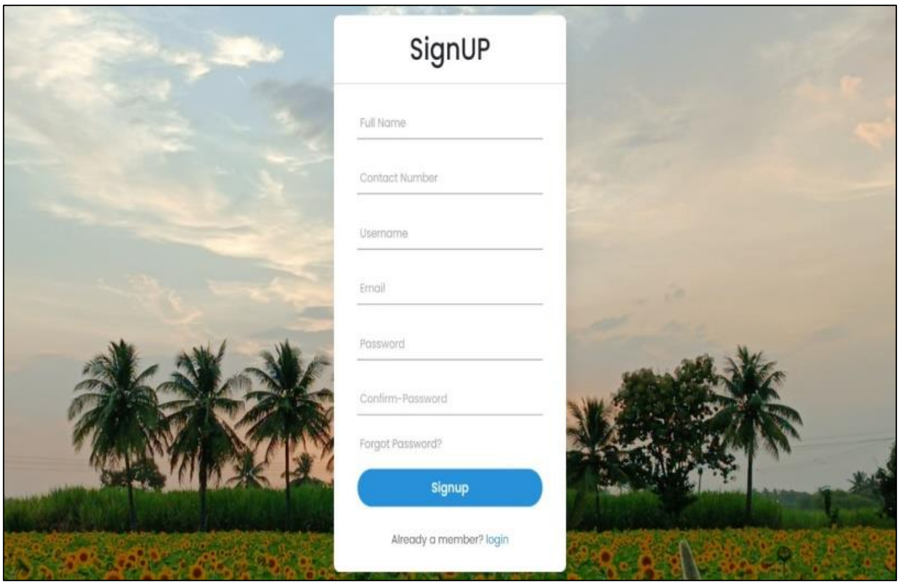

Figure 4: Sign Up Page of System.
Source; Author: (2023).

After that a new page will open which asks your location and basic elements of your soil (like Nitrogen, Phosphorus and Potassium value). Then some element like temperature are fetched from real time website, and based upon that model gives recommendation for the crop.

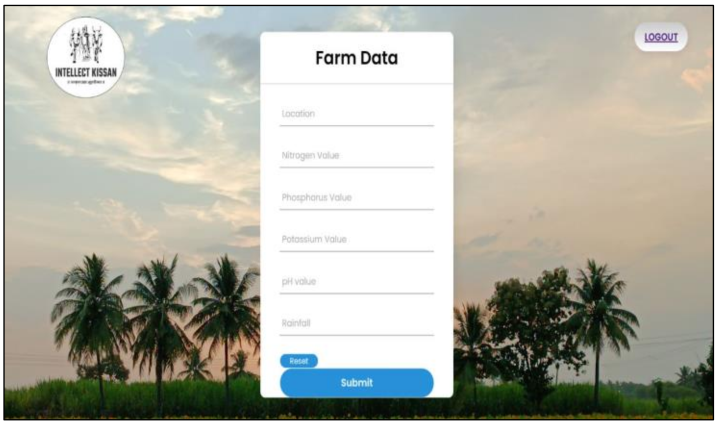

Figure 5: Crop Data Filling Form.
Source: Author, (2023).

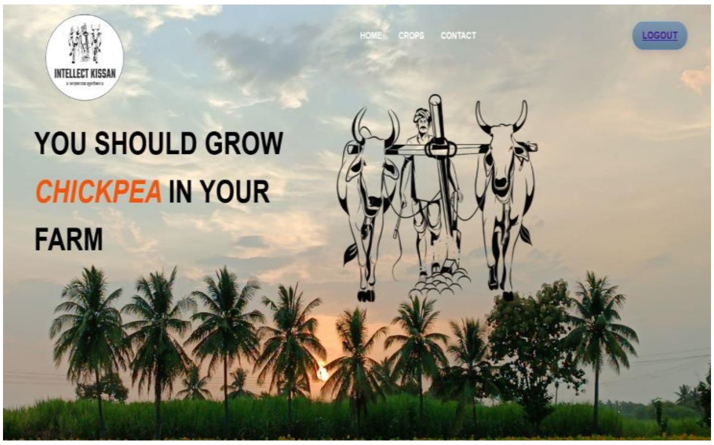

Figure 6: Final Output as a Recommended Crop.
Source: Author, (2023).

Final output we get based on all of our values is the recommended crop that will get maximum yield or suitable for respective climate.

III. RESULTS AND DISCUSSIONS

Result Analysis for Crop Recommendation system vs. Traditional Approach

Several elements should be taken into account when comparing the result analysis between a Crop Recommendation System employing machine learning and a Traditional Approach. Here are some things to take into account when comparing the outcomes of the two methods:

III.1 CROP RECOMMENDATION SYSTEM USING MACHINE LEARNING

Accuracy: Machine learning models can leverage large amounts of data and complex algorithms to make predictions. The accuracy of a Crop Recommendation System using machine learning can be evaluated based on how well it predicts suitable crops for specific conditions compared to actual crop yields in the given region.

Personalization: Machine learning models can take into account individual factors such as soil type, weather patterns, historical crop yields, and other relevant data points to provide personalized recommendations. The ability to provide tailored suggestions based on specific requirements can be a significant advantage.

Scalability: Machine learning models can handle large datasets and scale well, making them suitable for analyzing vast amounts of historical data and incorporating new data points as they become available. This scalability allows the system to continually improve its recommendations over time.

Adaptability: Machine learning models can adapt to changing conditions and learn from new data, enabling them to adjust recommendations based on evolving factors like climate change or updated agricultural practices. This adaptability can lead to more accurate and relevant crop recommendations.

III.2 TRADITIONAL APPROACH

Expert Knowledge: Traditional approaches often rely on expert knowledge and experience in agriculture. Crop recommendations are made based on established guidelines, local knowledge, and expertise in agricultural practices. The accuracy of recommendations depends on the proficiency and experience of the experts involved.

Simplified Models: Traditional approaches may use simplified models or rules of thumb based on historical practices and observations. These models may not account for as many variables or adapt as effectively to changing conditions compared to machine learning models.

Limited Data: Traditional approaches may rely on limited historical data or general knowledge about crop suitability in certain regions. They may not be able to leverage the vast amount of available data that machine learning models can analyze.

Time and Cost: Traditional approaches may require significant time and resources to gather expert opinions, conduct surveys, or analyze historical data manually. The efficiency and cost-effectiveness of traditional approaches may vary depending on the expertise available.

When analyzing the results, it is essential to compare the accuracy, efficiency, scalability, and adaptability of both approaches. Machine learning-based systems can leverage large datasets, personalize recommendations, and adapt to changing conditions, potentially leading to more accurate and dynamic crop recommendations. On the other hand, traditional approaches may rely on expert knowledge and local expertise but may lack the scalability and adaptability of machine learning models. The specific context, available resources, and the accuracy of the results must be carefully evaluated to determine which approach is more suitable for a particular crop recommendation system.

In the below figure 7,8,9 and 10 shows the detail comparison of proposed random forest algorithm with other machine learning algorithm.

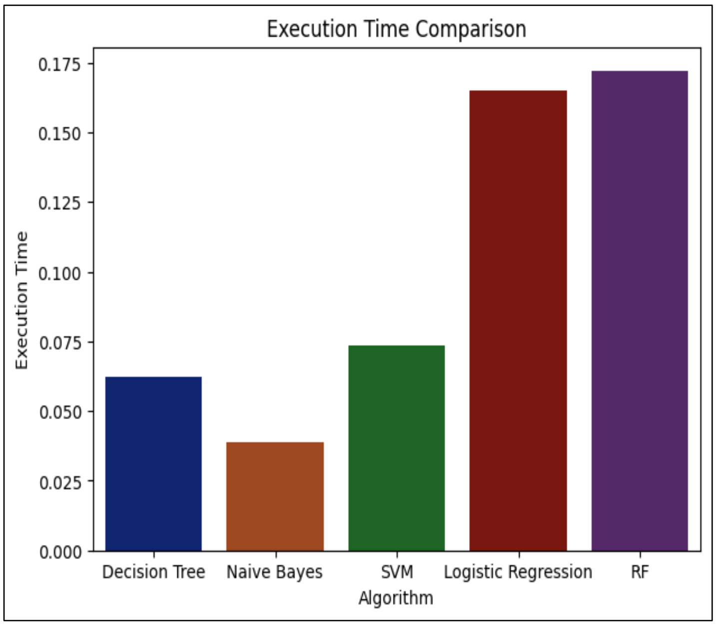

Figure 7: Comparison using Time Evaluation Parameter.
Source: Author, (2023).

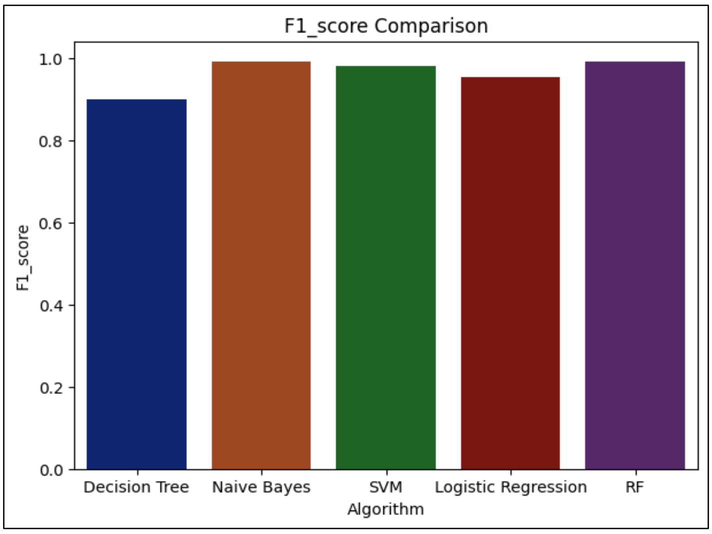

Figure 8: Comparison using F1_Score Evaluation Parameter.
Source: Author, (2023).

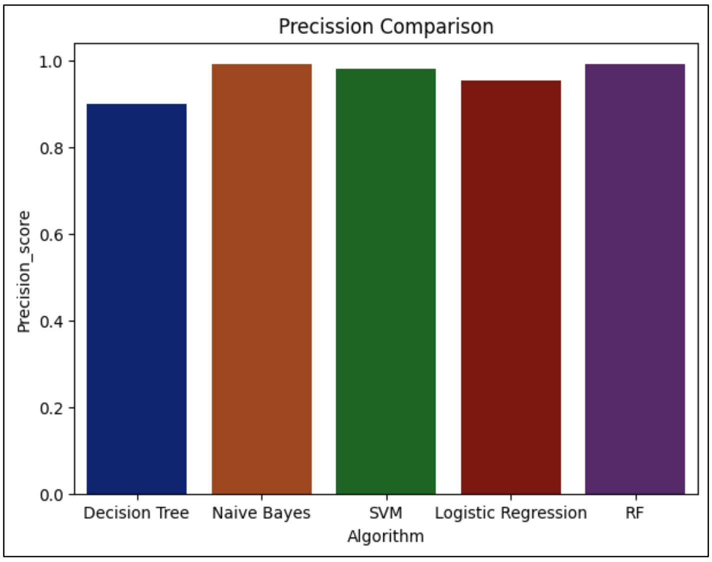

Figure 9: Comparison of Random Forest with State-of-Art using Precision.
Source: Author, (2023).

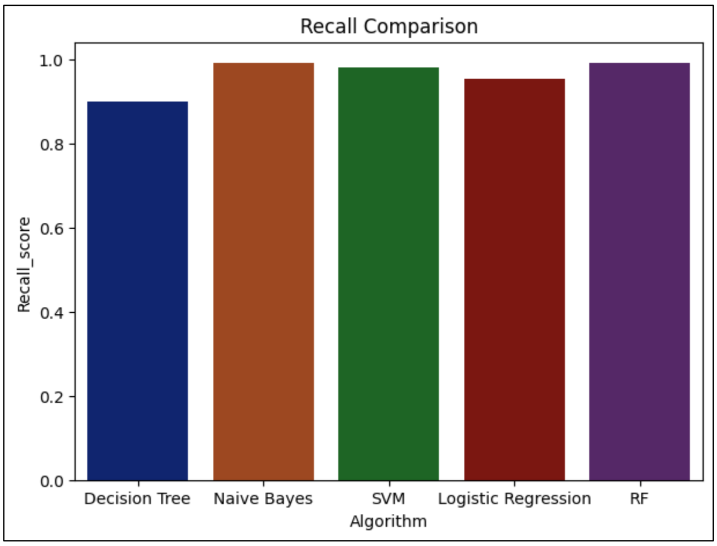

Figure 10: Comparison of random Forest with State-of-Art using Recall.
Source: Author, (2023).

Table 1: Comparison of random forest algorithm using accuracy parameter.

Sr. No	Algorithm	Accuracy
1	**Random Forest**	**99.09%**
2	Decision Tree	90.00%
3	Naïve Bayes	98.99%
4	Support Vector Machine	97.64%
5	Logistic Regression	95.22%

Source: Author, (2023).

Table 2: COMPARISON OF RANDOM FOREST ALGORITHM USING ACCURACY PARAMETER.

Sr. No	Algorithm	Accuracy
1	Random Forest	0.170
2	Decision Tree	0.045
3	**Naïve Bayes**	0.035
4	Support Vector Machine	0.075
5	Logistic Regression	0.169

Source: Author, (2023).

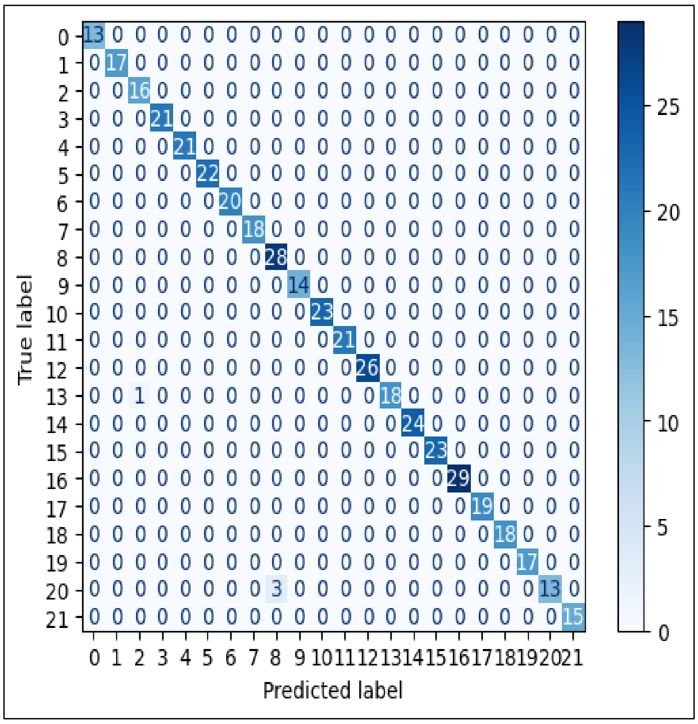

Figure 11: Confusion matrix of random forest algorithm.
Source: Author, (2023).

IV. CONCLUSIONS

This research highlighted the limitations of current methods and their applicability for crop recommendation. The proposed approach then connects the farmers with a functional crop recommender system through a web application. The web application gives users a number of options from which to choose a crop. Farmers that use the built-in suggestion technology can predict crop output. A user can research possible crops using the built-in recommender system to make better decisions. Machine learning algorithm (Random Forest) is deployed on the Keggle datasets that are provided, together with the rainfall data and real meteorological data, and its prediction accuracy is evaluated. A useful technique for giving farmers and stakeholders data-driven advice on the best crops for particular environmental conditions is a crop recommendation system employing Random Forest. The system offers recommendations that can help optimize agricultural practices and maximize yields by utilizing historical crop yield data and analyzing the correlations between input features and crop performance. The random forest algorithm's accuracy is higher than that of Naïve bias, SVM, Decision Tree, and Logistic Regression, but its execution time is longer than that of Decision Tree.

In future, to reduce execution time of random forest algorithm is next step of this research

V. AUTHOR'S CONTRIBUTION

Conceptualization: Dr.Pradip Mukundrao Paithane.
Methodology: Dr.Pradip Mukundrao Paithane.
Investigation: Dr.Pradip Mukundrao Paithane.
Discussion of results: Dr.Pradip Mukundrao Paithane.
Writing – Original Draft: Dr.Pradip Mukundrao Paithane.
Writing – Review and Editing: Dr.Pradip Mukundrao Paithane.
Resources: Dr.Pradip Mukundrao Paithane.
Supervision: Dr.Pradip Mukundrao Paithane.
Approval of the final text: Dr.Pradip Mukundrao Paithane.

VI. REFERENCES

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RESEARCH ARTICLE OPEN ACCESS

A MULTI-OBJECTIVE HUNTER-PREY OPTIMIZATION FOR OPTIMAL INTEGRATION OF CAPACITOR BANKS AND PHOTOVOLTAIC DISTRIBUTION GENERATION UNITS IN RADIAL DISTRIBUTION SYSTEMS

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ABSTRACT

This article put forward the determination of the optimal siting and sizing of capacitor banks and PV-DG (Photo-Voltaic Distribution Generation) units in a radial distribution system. A modern population-based optimization algorithm, Hunter-Prey Optimization (HPO), is applied to determine the optimal capacitor bank and PV-DG placement. This algorithm, HPO, got its motivation from the trapping behaviour of the carnivore (predator/hunter) like lions and wolves towards their target animal like deer. The typical IEEE-33 & 69 test bus systems are scrutinized for validating the effectiveness of the suggested algorithm using MATLAB software R2021b version. The acquired results are collated with the existing heuristic algorithms for the active power loss criterion. The nominal or base values for system losses and voltage profile were considered for the comparison, with the results from HPO. The HPO application has an efficient performance in figuring out the most favourable location and capacity of the capacitor banks and PV DGs compared with the other techniques.

I. INTRODUCTION

I.1 CAPACITOR BANKS

Reactive power flow is observed as the sole basis for the power quality issues like increased power losses, higher voltage drop, and deprivation of power factor in the radial distribution systems [1]. “It is also estimated that of the entire power generation, 13% is dissipated as I2R loss in the distribution networks; hence, the optimal placement of capacitors can enhance the voltage stability and lower the power losses [2].” The entire system control gets endangered by improper placement of the capacitor [3, 4]. Hence, defining the optimal site and size, and the number of capacitors in the radial distribution systems to place a capacitor is necessary. Over the past few years, many algorithms and heuristic methods have been put forward to determine the optimal capacitor location.

The Cuckoo-Search Algorithm (CSA) is presented over the Particle-Swarm Optimization (PSO) technique for the optimal capacitor placement determination in the article [30]. The suggested algorithm is tested on IEEE-33 & 69 buses and then compared to the PSO to prove its superiority. A new technique of Multi-Verse Optimizer (MVO) has been presented in [5] to identify the fair allotment of the capacitor banks tested on IEEE-10, 33 & 69 buses using MATLAB. “Plant Growth Simulation Algorithm (PGSA) in [6] decides the best locations and size of the capacitor to upgrade the voltage profile and bring down the power loss.” Tested on IEEE-33, 34 & 69 systems, this algorithm avails loss sensitivity factors to identify the possible locations of the capacitors followed by the algorithm for the prime allocation of the same. [7] Proposes the Flower Pollination Algorithm (FPA) to determine the optimal capacitor positioning tested on IEEE-10, 33 & 69 bus systems in MATLAB. Interior Point (IP) method and Simulated Annealing (SA) methods are proposed in [8] and compared the obtained results with the Gravitational Search Algorithm (GSA), tested on IEEE-33, 69 & 85 bus systems. "New techniques of the Two-stage method, Practical Approach method, and Locust Search method (LS) are proposed in [9,10] for the optimal capacitor placement(OCP), tested in MATLAB for standard IEEE test bus systems." [12] Presents a Plant Growth Simulation Algorithm (PGSA) and a two-stage method for the best placement of the shunt capacitor in the radial distribution systems tested on the IEEE-69 bus system in MATLAB, similarly [13] proposes PSO for optimal capacitor placement. Genetic Algorithm and Heuristic approaches are proposed in the works of [14, 15] to pick out the finest positioning of the capacitor in the radial distribution system.

I.2 DISTRIBUTION GENERATION

The Distribution Generation, shortly DG, is the non/less-pollutant alternative to electricity production. According to [16], DG is the electricity generation nearer to the customer. In that way, the transmission losses are reduced; also, it is an economical option. DG technologies can be classified into traditional and non-traditional types. Micro-turbines and natural gas turbines come under the conventional variety of DG technologies, while fuel cells, PV generation, Wind turbines, flywheels, and batteries fall under non-traditional DG technologies [17]. Of all sorts of DG technologies, solar PV-type DG technology is anticipated to play a vital role in meeting the inevitable requirement [18]. Wind turbines are the other advancement in green energies. Since DG is expounded based on its location [16], it is essential to find its ideal allocation in the distribution network.

The optimal DG allocations may be discovered utilizing a variety of specified heuristic and meta-heuristic approaches. For optimal siting of wind and solar farms, [19] researchers have suggested using a Gray-Wolf Optimizer. The Lagrange multiplier approach is applied to identify the ideal site for PV-DG [20], which was assessed using the IEEE-37 bus system. On common IEEE-118, 85, 69, 33, and 15 test bus systems, the Whale Optimization approach is utilized to calculate the best allotment of DG operating at 0.9pf[21]. For the prime DG placement, [22] recommends a hybrid approach using GA and PSO. "In order to decrease real power losses and enhance voltage profiles, the Ant Lion Optimization (ALO) algorithm for the RE-DG (Renewable Energy based Distribution Generating) was assessed on IEEE-33 & 69 bus systems [23]." A unique backtracking search optimization method (BSOA) is described in [24] to govern the best DG placement implemented on the IEEE-94 and 33 bus systems, pondering various DG kinds. A novel approach of Effective -Analytic Ideal Power Flow (EA-OPF) is examined in [25] to identify the optimal DG placement evaluated on IEEE- 33 and 69bus systems using C ++ considering three kinds of DGs. Through the use of the cutting-edge Ant Bee Colony (ABC) optimization method, the best location of DG is defined in the article [26]. The technique is implemented on an IEEE-33 bus system and tested for four situations with a single DG, two DGs, and three and four DGs with a goal of maximum active power loss curtailment.

The Hunter-Prey Algorithm (HPO), tested on the IEEE-33 and IEEE-69 bus systems, was used in this paper's study to determine the best location for capacitors and the integration of PV-DG. Its effectiveness was proven by comparing it to other previous studies. The subsections of the article are divided into the following groups: 2. Formulation of the mathematical issue; 3. Proposed Hunter-Prey Algorithm (HPO); 4. Results and discussions; and 5. Drawn conclusions.

II. PROBLEM FOMULATION

II.1 POWERFLOW ANALYSIS

The Backward/Forward Sweep (BFS) was taken on to perform the load flow on the IEEE-33 bus system considered due to its analytic performance, and mastery of convergence [27].

The branch currents are calculated using Kirchoff's Current Law (KCL) from the ending node and proceeded back to the first node comprising a backward sweep.

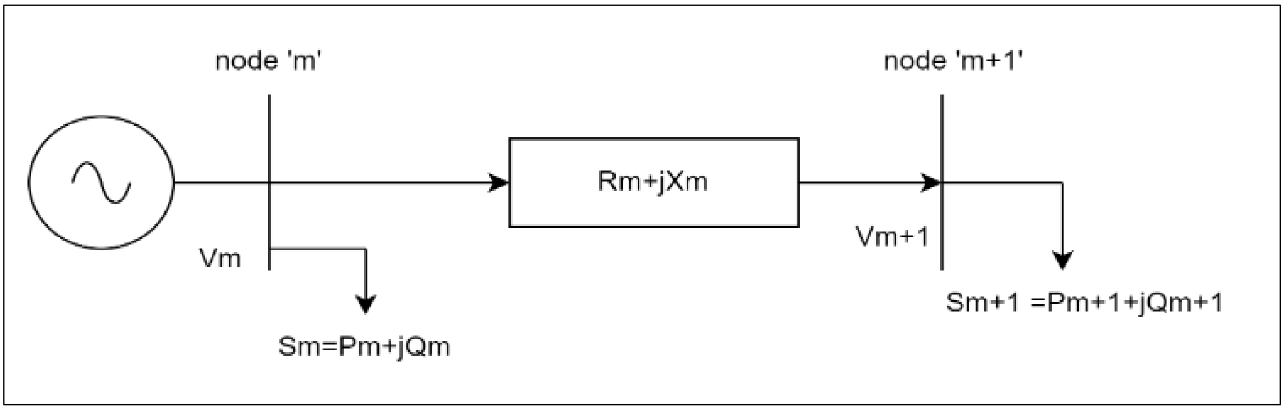

Figure 1: Sample Distribution Network.
Source: Authors, (2023).

$$I_{m+1} = \frac{(P_{l(m+1)} - jQ_{l(m+1)})}{V_{m+1}} \quad (1)$$

From the above equation, one can determine the end bus current from the known load data of the considered system and then the other branch currents are determined moving backward using the KCL. After determining the branch currents the node voltages are determined in the forward sweep.

$$V_{m+1} = V_m - (I_m \times (R_m + jX_m)) \quad (2)$$

The power loss can be calculated as,

$$P_{loss} = \sum_{m=1}^{n} i_m^2 R_m \quad (3)$$

n gives the number of buses of the system taken. For,

$$S_G = V_0 \times \overline{I_0} \tag{4}$$

S_G is the generated Power, V_0 and I_0 are the voltage and the current values at the generating node and

$$S_{load} = \sum_{m=1}^{n}(P_{lm} + jQ_{lm}) \tag{5}$$

S_{loid} is the total load demand which is obtained by summing up all solitary loads at all the buses. The system losses can be determined from

$$S_{losses} = S_G - S_{load} \tag{6}$$

$$S_{losses} = P_{losses} + jQ_{losses} \tag{7}$$

II.1.1 Objective Function

Lessening the true power loss with Voltage Stability improvement is considered as the objective function to estimate the ideal positioning and capacities of the three shunt capacitor banks and three PV-DG units.

$$F_1 = \min(P_{loss}) + max(\text{VSI}) \tag{8}$$

$$S_{loss} = S_{generated} - S_{total\ load} \tag{9}$$

$$P_{loss} = real(S_{loss}) \ \&\ Q_{loss} = imag(S_{loss}) \tag{10}$$

$S_{generated}$ is the power fed at the substation and $S_{total\ load}$ is the total load on the distribution system given by

$$S_{generated} = V_1 \times \overline{I_{b1}} \tag{11},$$

Where V_1 is the generated voltage at the substation and $\overline{I_{b1}}$ is the conjugate of the current through the first bus obtained from the load flow analysis.

$$S_{total\ load} = \sum_{i=1}^{33} P_i + jQ_i \tag{12}$$

Where P_i and Q_i are the active and reactive powers at the 'i^{th}' bus respectively.

II.1.2 System Constraints

1. **Equality Constraints:**

$$S_{generated} - S_{losses} = S_{demand} \tag{13}$$

$$P_{generated} - P_{losses} = P_{demand} \tag{14}$$

$$Q_{generated} - Q_{losses} = Q_{demand} \tag{15}$$

The above equations pertain to the power balance in the considered system.

2. **Inequality Constraints:**

The inequality conditions set the limits for the shunt capacitor capacity, for the safe run of the system.

a. Operating limits of generation:

The generation of active and reactive powers should be within the permissible limits,

$$P_{g\ min} \leq P_g \leq P_{g\ max} \tag{16}$$

$$Q_{g\ min} \leq Q_g \leq Q_{g\ max} \tag{17}$$

Where, $P_{g\ min}$, $P_{g\ max}$, $Q_{q\ min}$, and $Q_{g\ max}$ are the minimum and maximum active and reactive power generation limits

b. Shunt capacitor limits:

$$Q_{min} \leq Q_{size} \leq Q_{max} \tag{18}$$

Where $Qmin$ = minimum capacitor size,
$Qmax$ = maximum capacitor size, and
$Qsize$ = selected capacitor size for reactive power compensation

$$Q_c < Q_{total} \tag{19}$$

Equation (7) states that reactive power injected should be less than the total reactive power load.

c. *Bus Voltage limits*:

$$V_{min} \leq V_i \leq V_{max}\ (i = 1,2, \ldots .n - bus\ number) \tag{20}$$

Usually, the least and crest voltage limits are taken as $V_{min} = 0.95$ & $V_{max} = 1.05$

II.2 MATHEMATICAL PROBLEM FORMULATION FOR SYSTEM LOSSES AND VOLTAGE STABILITY INDEX

Let us consider two nodes of a radial distribution network for the calculation of system losses and the voltage stability index.

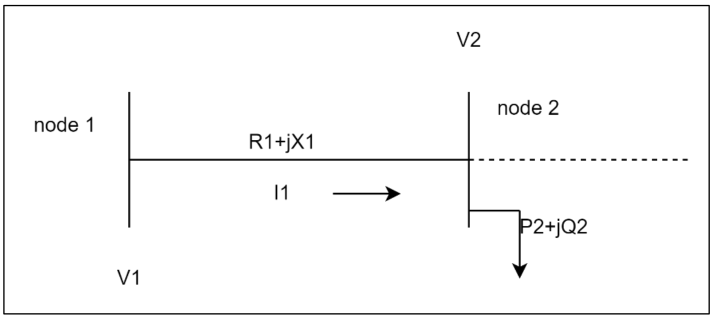

Figure 2: An electrical equivalent network of a radial distribution system considering two nodes.
Source: Authors, (2023).

From the figure we can evaluate I_1 as

$$I_1 = \frac{(V_1 - V_2)}{(R_1 + jX_1)} \tag{21}$$

$Also, we\ have,$

$$S = P_2 + jQ_2 \tag{22}$$

$we\ can\ also\ get\ from,$

$$I_1 = \frac{P_2 - jQ_2}{V_2} = \frac{(P_2 + jQ_2)}{\overline{V_2}} \tag{23}$$

V1 is the voltage at node 1,
V2 is the voltage at node 2, $\overline{V_2}$ is its conjugate.
P2 and Q2 are the real and reactive powers at node 2,
R2 and X2 are the resistance and reactance of the branch bridging the nodes 1 & 2

II.2.1 Active Power Loss Reduction

$$active\ power\ losses, P_{losses} = I^2R, \quad (24)$$

$from$ (3),

$$P_{losses} = (\frac{(P_2+Q_2)}{V_2})^2 \times R_1 \quad (25)$$

$$P_{losses(1)} = \frac{R_1({P_2}^2+{Q_2}^2)}{{V_2}^2} \quad (26)$$

Similarly, we can get the reactive power losses as,

$$Q_{losses(1)} = \frac{X_1({P_2}^2+{Q_2}^2)}{{V_2}^2} \quad (27)$$

For, Plosses (1) and Qlosses (1) are the real and reactive power losses through the branch tieing nodes 1&2,

$$P_{losses(i)} = \frac{R_i({P_{i+1}}^2+{Q_{i+1}}^2)}{{V_{i+1}}^2} \quad (28)$$

$$Q_{losses(i)} = \frac{X_i({P_{i+1}}^2+{Q_{i+1}}^2)}{{V_{i+1}}^2} \quad (29)$$

II.2.2 Voltage stability index

Voltage stability index is proposed to identify the feeble node prior to voltage collapse [28].

Equating (21) and (23),

$$I_1 = \frac{V_1-V_2}{R_1+jX_1} = \frac{P_2-jQ_2}{V_2} \quad (30)$$

$$(P_2 - jQ_2) * (R_1 + jX_1) = (V_1 - V_2) * V_2 \quad (31)$$

taking the voltage angles into consideration we have $V_1\angle\delta1$ and $V_2\angle\delta2$

Thus, the above equation becomes,

$$\begin{aligned}(P_2R_1 + Q_2X_1) + j(P_2X_1 - Q_2R_1) &= (V_1\angle\delta1 - V_2\angle\delta2) * V_2\angle\delta2 \\ &= (V_1V_2\cos(\delta1 - \delta2) - {V_2}^2) \\ &+ \ j(V_1V_2\sin(\delta1 - \delta2))\end{aligned} \quad (32)$$

(Since $x\angle\theta = x(\cos\theta + jsin\theta)$)

Now, equating the real parts and imaginary parts on both sides of the equation, we get,

$$V_1V_2\cos(\delta1 - \delta2) - {V_2}^2 = P_2R_1 + Q_2X_1 \quad (33)$$

$$V_1V_2\sin(\delta1 - \delta2) = P_2X_1 - Q_2R_1 \quad (34)$$

On squaring and adding on both the equations (33) & (34), (we know$(\cos\theta)^2 + (sin\theta)^2 = 1$)

$${V_1}^2{V_2}^2 = (V_2)^4 + (P_2R_1 + Q_2X_1)\text{^}2 + 2\left({V_2}^2(P_2R_1 + Q_2X_1)\right) + (P_2X_1)^2 + (Q_2R_1)^2 - 2P_2Q_2R_1X_1 \quad (35)$$

On getting the above equation in quadratic equation form,

$${V_2}^4 + {V_2}^2(2P_2R_1 + 2Q_2X_1 - {V_1}^2) + ({P_2}^2 + {Q_2}^2)({R_1}^2 + {X_1}^2) = 0 \quad (36)$$

On comparing it to the standard form of $ax^2 + bx + c = 0$, with roots of $x_1, x_2 = \frac{-b\pm\sqrt{b^2-4ac}}{2a}$

We have,$x = {V_2}^2$ $a = 1, b = (2P_2R_1 + 2Q_2X_1 - {V_1}^2), c = ({P_2}^2 + {Q_2}^2)({R_1}^2 + {X_1}^2)$

Since, the solution is unique as the root term is square, and only positive value is applicable we consider $b^2 - 4ac \geq 0$, thus we get,

$$(2P_2R_1 + 2Q_2X_1 - {V_1}^2)^2 - 4\{({P_2}^2 + {Q_2}^2)({R_1}^2 + {X_1}^2)\} \geq 0$$

On simplifying,

$${V_1}^4 - 4(P_2X_1 - Q_2R_1)^2 - 4(P_2R_1 + Q_2X_1){V_1}^2 \geq 0 \quad (37)$$

Thus, defining Stability Index, in generalized form for 'i',

$$VSI(i + 1) = {V_i}^4 - 4(P_{i+1}X_i - Q_{i+1}R_i)^2 - 4(P_{i+1}R_i + Q_{i+1}X_i){V_i}^2 \geq 0 \quad (38)$$

The node at which the value of VSI is least, is more feeble and prior to the voltage fall-out.

III. HUNTER-PREY OPTIMIZATION (HPO)

Choosing the hunting and protection mechanisms of various flora and fauna for effective optimization can be termed the Nature Inspired Optimization Algorithm (NIOA). There are many scenarios of animal hunting behaviour considered for optimization algorithms [29]. The Hunter-Prey Optimization (HPO) algorithm mimics the hunting behaviour of carnivorous hyenas, tigers, and lions for their prey like deers and gazelles.

III.1 ALGORITHM

The scheme of the optimization algorithm involves three steps. Step1 initializes of the population arbitarily. Step2 calculates the fitness function (local best solution), constricting the search area or exploration. Step3 is exploitation that mostly involves crucial operations executed amongst the whole population to evolve eminent individuals.

There are two stages to the search process, and they are called "exploration" and "exploitation," respectively. The algorithm's propensity for very erratic behaviors and substantial solution variations is referred to as "exploration." The striking shifts in solutions prompt more exploration of the search space, leading to the identification of previously unexplored potential regions. Once the favorable areas have been located, random behaviors must be reduced so that the algorithm may explore the areas around the bright spots (also known as exploitation).

Step 1: *Population Initialization:*

The population is randomly initialized as$\left(\underset{x}{\rightarrow}\right) = \{\underset{x_1}{\rightarrow} + \underset{x_2}{\rightarrow} + \underset{x_3}{\rightarrow} + \cdots, \underset{x_{n-1}}{\longrightarrow}, \underset{x_n}{\rightarrow}\}$, for each random variable is bounded between lower and an upper limits and thus defining the search space as

$$x_i = rand(1, d) * (ub - lb) + lb \quad (39)$$

Where, ub and lb are the upper and lower boundaries defining the minimum and maximum values, d is the dimension or the number of variables. x_i Is position vector.

For every variable we define, there will be a minimum and a maximum for each, i.e.

$$lb = (lb_1, lb_2, \ldots \ldots lb_d) \text{ And } ub = (ub_1, ub_2 \ldots \ldots ub_d) \quad (40)$$

Step 2: *Calculation of Fitness function/ local minima (Exploration):*

After the initialization of population variables and their respective lower and upper limits, the fitness function is calculated by using the objective function. $O = f(\underset{x}{\rightarrow})$. It is be noted that a search procedure must be repeated numerous times to pilot the search agents to the best position as single run cannot give an optimal solution.

$$x_{m,n}(t+1) = x_{m,n}(t) + 0.5\left[\left(2CZP_{pos(n)} - x_{m,n}(t)\right) + \left(2(1-C)Z\mu_n - x_{m,n}(t)\right)\right] \quad (41)$$

The above equation defines the hunter prey mechanism, which updates the position of hunter at every iteration.

$x_{m,n}(t)$ *is the current position of the hunter* $x_{m,n}(+1)$ *gives the updated position of the hunter for next it* $P_{pos(n)}$ *defines the prey position,*

"μ" is the average (mean) of all position and is given by

$$\mu = \frac{1}{n}\sum_{m=1}^{n} x_i \quad (42)$$

In this algorithm, the hunter targets the prey which is away from the rest of the praise and how the prey reaches its group before getting attacked by the hunter. P is a random vector between [0, 1], Z is an adaptive parameter and C is a balance parameter between the steps 2 &3, i.e., exploration and exploitation.

$$C = 1 - iter\left(\frac{0.98}{Maxiter}\right) \quad (43)$$

Where *iter* is the current iteration and *Maxiter* is the maximum number of iteration user defines; the C value decreased from 1 to 0.02 during the run of iterations.

For R_1 be any random number between [0,1] and R_2 and R_3 be any any random vectors defined within the same range, INX defines the index number of vector R_3 ,the values of P and Z are calculated as

$$Z = (R_1 * INX) + (\vec{R_2} * INX) \quad (44)$$

$$P = \vec{R_3} < C, satisfying\ INX = (P == 0) \quad (45)$$

Step 3: Exploitation:

"We discusses earlier that the prey far from the group is considered by the hunter, but if we consistently suppose the search agent with the longest distance from the average position in each iteration, the algorithm will have a delayed convergence."

$$P_{pos} = x_i|maximum\ of\ (D_{euclid})| \quad (46)$$

$$D_{euclid} = \sqrt{\sum_{n=1}^{d}(x_{m,n} - \mu_n)^\wedge 2} \quad (47)$$

D_{euclid} is the prey-to-searcher distance as measured by the Euclidean algorithm. When the hunter catches his prey, kills it, and moves on to another target, he solves the problem described by the hunting scenario.

$$kbest = round(C \times N) \quad (48)$$

Using which the position vector is updated as

$$P_{pos} = x_i|maximum\ of\ D_{euclid}(kbest)| \quad (49)$$

, and the search agent equation is updated as

$$x_{m,n}(t+1) = (T_{pos(n)} + CZcos(2\pi R_4) \times (T_{pos(j)} - x_{m,n}(t))) \quad (50)$$

Where T_{ops} is the optimal global position, and R_4 is a random number between [-1, 1].

For the question of how to choose hunter and prey, we define another random number R_5 between [0 and 1] and get it compared with β (a regulator parameter fixed at 0.1);

$$x_m(t+1) = \begin{cases} x_m(t) + 0.5[\left(2CZP_{pos} - x_m(t)\right) + (2(1-c)Z\mu - x_m(t), & for\ R_5 < \beta \\ T_{pos} + CZ\cos(2\pi R_4) \times \left(T_{pos} - x_m(t)\right), & for\ R_5 > \beta \end{cases} \quad (51)$$

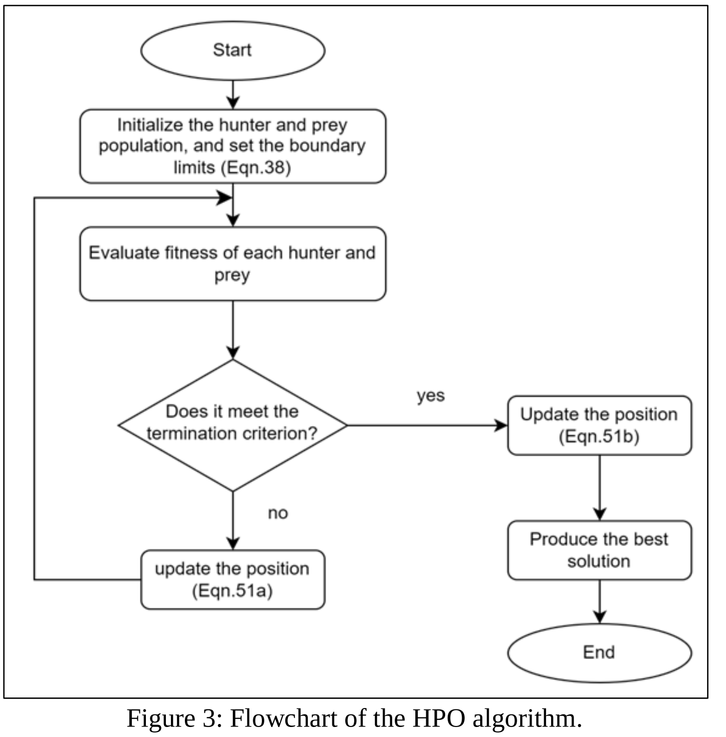

Figure 3: Flowchart of the HPO algorithm.
Source: Authors, (2023).

IV. RESULTS AND DISCUSSIONS

The proposed algorithm of the Hunter-Prey Optimization (HPO) is assayed on typical IEEE-33 and 69 test bus systems using MATLAB2021b. The main aim is the reduction of active power losses by determining the optimal siting and sizing of the capacitor banks and solar DG placement. In this work, the following cases are considered for both 33 and 69 test bus systems to compare and identify the efficiency of the suggested algorithm.

Case1: is the base or nominal case,

Case 2: is the active power loss reduction considering three shunt capacitor allocations,

Case 3: power loss reduction with three PV-Daunts in the considered radial distribution system. And an internal comparison is made within the studied cases for each system. The IEEE-33 and 69 bus systems are considered for the study.

The attained values from the performed algorithm (HPO) are compared with other existing heuristic and meta-heuristic algorithms taking the parameter of active power losses, with a tabulated comparison of the data below.

IV.1 IEEE-33 BUS SYSTEM

IV.1.1 Base or Nominal Case

The load flow analysis is calculated using the Backward-Forward Sweep algorithm and the results are taken into consideration for the comparison. It is to be noted that, for the active loss two values of 202.65kW and 210.8kW are taken into consideration.

Table 1: Nominal values of a 33-bus systems (for 202.65 kW).

Ploss(kW)	**Vmin(p.u.)**	**VSI**
202.65	0.8541	0.6821

Source: Authors, (2023).

Table 2: Nominal values of a 33- bus system (for 210.0kW).

Ploss(kW)	**Vmin(p.u.)**	**VSI**
210.0	0.9038	0.6685

Source: Authors, (2023).

IV.1.2 Three Shunt Capacitor Banks Allocation

In this case, the system performance with three shunt capacitor bank is analysed using the proposed algorithm of HPO, and the obtained results are compared with that of existing algorithms to highlight the effectiveness of HPO.

Table 3 and 4 gives the comparison among Particle Swarm Optimization (PSO), Cuckoo Search Algorithm (CSA) [30], Multi-Verse Optimizer [5], Plant Growth Simulation Algorithm (PGSA), and Flower Pollination Algorithm (FPA) with the proposed algorithm of Hunter-Prey Optimization (HPO) for the nominal value of active power loss 202.5kW and with Interior Point (IP)[6], Simulated Annealing(SA)[6], Practical Approach[7], Two-Stage method and Locust Search(LS) [8] for nominal active power loss of 210.8kW and the HPO can be found more efficient in loss reduction of other all.

Table 3: Comparitive Analysis for Active power loss for a 33-bus system using HPO and other algorithms.

Parameter	**base case**	**Compensated values**					
		IP [8]	AS [8]	Two-stage method [10]	Practical Approach method [9]	LS [10]	HPO
Active power loss (kW) % loss reduction	210.8 kW	171.78 18.5%	151.75 28.01%	144.04 31.67%	138.61 34.25%	139.23 33.95%	**138.43** **34.33%**
Optimal site (bus number) and size of three capacitor banks (car)		9 450 29 800 30 900	10 450 14 900 30 350	7 850 29 250 30 900	12 500 24 500 30 1000	12 450 25 350 30 900	12 450 24 450 30 1050

Source: Authors, (2023).

Table 4: Comparative Analysis for HPO algorithm with other algorithms for 33-bus system (Extended).

Parameter	**Nominal values**	**Compensated values**					
		PSO [30]	CSA [30]	MVO [5]	PGSA [6]	FPA [7]	HPO
Active power loss (kW)	202.65	133.12	133.0851	132.68	135.40	134.47	**132.37**
%loss reduction		34.31%	34.32%	34.53%	33.18%	33.64%	**34.68%**
The optimal site and size(kVAr) of capacitor banks		14 300 24 600 30 1050	10 600 24 600 30 900	12 450 24 600 30 900	6 1200 28 760 29 200	6 250 9 400 30 950	12 450 24 450 30 1050

Source: Authors, (2023).

Relative Results for IEEE-33-bus system with Capacitor bank allocation

The proposed algorithm of Hunter Prey Optimization is tested for decreasing the active power losses for the standard IEEE-33 bus system. The obtained results of real power loss reduction from 202.6kW to 132.37kW subjecting to 34.68% are compared with other existing algorithms of Particle Swarm Optimization(PSO) [30] for active power loss reduction from 202.6 kW to 133.12 kW with 34.31% reduction, Cuckoo Search Algorithm (CSA) [30] for 34.32% reduction from 202.6kW to 133.08kW, Multiverse Optimizer(MVO) [5]with a loss reduction of 132.68kW from 202.6kW accounting to 34.53%, Plant Growth Simulation Algorithm(PGSA)[6] with 33.18% of active power loss reduction, i.e., real power loss reduced from 202.6kW to 135.4kW and Flower Pollination Algorithm(FPA) [7] lowering losses from 202.6kW to 134.47kW for 33.64%. The variation can be graphically observed as:

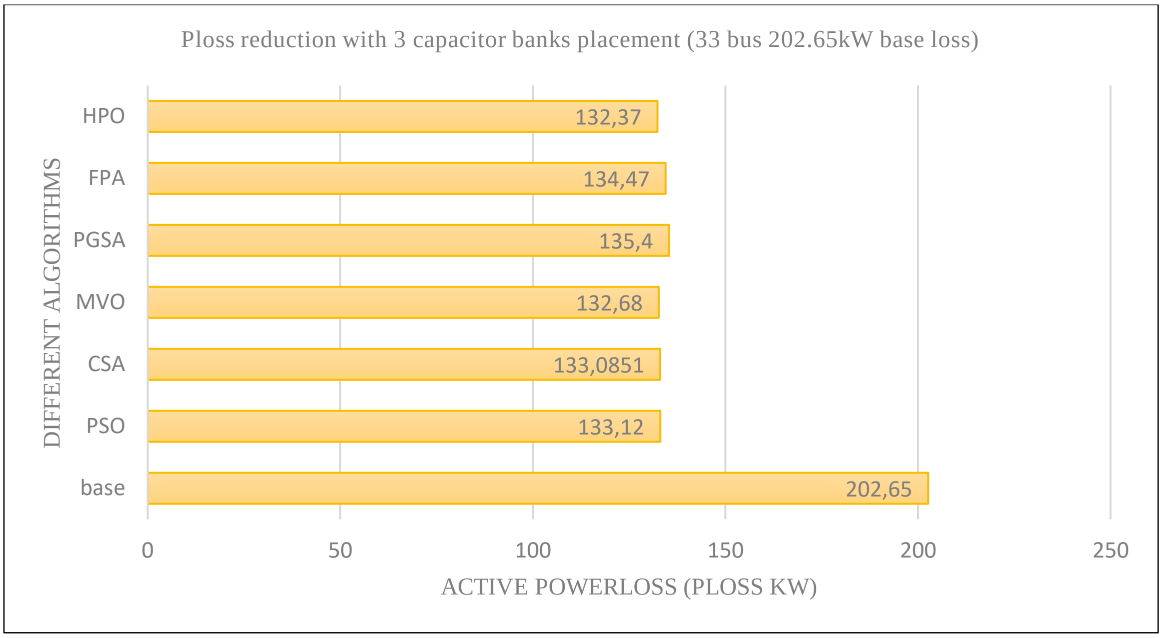

Figure 4: Bar diagram representing active power loss reduction with CB placement (33 bus_202kW).
Source: Authors, (2023).

The comparison is also made with other algorithms of Interior Point (IP)[8,12] for a loss reduction of 171.78kW from 210.8kW (18.5%), Simulated Annealing(SA)[8,10] 151.71 from 210.8kW(28.01%), Two-stage method[11] for deduction of 31.67%,i.e., from 210.8kW to 144.04kW, Practical-Approach[9,10] method reducing the real losses from 210.8kW to 138.61kW(34.25%), Locust Search(LS)[10] algorithm reducing to 139.23kW from 210.8kW(33.95%); while the proposed algorithm reduces the active losses to 138.43kW from 210.8kW accounting to 34.33% reduction proves to be effective in comparison.

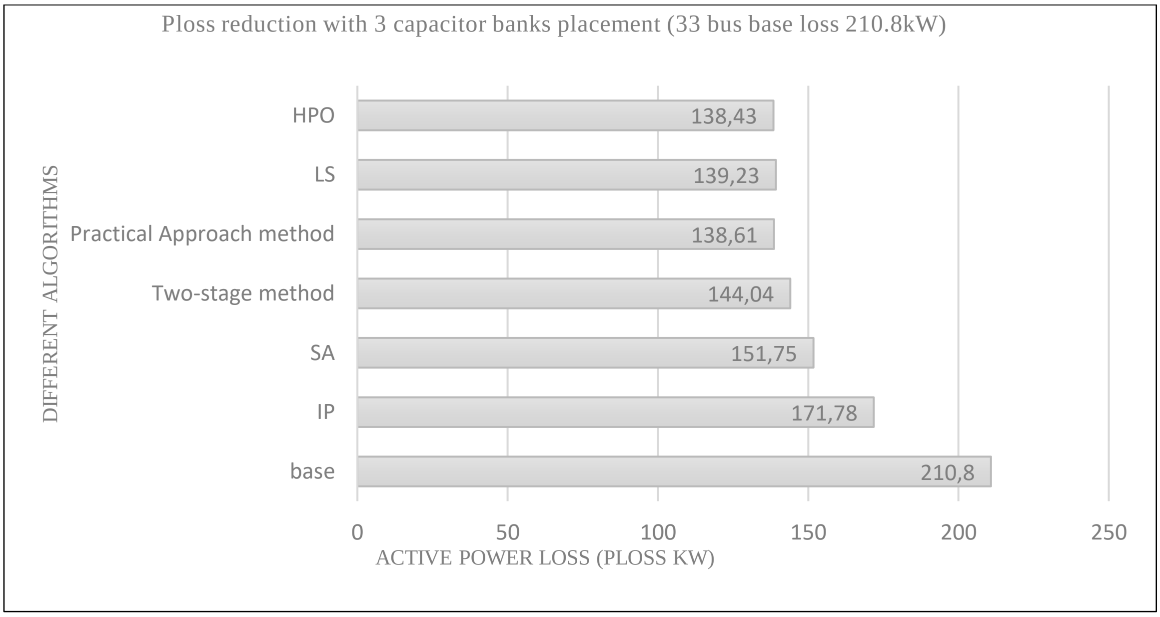

Figure 5: Bar diagram representing active power loss reduction with CB placement (33 bus_210kW).
Source: Authors, (2023).

IV.1.3 Three PV-DG Allocation

The performance analysis of the IEEE-33 bus system with three PV units is considered for this case. Applying the proposed HPO algorithm, the results are obtained of which, the active power losses are compared with the of other algorithms to test the efficiency of the HPO algorithm.

From the tabulated data, it can be noticed that the active power loss reduction using HPO is more, i.e., from 210kW to 71.45kW comprising to 65.97% while GA accounts for 49.38%, PSO for 49.85%, GA-PSO for 50.76%, EA for 65.34%, while EA-OPF and Exhaustive OPF account for 65.33%, upon ABC algorithm there is a loss reduction of 61.08%. Also, we can observe the total DG capacity is also less comparatively with the other algorithms. The sum of the three PV DGs size owing its total capacity using HPO is 2925kW, while it is 2951kW for EA, 2947kW for EA-OPF and Exhaustive-OPF methods, 3114 kW using ABC, 2994 kW using GA and 2988.1kW and 2988kW using PSO and GA-PSO respectively. We can also notice that the total PV-DG capacity is minimum, 2925kW using the HPO algorithm, which is less than that obtained from other algorithms.

Table 5: A comparative Table of active power loss with PV_DG placement within algorithms for 33 bus system.

Parameter	Efficient Method (EA) [25]	Efficient Analytic Optimal Power Flow(EA-OPF)[25]	Exhaustive Power flow method [25]	Ant Bee Colony (ABC) [26]	Genetic Algorithm (GA) [22]	Particle Swarm Optimization (PSO) [22]	GA-PSO [22]	HPO
Active Power loss(kW)	72.78 (65.34%)	72.79 (65.33%)	72.79 (65.33%)	79.26 (61.08%)	106.3 (49.38%)	105.3 (49.85%)	103.4 (50.76%)	**71.45 (65.97%)**
DG site(bus number) and size(kVAr)	13 798 24 1099 30 1054	13 802 24 1091 30 1054	13 802 24 1091 30 1054	6 1756 15 575 25 783	11 1500 29 422.8 30 1071.4	13 981.6 32 829.7 8 1176.8	32 1200 16 863 11 925	14 754 24 1100 30 1071
Total capacity (kVAr)	2951	2947	2947	3114	2994	2988.1	2988	2925

Source: Authors, (2023).

Graphically the comparison among various algorithms for PV placement can be shown as a bar graph.

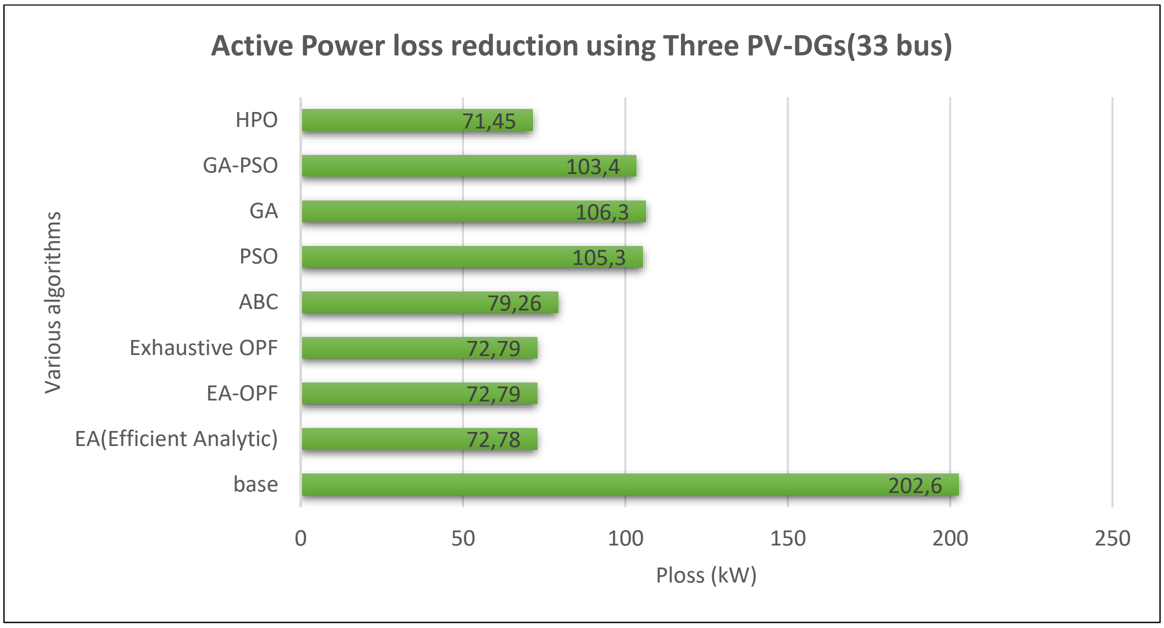

Figure 6: Bar diagram representing comparison among algorithms for PV integration (33 bus) Case.
Source: Authors, (2023).

IV.2 IEEE-69 TEST BUS SYSTEM

IV.2.1 Nominal or Base Case

The Backward-Forward Sweep algorithm is used to evaluate the load flow analysis and the value of active power loss of 225.0kW is taken into consideration for the comparison.

Table 6: Base values of a 69-bus system.

Ploss(kW)	Vmin(p.u.)	VSI
225.0	0.9093	0.6838

Source: Authors, (2023).

IV.2.2 Three Shunt Capacitor Banks Allocation

In this case the performance of the 69-bus radial system is analysed with three capacitor banks allocation and the results derived are compared with the existing algorithms.

The results of the HPO algorithm are compared to that of PSO, PGSA, Fuzzy-GA, Two-Stage method and heuristic approach. Table 7 depicts the comparison for active power losses also the optimal CB locations also noted.

Comparative results for 69 bus system

The preferred algorithm is assessed for 69 bus system and the results are compared for actual power loss with other contemporary algorithms. Particle Swarm Optimization (PSO) [12] with power loss reduction of 32.23% loss reduction from 225.0kW to 152.48kW. Plant Growth Simulation Algorithm (PGSA) proposed in [13] has a loss reduction of 147.40kW from 225.0kW comprising to 34.49%. Two-stage method [13] and Fuzzy-GA in [14] has 33.82% and 32.17% of loss reduction from 225.0kW to 148.91kW and 152.62kW respectively. The losses are decreased from 225.0kW to 148.48 kW comprising 34.01% using Heuristic Approach [15]. The proposed HPO has an active loss reduction of 145.228kW from 225.0kW accounting to 35.43%.

IV.2.3 Three PV-DG Allocation

The proposed HPO algorithm is executed on the IEEE-69 bus system and the active losses derived results are collated to the other existing algorithms of Effective Analytic(EA), EA_OPF(Effective Analytic-Optimal Power Flow), Exhausted Optimal Power Flow algorithm, Particle Swarm Optimization(PSO), Genetic Algorithm(GA), a combined GA-PSO and tabulated in table no. 8.

Table 7: Comparative results of active power loss for 69-bus system for different algorithms with HPO.

Parameter	Nominal values	Compensated				
		PSO [12]	PGSA [13]	Two-Stage method [13]	Fuzzy-GA [14]	Heuristic Approach [15]
Active power loss (kW)	225.0	152.48	147.40	148.91	152.62	148.48
%loss reduction		32.23%	34.49%	33.82%	32.17%	34.01%
The optimal site and size(kVAr) of capacitor banks		46 241 47 365 50 1015	57 1200 58 274 61 200	19 225 62 900 63 225	59 1100 61 800 64 1200	8 600 58 150 60 1050

Source: Authors, (2023).

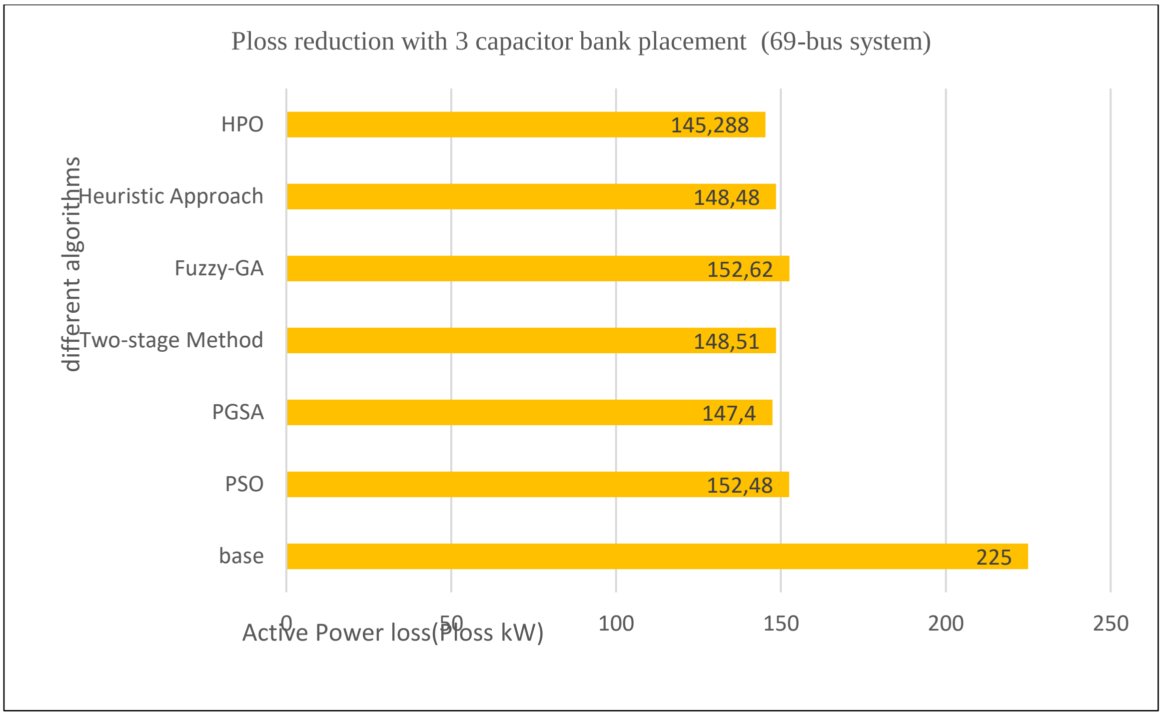

Figure 7: Bar diagram representing comparison among algorithms for CB integration (69 bus).
Source: Authors, (2023).

Table 8: A comparative table of active power loss with PV-DG placement within algorithms for 69 bus system.

Parameter	**Efficient Method (EA) [25]**	**Efficient Analytic Optimal Power Flow(EA-OPF)[25]**	**Exhaustive Power flow method [25]**	**Genetic Algorithm (GA) [22]**	**Particle Swarm Optimization (PSO) [22]**	**GA-PSO [22]**	**HPO**
Active Power loss(kW)	69.62 (69.05%)	69.45 (69.13%)	69.45 (69.13%)	89.0 (60.44%)	83.2 (63%)	81.1 (69.35%)	69.43 **(69.14%)**
DG site(bus number) and size(kVAr)	61 1785 18 380 11 467	61 1719 18 380 11 527	61 1719 18 380 11 527	21 929.7 62 1075.2 64 984.8	61 1199.8 63 795.6 17 992.5	63 884.9 61 1192.6 21 910.5	11 574 18 380 61 1719
Total capacity (kVAr)	2632	2626	2626	2989.7	2987.9	2988	2623

Source: Authors, (2023).

The productivity of the proposed algorithm of HPO is efficient in reduction of active power losses compared to that of other algorithms can be noticed from the table 8. There is a reduction of 69.43kW from 225.0kW comprising to 69.14%. It is 69.05%(69.62kW) using EA, 69.13%(69.45kW) using EA-OPF and Exhaustive OPF,60.44%(89kW) using GA, 63%(83.2kW) using PSO and 63.95%(81.1kW) using GA-PSO. It can also be noted that the total DG capacity (sum of all 3 units) is less when the HPO algorithm is applied, 2623kW using HPO, 2632kW using EA, 2626kW using EA-OPF and Exhaustive-OPF, 2989.7kW using GA, 2987.9kW using PSO and 2988 using GA-

PSO. Also from the last column that gives the DG capacities, we can notice that the total capacity of DGs is minimum using the HPO algorithm comparing with the other optimization technique. The comparison can be graphically depicted as in figure 8.

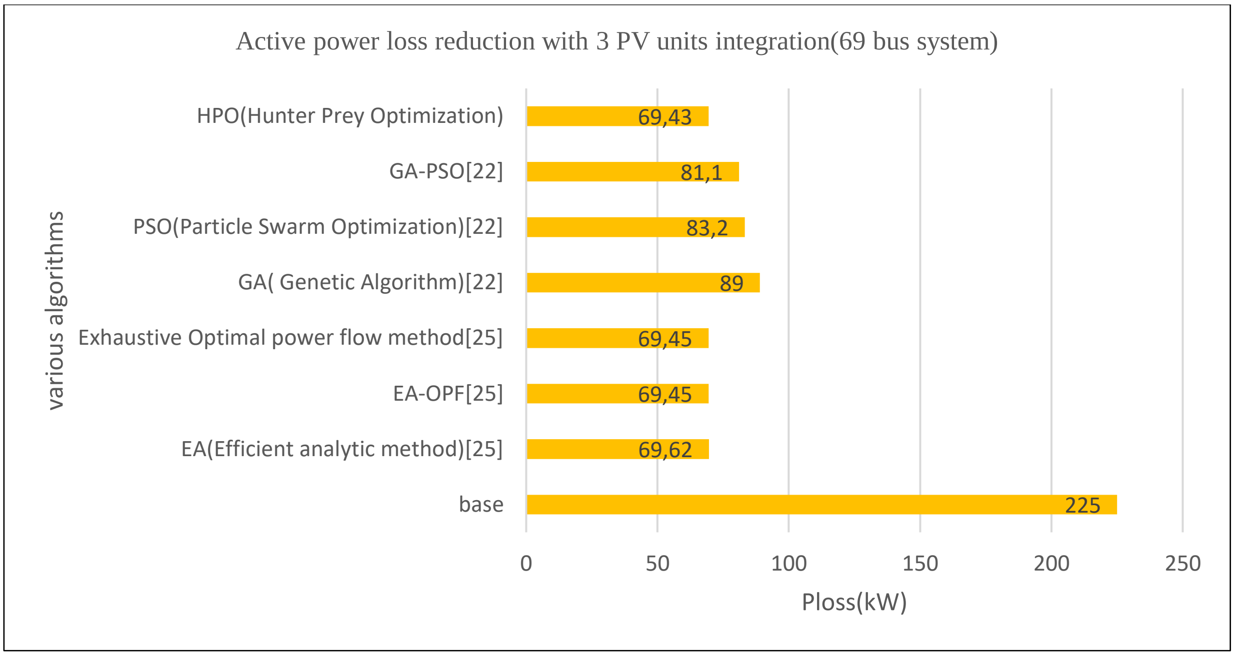

Figure 8: Bar diagram representing comparison among algorithms for PV integration (69 bus).
Source: Authors, (2023).

IV.3 PERFORMANCE ANALYSIS OF HPO FOR IEEE-33 AND 69 BUS SYSTEMS WITH SWITCHED CAPACITOR BANKS, FIXED CAPACITOR BANKS AND PV-DG PLACEMENT

The simulations are done for IEEE 33 and 69 standard test bus systems using the proposed algorithm of HPO (Hunter-Prey Optimization), for the integration with fixed capacitor banks, switched capacitor banks, and solar PV DG integration. Switched capacitors are the automatic capacitors where the kVAr can be varied, while the fixed capacitors supply a constant amount of correction kVAr. The obtained results for each case with loss reduction, both active and reactive power loss reduction and voltage profile improvement are tabulated in tables 9, 10 and 11.

The above tables give results of HPO application which clearly depicts the ease and efficiency of the algorithm. The parameters of active power loss, reactive power loss, minimum voltage and voltage stability index are neffectively varied, with a notable loss reduction and voltage profile amplification. The same can be observed in all three cases of fixed capacitor bank, switched capacitor bank and solar DG integrations in the 33 and 69 bus systems from tables 9, 10 and 11 respectively. The optimal allocation of CBs and DGs are also tabulated.

According to the theory of the algorithm, the prey dies when hunter attacks and kills it and thus the safe position of the hunter will be the best solution. In this context, the bus with minimum number of losses will be the ideal or optimal location for a DG or a CB. The algorithm is found efficient for loss deduction and voltage profile amelioration when compared with other contemporary techniques and nominal values. From the tables of 5 and 8, the total capacity of PV DGs using the algorithm is found minimum but not in case with CBs which could be counted as the limitation of the algorithm.

Table 9: Parameter tabulation of IEEE-33 & 69 bus systems with fixed CBs using HPO.

Parameter-fixed CB (3 units)	**33 bus (202 kw loss)**	**33-bus (210 kW loss)**	**69 bus**
Ploss (kW)	132.4238	137.1657	145.2824
Loss (kVAr)	88.4249	93.4183	67.7404
Vmin p.u.(bus)	0.9362 (18)	0.9309 (18)	0.9308 (65)
VSI(bus)	0.7483 (16)	0.7312 (16)	0.7120(63)
DG site (bus no.)	24 30 11	12 24 30	11 61 18
DG size (kVAr)	450 1050 450	450 450 1050	300 1200 300

Source: Authors, (2023).

Table 10: Parameter tabulation of IEEE-33 and 69 bus systems with switched CBs using HPO.

Parameter-switched CB (3 units)	**33- bus (202 kW)**	**33-bus (210 kW)**	**69-bus**
Ploss (kW)	132.1726	138.2644	145.2876
Qloss (kVAr)	88.3306	94.2155	67.7227
Vmin p.u.(bus)	0.9377 (18)	0.9317 (18)	0.9314 (65)
VSI(bus)	0.7533 (16)	0.7337 (16)	0.7173 (63)
DG site (bus no.)	24 13 30	30 24 13	17 66 61
DG size (kVAr)	544 379 1037	1037 544 388	267 341 1238

Source: Authors, (2023).

Table 11: parameter tabulation of IEEE-33 and 69 bus systems with PV-DG integration using HPO.

Parameter-three units of PV-DG	33-bus (202 kW)	33-bus (210 kW)	69-bus
Ploss (kW)	71.4572	74.0870	69.4284
Qloss (kVAr)	49.3909	51.3923	34.9618
Vmin p.u.(bus)	0.9686 (33)	0.9646 (18)	0.9790 (65)
VSI(bus)	0.8485 (30)	0.8053 (29)	0.8521 (60)
DG site (bus no.)	24 30 14	12 24 31	11 61 18
DG size (kW)	1100 1071 754	932 1101 899	527 1719 380

Source: Authors, (2023).

V. CONCLUSIONS

To determine where and how big capacitor banks and solar DGs should be installed in a radial distribution ssytem, a novel methodology called Hunter- Prey Optimization (HPO) is presented. The fundamental motivation for this optimization approach is the ability to pull a target away from the rest of the pack and strike it in the direction of the pack leader. The algorithm is tested on the IEEE-33 and 69 test bus systems, and the results are compared to those of other popular algorithms to determine where to put the capacitor banks and the PV type DG. For a more thorough evaluation of the radial distribution system's competitiveness, simultaneous installation of PV-DG and capacitor banks may be expanded.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Varaprasad Janamala.
Methodology: Varaprasad Janamala.
Investigation: Varaprasad Janamala.
Discussion of results: Soundarya Lahari Pappu.
Writing – Original Draft: Soundarya Lahari Pappu.
Writing – Review and Editing: Soundarya Lahari Pappu.
Resources: Varaprasad Janamala.
Supervision: Varaprasad Janamala.
Approval of the final text: Soundarya Lahari Pappu and Varaprasad Janamala.

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RESEARCH ARTICLE OPEN ACCESS

AN INNOVATIVE DANDELION OPTIMIZED NETWORK CONTROL (DONC) BASED EFFECTIVE ENERGY MANAGEMENT SYSTEM FOR ELECTRIC SHIPS

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ABSTRACT

Energy Management System (EMS) plays a vital role in an international marine shipboard, due to their increased energy demand. The main purpose of this research work is to develop a new energy management system for satisfying the load demand of ship board applications. For accomplishing this objective, an advanced controlling mechanism, named as, Dandelion Optimized Network Control (DONC) is developed in this work. Also, the hybridized energy source including the fuel cell and battery storage are used in this design, where the fuel cell is main source of energy, and the battery storage is used as the supplementary storage device. Moreover, two different converter topologies such as interleaved zeta converter for fuel cell and bi-directional converter for battery storage are implemented in this study. The main purpose of using these converters are to effectively boost the output voltage of hybridized energy sources with reduced ripple current and distortions. The proposed DONC integrates the functions of DO technique as well as FNN for predicting the output power of fuel cell. During this process, the Fictitious Neural Network (FNN) technique obtains the input parameters of load demand power and battery SoC, and produces the predicted power of fuel cell for an effective energy management in electric ship board. In this mechanism, the weight value of FNN is optimally computed with the use of DO algorithm. The key benefits of the proposed DONC are increased efficiency, proper energy management according to the load demand, and reliable for ship applications. During simulation analysis, the load demand and fuel cell power are estimated with the normal, high, and low battery SoC states. The findings indicate that the proposed DONC can effectively manage and control the energy need of electric ship with the hybridized energy system.

I. INTRODUCTION

Global trade is largely fueled by international shipping, notably maritime merchandise transportation [1, 2]. In fact, ocean transport accounts for a sizable portion of global trade in terms of both capacity (80%) as well as value (70%). The continuous expansion of international trade and ocean transport activities have been projected as contributing to the rise in CO2 levels globally in the future. Shipping is responsible for a sizeable share of the world's greenhouse gas (GHG) emissions, particularly CO_2. Electrical energy is an invisible, universal item that is frequently available worldwide at an affordable cost, and it is currently regarded as a basic need for consumers [3-5]. Electricity must typically be converted into other kinds of power because storing energy is not an easy operation. When needed, the electricity can be converted into chemical, biological, mechanical heat, and other forms. The ultimate consumption up to 2040 is expected to see a 40% increase in electricity demand. Industrial electric motors are responsible for more than thirty percent of the rise in electricity demand. The main causes of the rise in power demand are the gain in income, the release of smart linked technologies onto the market, and the installation of new cooling systems. Similar to how demand for electricity fluctuates during the day, so does its price. Electric utilities used multiple pricey power generating plants during the period of peak load [6-8]. To accommodate demand, the plants run alongside the base load power unit. It also refers to the choice of fuels made in light of analyses of economic dispatch for various electric power plants. In this situation, an adequate energy storage system (ESS) is always needed to handle the abrupt fluctuations in load.

In all-electric systems, an intelligent system is a recent development. The inclusion of numerous non-homogeneous energy sources in the framework encourages the widespread usage of renewable energy. Moreover, AI improves efficiency and fixes the non-optimality problem. An appropriate control and management approach for the traction system can be provided by the proposed ship hybrid power systems [9]. An important fuel cell and battery hybridized energy management strategy controls the flow of electricity between various energy sources [10]. A key component of the smart control method is adapting the hybrid system electrical power to variations in load power and battery state of charge (SoC). The fuel cell and battery storage are the vital components of the proposed energy management system used for ship applications [11, 12]. Typically, the flow of power among different energy sources can be effectively managed and controlled with the use of energy management system. Moreover, controlling the distribution of hybrid system power to changes in load power and battery SoC is a crucial component of the automated control scheme. The main contributions of this research work are given below:

- A new AI based energy management technique, named as, Dandelion Optimized Network Control (DONC) is developed for shipboard.
- The advanced converter circuits such as interleaved Zeta and Bi-directional are used to improve the voltage gain with high efficiency.
- In this study, a hybridized sources including fuel cell and battery storage have been used for satisfying the need of electrical ship.
- An extensive simulation analysis is carried out in this study for examining the performance and results of the proposed framework.

The following units make up the remaining sections of this paper: Section 2 presents the thorough literature assessment on various energy management techniques. The block diagram, descriptions, and general description of the proposed work are all provided in Section 3. In Section 4, numerous measures are used to validate the simulation analysis and compare the outcomes of the suggested methodology. Finally, Section 5 summarizes the entire study together with the conclusions and suggested next steps.

II. RELATED WORKS

Chen, et al [13] developed a hybrid energy storage system by optimizing the size and frequency of battery and super capacitor. For this purpose, a multi-objective optimization algorithm has been deployed for improving energy management with ensured power quality and components' life. This study indicates that a variety of energy management strategies are implemented in the previous works for improving energy efficiency. The methods are typically applied in accordance with the fact that these strategies may effectively control the power allocation in real-time. However, the effectiveness of these solutions mainly depends on subject-matter expertise and knowledge of engineering. In this design, the fuel cell stack is used as the main power source, which helps to satisfy the energy demand of ship. Here, both the passive and fully active topologies are used for an effective energy management of ship load. Wu, et al [14] deployed a reinforcement learning strategy for reducing the high cost consumption of hybridized energy sources. In this work, hybrid fuel cell and battery storage systems are used for satisfying the energy demand of ships. Here, the Markov Decision Process (MDP) based mathematical framework is deployed to solve the sequential decision-making problems. According to the availability of power and demand, the current system status is updated in this model. The suggested methodology considers the input of historical voyage power profile, and energy management solution to the future voyage is delivered as output for solving the energy management problem. In addition, this study considers some other parameter such as power demand, battery state of charge, power level of fuel cell, shore power availability, and power change fraction for reducing the cost.

Iris, et al [15] investigated the recent operational strategies, and technologies for improving the environment performance with better energy management. In this study, the different types of load applications including smart grid and micro-grid have been considered for analysis. Letafat, et al [5] utilized an improved Sine Cosine Algorithm (SCA) to optimize the energy management problem for ferry boat applications. Here, the non-linearity of fuel cell efficiency and operational limitations of fuel cells are taken into account for minimizing the operation cost of ferry ship. In addition, the authors concentrated on the simultaneous energy management and component sizing in the hybridized system. Nuchturee, et al [16] conducted a comprehensive review for maximizing the energy efficiency of maritime transportation. Moreover, an intelligent power management framework has been developed for optimally splitting power among different sources. In addition, several parameters used for validating the energy efficiency of ship management are investigated in this study, which includes ship energy efficiency management plan, energy efficiency operational indicator, and reference line. Furthermore, the distinct characteristics of various energy storage devices are analyzed in this paper that comprises the followings: power density, energy density, capacity, response time, efficiency and cycle life. The common drawbacks of the previous energy storage systems are requirement of high temperature, short life cycle, low reliability, and high environmental impact.

Fang, et al [17] provided a detailed overview about green maritime transportation with an economic and environmental benefits. Typically, seaport micro-grid is one of the newest technology for seaport management, which helps to improve the energy penetration and storage capacity. The study indicated that an active synchronization is the best way for connecting electric ship with seaport micro-grid. Han, et al [18] investigated about the voltage restoration and stabilization techniques in a hierarchical systems. Here, the Takagi-Sugeno and Lyapunov-Krasovskii models are implemented for minimizing the complexity of distributed energy systems. Moreover, the control and stability techniques are categorized into the types of primary control, upper control, and stability. The authors indicated that an optimization techniques play a major role in enhancing the current sharing performance of droop control. Yuan, et al [19] introduced a multi-energy hybrid power system with better reliability and efficiency for large-scale ship applications. Here, the different types of propulsion modes have been discussed in this study, which includes mechanical propulsion, electric propulsion, and hybrid propulsion mode. With additional working modes and significantly less fuel use, a hybrid series-parallel power system combines the benefits of both series and parallel designs, allowing for more flexible energy flow regulation and consumption optimization. A suitable control method is necessary due to the system's very complex structure and high cost. Hoang, et al [20] deployed a critical strategy to determine the best pathway for port to ship with reduced carbon emissions. One of the initiatives to ensure that the global shipping sector has a more sustainable and low-carbon future is to reduce the reliance of marine vessels on fossil fuels. This is accomplished by introducing ship propulsion systems that use alternate and cleaner fuels. Elberry, et al [21] investigated about the major issues and challenges in the electricity based storage systems. In this study, the energy storage systems are investigated and compared based on their storage time, size and cost. Nuchturee, et al [22] studied the recent developments in the field of electric propulsion for ship applications. The authors also discussed about the recent challenges and opportunities for an intelligent energy management. Khan, et al [23] presented a new study for examining the different types of energy storage techniques with the current status and trends. Table 1 shows the characteristic analysis of the different types of technologies used for ship energy management with their pros and cons.

Table 1: Characteristic analysis on RES in ships.

Reference	Technology used	Pros	Cons
[24]	Energy storage systems	Increased stability and reliability;	Lower lifetime and high cost consumption;
[25]	Solar-PV systems	Maximized energy efficiency, and requires low initial cost;	Requires frequent maintenance and limited lifetime;
[26]	Wind	Increased efficiency;	Increased capital cost, and fast degrading;
[27]	Ocean based energy generation	Suitable for multi-application domain, and maximized energy efficiency;	Ineffective technology development, and low reliability;
[28]	Geothermal	Maximized energy efficiency;	High-cost consumption, and low level of expertise;
[29]	Alternative fuels	Requires low cost and circular economy;	Low level of expertise and knowledge;
[31]	Power	Power quality problem	Always growing and becoming more sophisticated.

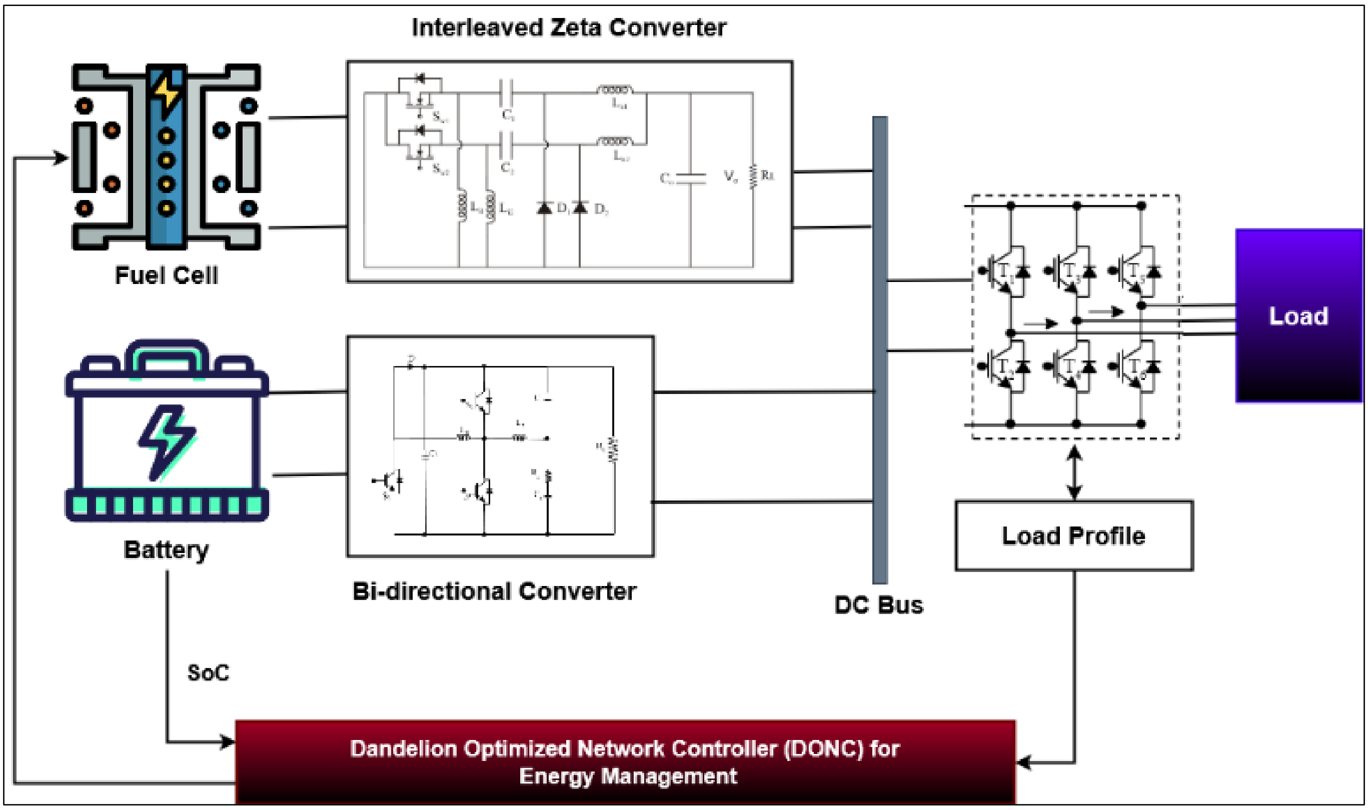
Source: Authors, (2023).

III. PROPOSED METHODOLOGY

This section provides the complete explanation for the proposed energy management system using hybridized sources for ship. The main contribution of this work is to effectively manage and control the power system of electric ship with the use of artificial intelligence algorithm. In order to control the energy consumption of electric ships, this article proposes an intelligent DONC model. Determining the proposed model's effectiveness at maintaining a constant DC bus voltage is the major goal of this investigation. These studies emphasize the EMS while focusing on the process of power decisions in hybrid power systems. The proposed design is a hybrid power model that includes a fuel cell as the main DC power source and a battery bank and supercapacitor as the energy storage system. The proposed block diagram is shown in Fig 1, which comprises the following components:

- Fuel cell modeling
- Battery storage modelling
- Interleaved Zeta converter
- Bi-directional converter
- Dandelion Optimized Network Control (DONC)

The battery and the output power of the fuel cell are regulated by a controller using the DC/DC converters that are connected to them in the control circuit block. According to the energy conservation strategy being employed, this control system has been set up accordingly. In order to allow DC/DC converters to adhere to the energy management system-determined DC bus voltage level, they need an output voltage reference and a minimal input/output current reference. This work aims to develop a new energy management system by using a hybridized energy sources with advanced controlling technique. In this framework, the electrical energy is obtained from the fuel cell and battery systems for satisfying the demand of ships. Then, the voltage regulation is performed with the use of interleaved zeta and bi-directional converters, which helps to improve the voltage gain. Moreover, the novel Dandelion Optimized Network Controller (DONC) is implemented to effectively perform energy management. Finally, the harmonic suppression is carried out with the use of inverter circuit, and the output is fed to the ship load.



Fi gure 1: Block diagram of the proposed ship controlling system.
Source: Authors, (2023).

III.1 HYBRID ENERGY SYSTEM

In hybrid systems, the required amount of power for the load is provided by at least two energy sources. Typically, the system is coupled with one or more renewable energy sources, a system for storing energy, or a fuel system that runs on fossil fuels or hydrogen [30]. One of the main issues is the stochastic existence of wind and photovoltaic (PV) energy resources. When wind is readily usable, it is typically ignored since it is frequently uncorrelated with load patterns. Additionally, solar energy may only be used throughout the daytime. In order to ensure cost-effectiveness, scientific, and design goals, it is necessary to optimize the hybrid system components with the fewest significant random variables. Hybrid systems are anticipated to use an optimization method that coordinates with the (EMS) to determine which source provides the load with the required amount of power or the amount of power should be provided for every point of reference to reduce the use of fuel while preserving stability of the system. The supercapacitor power is not taken into consideration in the optimization problem because the battery converter controls the DC-bus voltage. The supercapacitors are discharged or recharged with the identical energy from the battery device during each cycle, which balancing the load power between the fuel cell and the battery.

$$\mathrm{Pow_L} = \mathrm{Pow_{FC}} + \mathrm{Pow_B} \qquad (1)$$

$$\mathrm{Pow_{FC}} = \mathrm{minimum}\ (\mathrm{N_{FC}} + \varphi_1 \mathrm{N_B} + \varphi_2 \mathrm{N_{SC}}) \qquad (2)$$

Where, $\mathrm{Pow_L}$ is the load power, $\mathrm{Pow_{FC}}$ denotes the fuel cell power, $\mathrm{Pow_B}$ represents the battery power, $\mathrm{N_{FC}}$ indicates the number of fuel cells, $\mathrm{N_B}$ represents the number of battery storage systems, and φ_1 and φ_2 are the penalty coefficients.

III.2 INTERLEAVED ZETA CONVERTER

In the proposed framework, an interleaved Zeta converter has been used to regulate the output voltage of fuel cells. The output voltage of the Zeta converter is not inverting. To achieve high efficiency along with excellent control of the voltage to its load, a single-stage dc-dc power converter is used. Compared to the traditional Zeta converter, this converter has a larger duty-ratio range and a greater voltage of supply variance. High efficiency, a lower voltage ripple, reduced distortion, and controllable voltage of the output are only a few of the operating benefits of the Interleaved Zeta converter. The electromagnetic interference will also be lessened as a consequence of the continuous input current and smaller filter component sizes. The circuit model of an interleaved zeta-converter is shown in Fig 2, and its mode of operations from mode 1 to mode 4 are represented in Fig 3 (a) to (d) respectively.

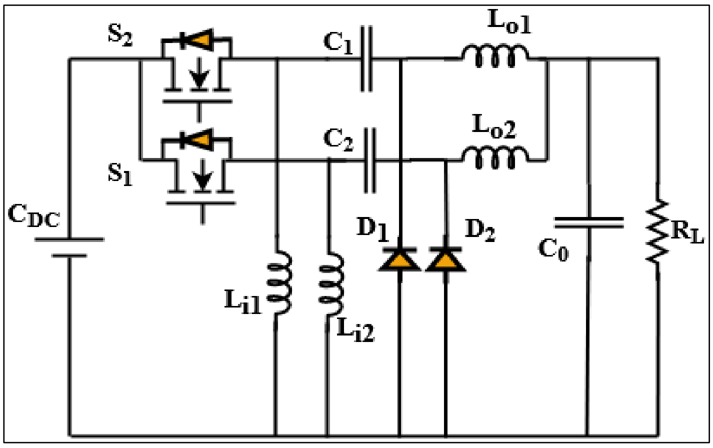


Figure 2: Circuit model of interleaved Zeta converter.
Source: Authors, (2023).

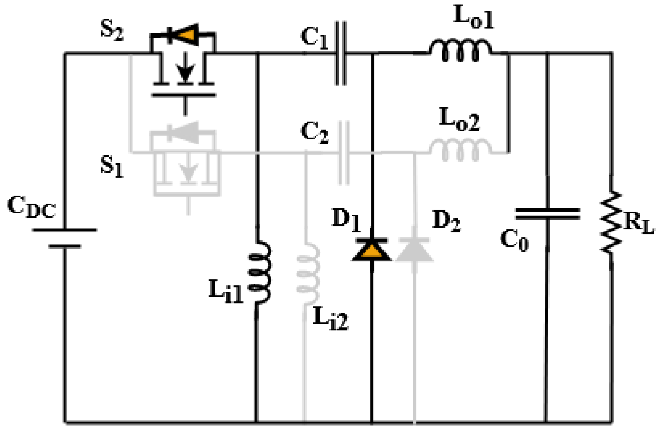


Figure 3 (a): Converter mode 1.

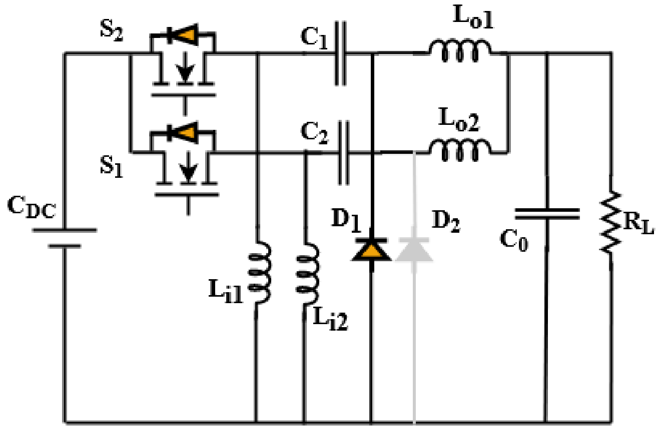


Figure 3 (b): Converter mode 2.

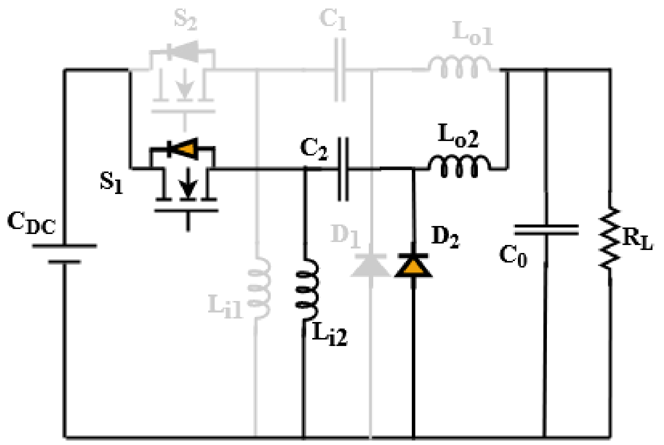


Figure 3 (c): Converter mode 3.

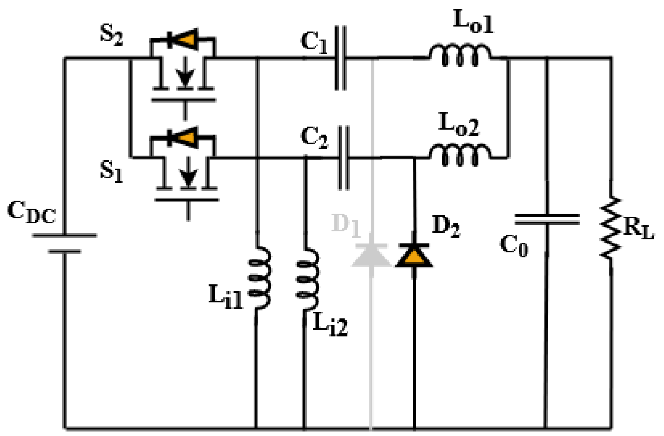


Figure 3 (d): Converter mode 4.

Figure 3: Converter mode 1, 2, 3 and 4.
Source: Authors, (2023).

III.3 BI-DIRECTIONAL CONVERTER

The bi-directional DC-DC converter is used in this instance to charge the batteries and provide increased power to the ship board. Fig 4 depicts the suggested bidirectional converter's schematic diagram, which has 3 switches, 4 capacitors, and 2 inductors that are used to raise the load's current. With a smaller circuit size and less power loss, this converter design achieves higher efficiency. The inductors' and capacitors' charging and discharging periods have a big impact on how well this converter functions. Here, modes 0 and 1 of the bidirectional converter equivalent circuit can be used. During mode 0, the voltage and current of the converter is estimated by using the following equations:

$$V_{L1} = V_{FC} - V_{R_S} \tag{3}$$

$$V_{L2} = V_{FC} - V_{C1} \tag{4}$$

$$i_{c1} = i_{c4} = I_{FC} - I_{R_S} \tag{5}$$

$$V_{c4} = i_{L2} - \frac{V_{R2}}{R_L} \tag{6}$$

Similarly, the voltage and current during mode 1 state are estimated by using the following equations:

$$V_{L1} = V_{FC} - V_{c1} - V_{L2} \tag{7}$$

$$V_{L2} = -V_B + V_{C4} \tag{8}$$

$$i_{c1} = \frac{I_{L1} - I_{L2}}{2} \tag{9}$$

$$i_{c4} = i_{L2} - \frac{V_{R2}}{R_1} \tag{10}$$

Where, V_{L1} and V_{L2} represents the voltage of inductors, V_{c1} and V_{c2} are the voltage of capacitors, I_{L1} and I_{L2} represents the inductors' current, R_1 and R_2 are the resistors, R_L is the resistive load, and R_S is the series resistance. The circuit model of converters' operating modes are presented in Fig 5 (a) and (b).

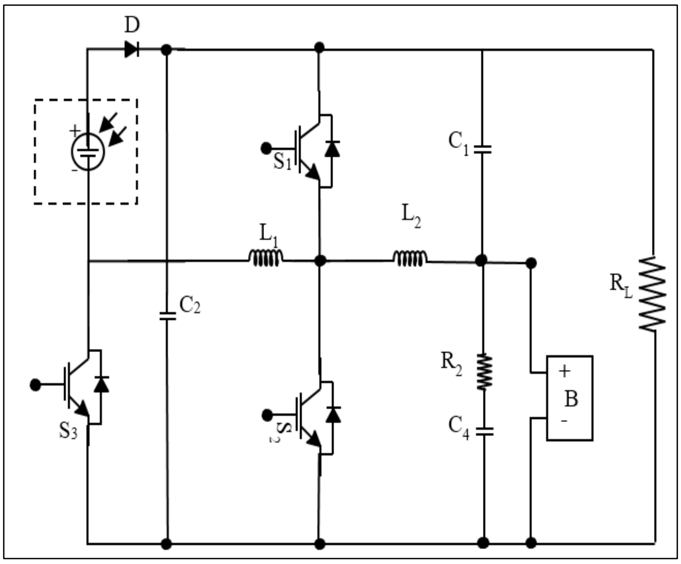


Figure 4: Bi-directional converter circuit model.
Source: Authors, (2023).

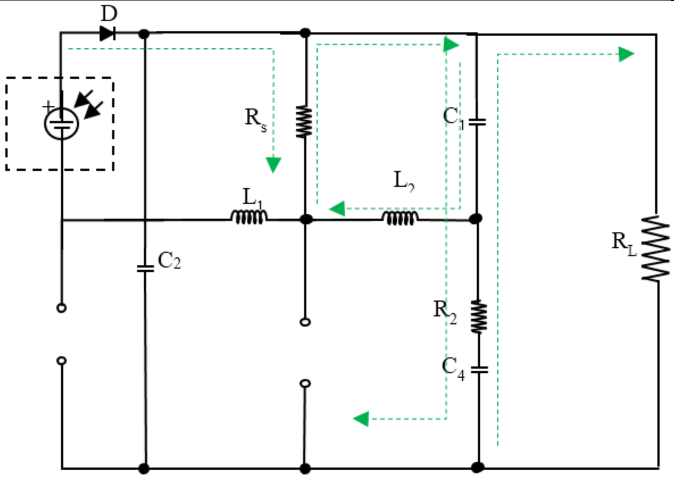


Figure 5 (a): Converter Mode 0.

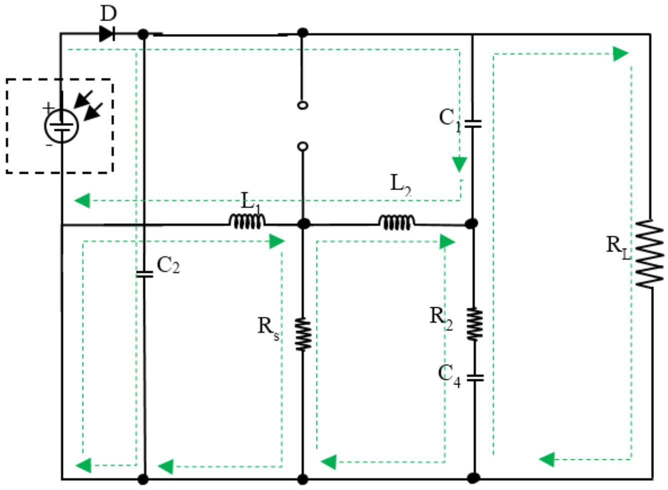


Figure 5 (b): Converter Mode 1.

Figure 5: Converter Mode 0 and 1.
Source: Authors, (2023).

III.4 DANDELION OPTIMIZED NETWORK CONTROLLER (DONC)

In order to ensure an effective energy management for electric ship applications, an advanced Dandelion Optimized Network Controller (DONC) is used in this study. In the previous works, several AI based controlling mechanisms are applied for an effective energy management, but they facing issues with high computational complexity, larger computational time, and slow processing speed. Therefore, this research work aims to develop a new controlling algorithm by integrating the functions Dandelion Optimization (DO) technique with a Fictitious Neural Network (FNN). In this technique, the output power of load and battery SoC are considered as the input parameters, and the predicted output power of fuel cell is produced as the output. The FNN is an advanced neural network model, which is used to solve the complex prediction problems with suitable solutions. In this work, it is used to predict the output power of the fuel cell for an effective energy management of ship board. It comprises the layers of input, hidden and output, where the input layer gets parameters of output power of load and battery SoC, and the output layer produces the predicted power of fuel cell as the output. During this process, the weight value is optimally computed with the use of DOA. The DO algorithm models the three phases of the dandelion seed's journey from one location to another dependent on the direction of the wind. The seeds rise in a spiral pattern during the first phase of development, which is aided by bright conditions and drag force. Additionally, the dandelion seeds scatter locally when it rains. This variation in height results in two distinct possibilities for the search, namely a randomly settle at various spots while being influenced by the wind and weather, eventually growing into new dandelions. It works based on the iterative process similar to other optimization techniques. Prior to starting the optimization process, the DO algorithm entails setting up the dandelion seeds and figuring out their fitness function. Moreover, it includes the following stages:

1. Parameter initialization
2. Rising phase
3. Descending phase
4. Landing phase
5. Best optimal solution

By using these operations, it provides the best optimal solution as the output, which is used to compute the weight value of FNN. According to this, the FNN technique predicts the output power of fuel cell for an efficient energy management.

IV. RESULTS AND DISCUSSION

This section provides the simulation results of the proposed energy management system used for shipboard applications. In this study, the MATLAB/Simulink tool has been used to test the results of the proposed energy management system. The simulation parameters are given in Table 1. The fuel cell system is made to handle load demands between 0 and 10 kW. Under interrupted and continuous peak demand scenarios, the storage system's supercapacitors and batteries are intended to make up for the fuel cell's sluggish dynamic response.

Table 1: Energy management simulation parameters.

Parameters	Specifications
Fuel cell	10 kW
Battery power for charging mode	-1.2 kW
Battery power for discharging mode	4 kW
Battery SoC	40% to 100%
DC Voltage	280 V

Source: Authors, (2023).

Fig 6 shows the load power and fuel cell power with respect to varying time in terms of seconds. Here, the load power denotes the actual demand of load, and the fuel cell power represents the energy generated by the fuel cell. The findings reveal that the load demand is higher than the energy generated by the fuel cell. Here, the battery is used as the supplementary storage that satisfies the remaining required energy of load. Consequently, the battery current is estimated with respect to varying time in terms of seconds as shown in Fig 7. Consequently, the load power and fuel cell power, and the battery current for normal SoC are represented in Fig 8 and Fig 9 respectively.

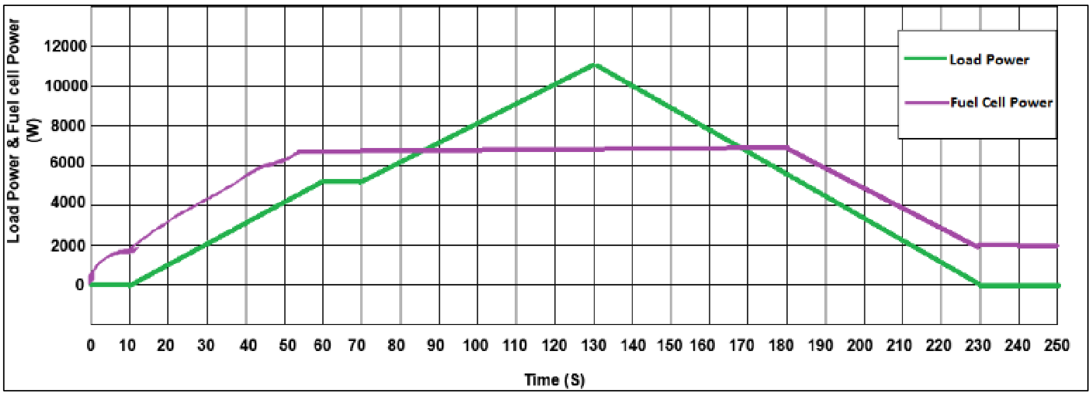


Figure 6: Load power and fuel cell power for high SoC.
Source: Authors, (2023).

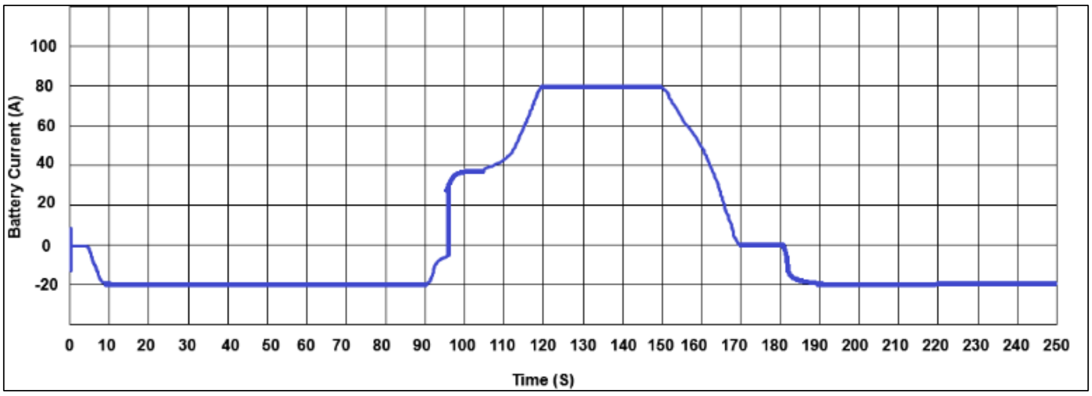


Figure 7: Battery current for high SoC.
Source: Authors, (2023).

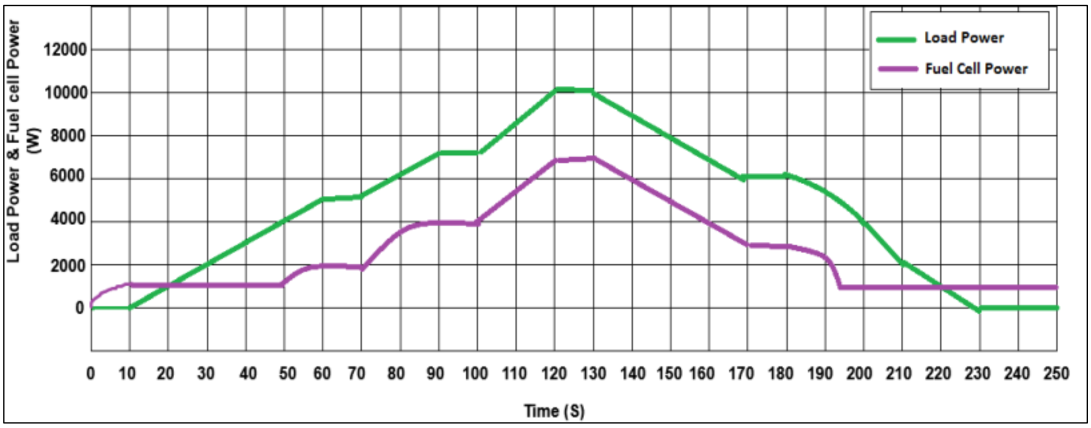


Figure 8: Load power and fuel cell power for normal SoC.
Source: Authors, (2023).

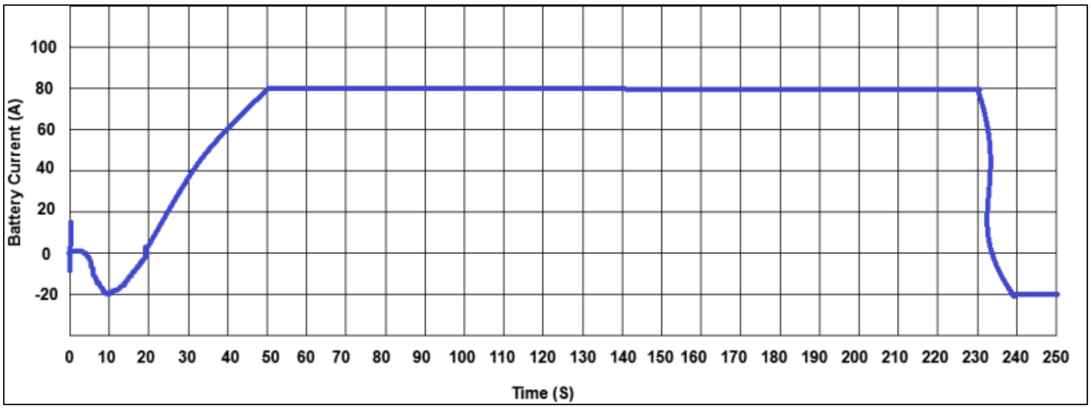


Figure 9: Battery current for normal SoC.
Source: Authors, (2023).

Fig 10 shows the fuel cell power with high SoC of battery storage. Due to the high battery storage capacity in this mode, the EMS must draw power from the battery to lower the charge mode from high to regular SoC since the fuel cell cannot provide as much power as the load requires to supply the load. The results indicate that the output power of fuel cell is lower than the load demand, and the required remaining power is taken from the battery.

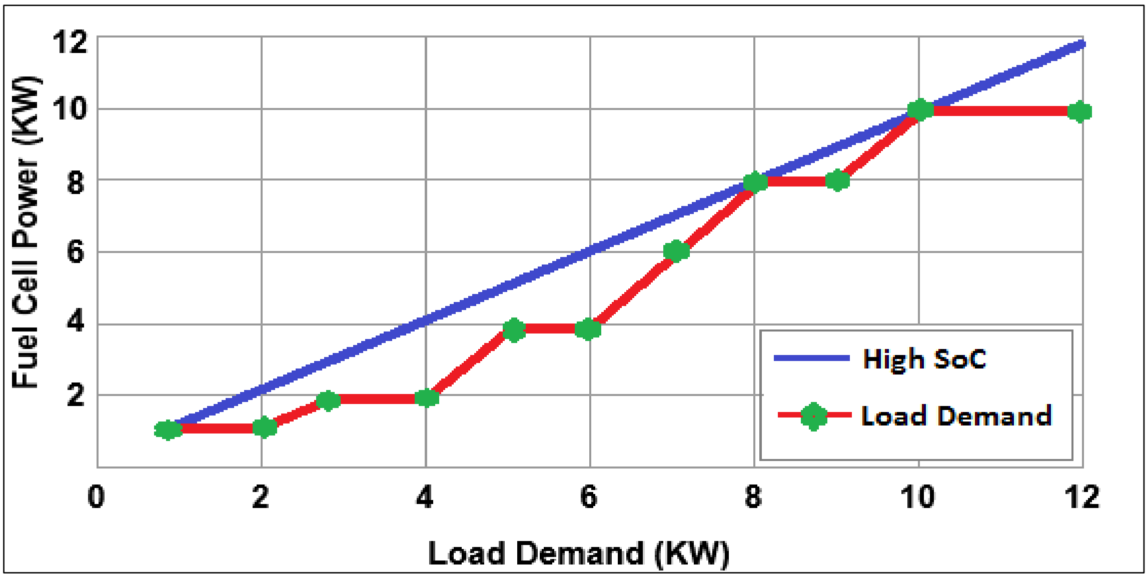


Figure 10: Fuel cell power Vs High SoC.
Source: Authors, (2023).

Similarly, Fig 11 shows the fuel cell power with respect to normal SoC of battery. In this mode, the ideal operation mode of battery efficiency and health of batteries is the SoC from 65% to 85%. In order to maintain the battery's condition of charge, the EMS tray only keeps up with the load demand. According to the waveforms, it is identified that the two waveforms are identical, which denotes that the load demand is equal to the output power of fuel cell.

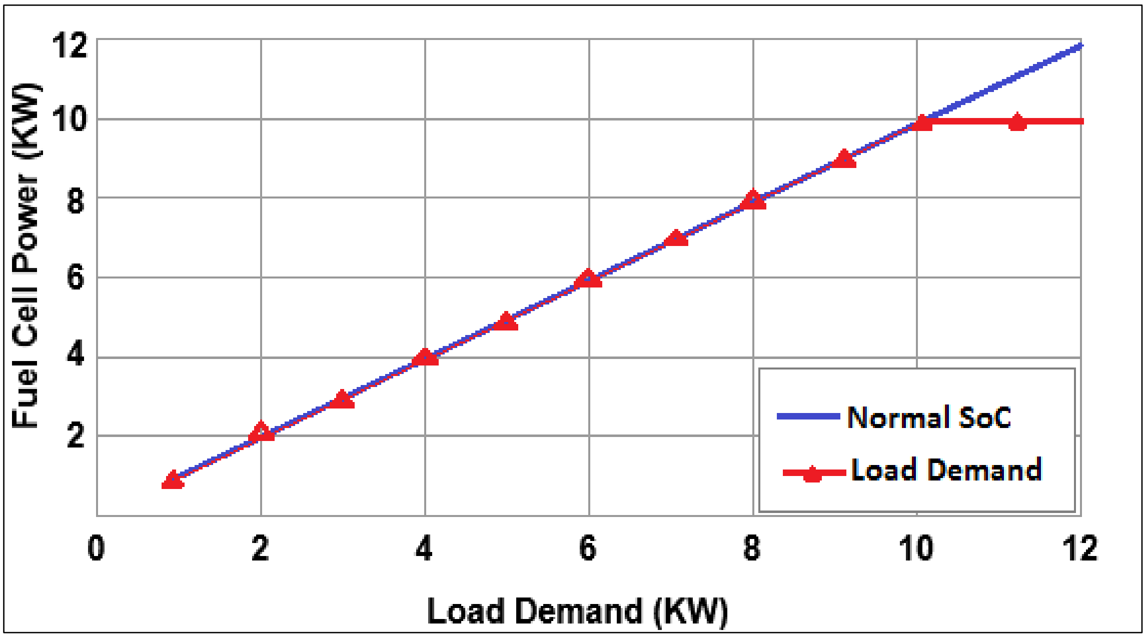


Figure 11: Fuel cell power Vs Normal SoC.
Source: Authors, (2023).

Fig 12 shows the fuel cell power with low SoC of battery. A low battery SoC shows that there is insufficient energy in the battery. This is because the EMS modifies the fuel cell to generate additional power than the load demand in order to serve the load and recharge the battery. The estimated waveforms indicate that the output power of fuel cell is higher than the load demand, and residual energy is used for charging battery.

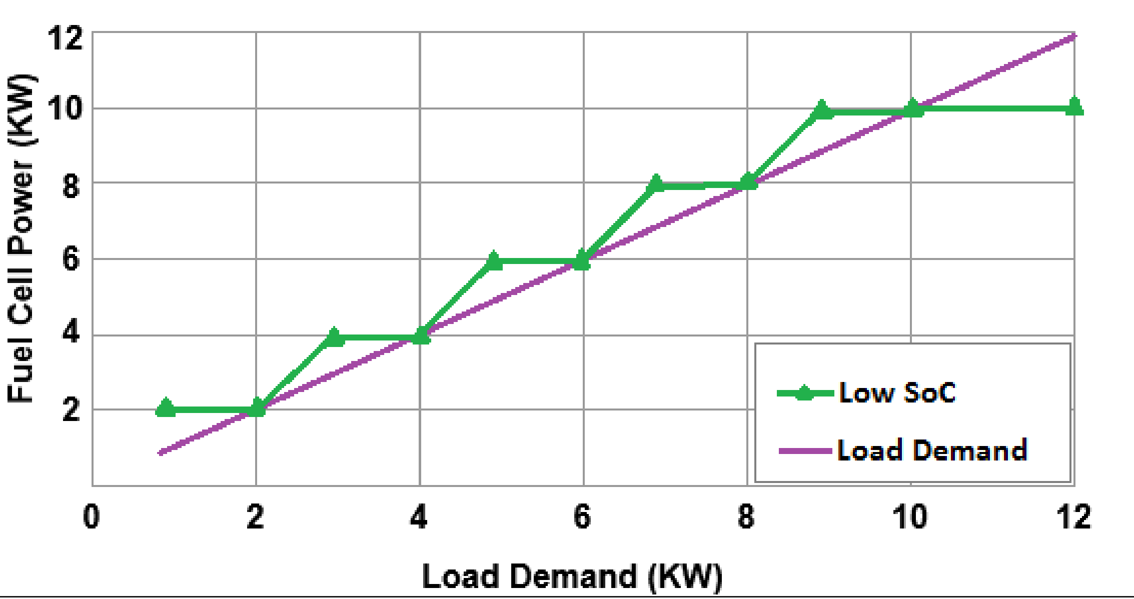


Figure 12: Fuel cell power Vs Low SoC.
Source: Authors, (2023).

V. CONCLUSION

This research's major goal is to create a new energy management system to meet the load requirements of ship board applications. In this work, an innovative controlling mechanism called DONC is devised to achieve this goal. In this design, the fuel cell serves as the primary source of energy while the battery storage serves as an additional storage device. This is known as a hybridized energy source. Additionally, two distinct converter topologies, including a bi-directional converter for battery storage and an interleaved zeta converter for fuel cells, are used in this work. These converters are primarily used to efficiently increase the output voltage of hybridized energy sources while minimizing ripple current and distortions. The suggested DONC blends the DO techniques and FNN's functionalities for forecasting fuel cell output power. In order to manage energy effectively on an electric ship board, the FNN technique collects the input parameters of load demand power and battery SoC during this process. With the help of the DO algorithm, the weight value of the FNN is ideally determined in this manner. Increased efficiency, effective energy management in accordance with load demand, and dependability for ship applications are the main advantages of the proposed DONC. In the simulation analysis, the normal, high, and low battery SoC states are used to determine the load demand and fuel cell power. The results show that the suggested DONC can efficiently monitor and control the energy requirements of electric ships using a hybridized energy system. The current study can be expanded in the future to include other renewable energy sources like solar panels and diesel generators for the control of electric ship energy.

VI. DECLARATION STATEMENT

Conflict of Interest: The authors declare that they have no conflict of interest.
Competing Interests: The authors have no competing interests to declare that are relevant to the content of this article.
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Data Availability: Data sharing not applicable to this article as no datasets were generated or analyzed during the current Study.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: P. Senthil Kumar and T. Kanimozhi.
Methodology: P. Senthil Kumar and T. Kanimozhi.
Investigation: P. Senthil Kumar and T. Kanimozhi.
Discussion of results: P. Senthil Kumar and T. Kanimozhi.
Writing – Original Draft: P. Senthil Kumar and T. Kanimozhi.
Writing – Review and Editing: P. Senthil Kumar and T. Kanimozhi.
Resources: P. Senthil Kumar and T. Kanimozhi.
Supervision: P. Senthil Kumar and T. Kanimozhi.
Approval of the final text: P. Senthil Kumar and T. Kanimozhi.

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RESEARCH ARTICLE OPEN ACCESS

MICROSTRUCTURAL CHARACTERIZATION OF FRICTION STIR WELDED AA5083 ALUMINUM ALLOY JOINTS

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ABSTRACT

The objective of the current work is to apply Taguchi L9 orthogonal array to enhance the welding process factors for friction stir welding (FSW) of AA5083 aluminium alloy plates. Using a randomized procedure, the Taguchi orthogonal array was implemented to identify the FSW process parameters such as the rotating speed of the tool, welding speed, and tilting angle of the tool. The optimum welding parameters for the ultimate tensile strength and hardness of the joints were predicted and the individual rank of each process parameter on the ultimate tensile strength and hardness of the friction stir weld was assessed by investigative ANOVA results and the S/N ratio (signal-to- noise ratio). The most desirable rotational speed of the tool, welding speed and tilting angle of the tool were 600 rev. per. min, 70 millimeter/min and 1o appropriately for the ultimate eluting strength and 600 rev. per. min, 80 millimeter/min and 1o correspondingly for summit joint hardness. The outcomes of Analysis of Variance (ANOVA) designated that the tilting angle of the tool has the higher statistical effect succeeded by the welding velocity and rotational speed of the tool. Furthermore, metallurgical properties of the weld cross-sections were investigated by using optical microscope (OM), scanning electron microscope (SEM), energy dispersive spectroscopy (EDS) analysis. The microstructure of the stir zone reveals finer grain structure, directed to the higher hardness, which gives rise to higher tensile strength.

I. INTRODUCTION

Aluminum alloy AA 5083 is an Al-Mg based alloy that has many interesting properties such as structural material, moderately high strength, good corrosion resistance and low cost. These benefits are very attractive in the automobile industry and marine applications. Also, AA5083 is having light weight structures, high specific strength, good fracture toughness and excellent corrosion resistance. Traditional fusion procedures are used to join typical aluminium alloy joints, which have an impact on the weld joint's dispersion and encourage the formation of enhanced efficiency during the heat cycle [1, 2]. It is challenging to attain a sound welded joint due to the incidence of petrification fissures, scum enclosures and coarse grain porosities in the fusion welding of aluminum alloys [3]. Friction stir welding (FSW) has developed a technology of extensive attention because of its several benefits, vital of which is its facility to weld otherwise unweldable alloys [4]. Compared with several of the fusion welding processes that are normally used for joining structural alloys, Friction Stir Welding is an emerging solid state joining method that avoids melting and recasting the material being joined [5].

II. THEORETICAL REFERENCE

The FSW process parameters are influenced by the mechanical and metallurgical properties of the welded joints [6]. Research has focused on examining how these factors, such as welding speed (mm/min), rotational speed of the tool (rpm), axial load (kN), tool geometry (like round, threaded, square, polygons etc.), tilting angle of the tool etc., affect the welded specimen's output characteristics to ascertain their separate influences [7, 8].

Taguchi statistical design is a powerful tool to identify significant factor from many by conducting relatively less number of experiments [9]. Furthermore, some authors aims to optimize the FSW process parameters of aluminum alloys using Taguchi orthogonal array technique [10]. Similarly, Kolraj et al. [11] studied the Taguchi method to optimization of FSW process parameters for joining of dissimilar AA2219 Al-Cu alloy and AA5083 Al-Mg alloy.

Shojaeefard et al. [12] optimized the FSW process parameters with different pin profile, rotational speed, welding speed, tilt angle, shoulder diameter, pin diameter, shoulder concave angle and penetration depth by using Taguchi orthogonal array. Ravichandran et al [13] studied the role of FSW process parameters like welding speed, tool rotation speed, tool pin profile and shoulder diameter of tool on the output of elongation percentage and tensile strength of the joint. Kimura et al [14] examined the optimized process parameters during the AA5052 friction welding process.

The joint, which was in the perimeter softened area, had a joint efficiency of about 93% and broke in the base metal (BM). Geng et al. [15] optimized friction welding of aeronautic aluminum alloy 2024 joints. The optimized joint efficiency from Taguchi analysis reaches 92% of base metal and the fine recrystallized grains caused by the high temperature and plastic deformation are observed in the friction interface zone. During the FSW process, the material undergoes intense plastic decomposition at high temperatures, resulting in fine and balanced recrystallized grains [16, 17].

Excellent microstructure in friction stir welds creates good mechanical properties. In this study, Taguchi L9 Orthogonal Array (OA) method was used in order to optimize the mechanical properties of friction stir welding on AA5083 joint. After identified the optimum joint, tensile and hardness test were done to investigate the mechanical properties of the weld. The metallurgical properties were investigated with various sectors like Nugget Zone (NZ) Heat-Affected Zone (HAZ) and Thermo Mechanically Affected Zone (TMAZ) by using Optical Microscope (OM), Scanning Electron Microscopic (SEM) and Energy Dispersive X-Ray Spectroscopy (EDS) analysis. Furthermore, the microhardness survey was conducted across the weld zone to study the metallurgical effects of the friction stir weld joint.

III. MATERIALS AND METHODS

The present study was performed on AA5083 aluminium alloy with a thickness of 6 mm plates. The chemical composition and mechanical properties of the base metal AA5083 is given in Table 1 & Table 2. The AA5083 plates with dimensions of 120 mm×100 mm×6 mm were friction stir welded in the butt configuration using a vertical CNC milling machine. Welding was carried out on the butt joint structure using a friction stir welding machine. The butt joints were fabricated standard to the rolling direction. The experiments were performed using FSW process parameters of the designed L_9 OA.

The following FSW process parameters were used for joiningof AA5083 like tool rotational speeds, tool welding speeds and Tool tilt angle (θ). The tools made of H13 grade tool steel with dimensions of pin length 5.70 mm, pin diameter 6 mm, tool shoulder 16 mm and shank 40 mm is shown in Fig.1. The pin is positioned at the center of the joint line and the welding tool is rotated clockwise direction during the joining process.

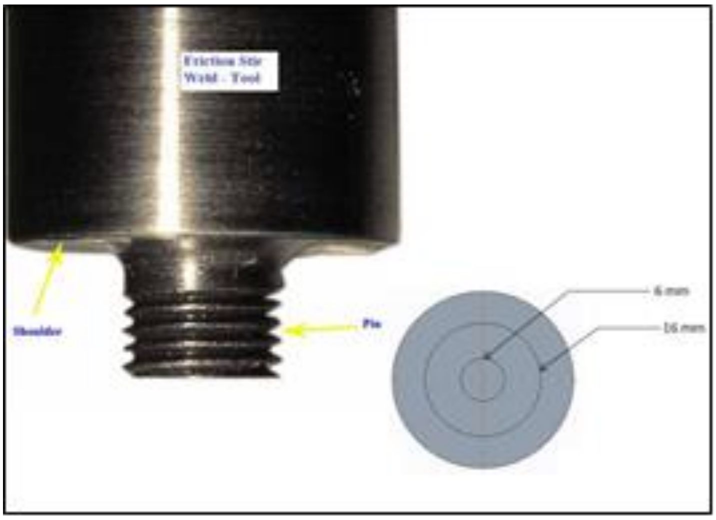

Figure 1: Friction Stir Welding Tool Specification.
Source: Authors, (2023).

The Taguchi method was used to optimize the welding parameters for friction stir welded AA5083 aluminium alloy for these investigations. In this method, the total degree of freedom (DOF), which can be computed by aggregating the individual DOF of each parameter, must be taken into consideration before selecting an appropriate orthogonal array.

Three levels were considered for each of the three process parameters for this experimentation. The levels of the each FSW process parameters were selected based on preceding literatures and given in Table 3. Hereafter, a L_9 orthogonal array with eight DOF was selected to assess how the welding parameters affect the final tensile strength and hardness of the joints.

Samples for tensile tests were prepared in accordance with ASTM E8 M-04 standard and the wire- cut Electrical Discharge Machining (EDM) was used to cut the smooth profile tensile specimens. The room-temperature tensile tests were conducted for all the samples on a universal tensile testing machine. Figure 5 shows tensile test samples of ASTME8M04 standard CAD model and FS welded AA5083 materials. Hardness test were conducted on weld nugget zone by using Vicker's microhardness machine. Microhardness tests samples were prepared according to ASTM standard and applied 0.5kgf with 10 seconds. The cross-sectioned samples were mounted in Bakelite, then ground and polished successively with diamond paste. The polished samples were etched with Keller's reagent for 25 s, and then analyzed optically for microstructural variations and possible flaws with a Nikon DIC microscope with a Clemex image analysis system. After fabricated FS welded specimens the SEM and EDX analysis were conducted.

Table 1: Chemical composition of AA5083 (Wt %).

Element	% (Percentage)
Silicon (Si)	0.14
Copper (Cu)	0.018
Ferrous (Fe)	0.30
Magnesium (Mg)	4.6
Chromium (Cr)	0.1
Titanium (Ti)	0.027
Zinc (Zn)	0.009
Manganese (Mn)	0.63
Aluminium (Al)	Bal

Source: Authors, (2023).

Table 2: Mechanical characteristics of AA5083.

Parent Material	AA5083
Ultimate Tensile Strength (MPa)	315
Yield Strength (MPa)	225
Percentage of Elongation (%)	15
Rigidity / Hardness (HV)	95

Source: Authors, (2023).

Table 3: Operational parameter – 3 Levels & 3 factors.

S.No	Operational Variables	Levels		
		1	2	3
1	Rotational Speed of the Tool (Rpm)	600	750	900
2	Welding Speed (mm/min)	70	85	100
3	Tilting Angle of the Tool (ϴ)	0	1	2

Source: Authors, (2023).

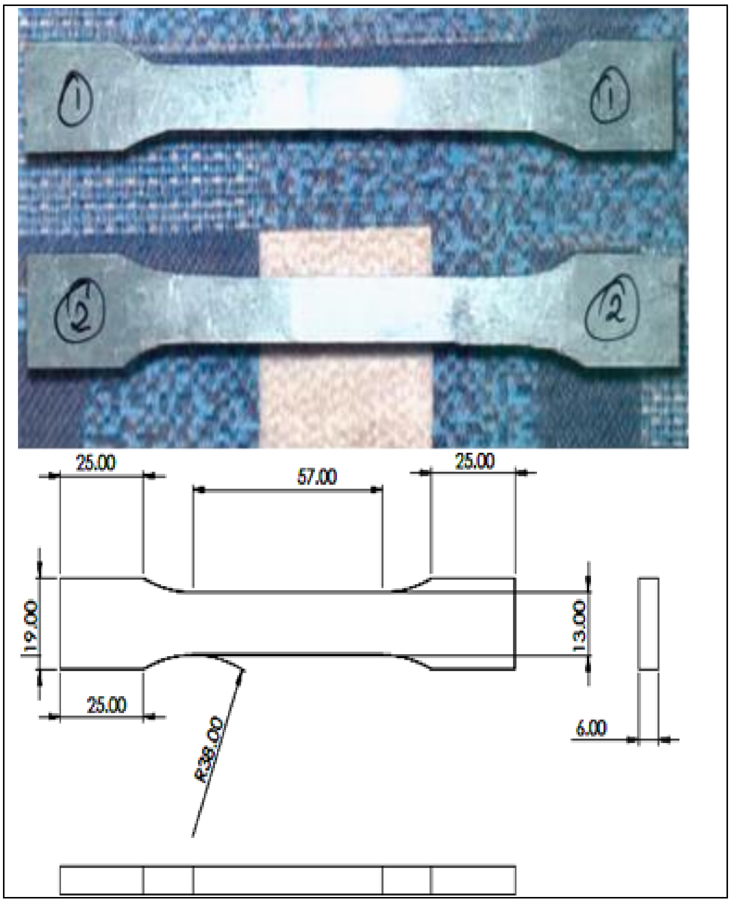

Figure 2: Tensile test specimens according to ASTM E8 M-04.
Source: Authors, (2023).

IV. RESULTS AND DISCUSSIONS

IV.1 SIGNAL TO NOISE (S/N) RATIO

The Signal to Noise (S/N) ratio is considered, based on the quality of the characteristics envisioned. The main aim designated in this study is maximization of the tensile strength and microhardness. Therefore, it is necessary to determine the higher and enhanced Signal-to-Noise ratio (S/N ratio). The tensile strength and microhardness of the nine test piece FSW joints values is considered to study the effects of the FSW process parameters given in Table 4. The experimental values of tensile strength and microhardness are converted into mean and SN ratio.

The calculated mean and S/N ratio values are tabulated in Table 5. The S/N ratio tensile strength and microhardness values of all levels are calculated and listed in Tables 6 and 7. The higher S/N ratio corresponds to the superior quality characteristics [18, 19]. The optimal level setting based on the S/N ratio values is R1S1T2 for tensile strength were obtained in Table 6. Based on S/N ratio values the optimal level setting is R1S2T2 for hardness were obtained in Table 7.

IV.2 ANALYSIS OF VARIANCE (ANOVA)

The purpose of ANOVA is to find a statistically significant factor. It gives a strong depiction as to exactly how distant the FSW process parameter affects the responses of tensile strength and hardness and the level of significance of the influence considered.

Table 4: Process parameters and their responses.

Trails	Rotational Speed of the Tool (RPM)	Welding Speed (mm/ min)	Tilting Angle of the Tool (ϴ)	Tensile Strength (MPa)	Rigidity/ Hardness (Hv)
1	600	70	0	190.15	87
2	600	85	1	189.09	93
3	600	100	2	151.54	81
4	750	70	1	206.01	86
5	750	85	2	136.90	89
6	750	100	0	150.98	84
7	900	70	2	141.03	80
8	900	85	0	133.30	85
9	900	100	1	192.33	87

Source: Authors, (2023).

Table 5: Investigational Report with S/N ratio value.

Trails	Rotational Speed of the Tool (RPM)	Welding Speed (mm/ min)	Tilting Angle of the Tool (ϴ)	Tensile Strength (MPa)	Rigidity/ Hardness (Hv)
1	600	70	0	45.58	38.79
2	600	85	1	45.53	39.36
3	600	100	2	43.61	38.16
4	750	70	1	46.27	38.69
5	750	85	2	42.72	38.98
6	750	100	0	43.57	38.48
7	900	70	2	42.98	38.06
8	900	85	0	42.49	38.58
9	900	100	1	45.68	38.79

Source: Authors, (2023).

Table 6: Response Table for S/N Ratios for Tensile strength.

Level	Rotational Speed of the Tool (RPM) (R)	Welding Speed (mm/min) (S)	Tilting angle of the Tool (ϴ) (T)
1	44.91	44.95	43.89
2	44.19	43.59	45.83
3	43.72	44.29	43.11
Delta	1.19	1.36	2.72
Rank	3	2	1

Source: Authors, (2023).

Table 7: Response Table for S/N Ratios for Microhardness.

Level	Rotational Speed of the Tool (RPM) (R)	Welding Speed (mm/min) (S)	Tilting angle of the Tool (Θ) (T)
1	38.78	38.51	38.62
2	38.72	38.98	38.95
3	38.48	38.48	38.41
Delta	0.30	0.50	0.54
Rank	3	2	1

Source: Authors, (2023).

The ANOVA table for mean value of tensile strength and hardness are calculated and given in Table 8 and Table 9. Figures 3 and 4 depict the mean and S/N ratio main effects plots, respectively. Furthermore, the F-test termed after Fisher can also be used to determine which process has a significant effect on tensile strength and hardness.

The high F value indicates that the factor is highly significant in affecting the response of the process. In our investigation, tool tilt angle is a highly significant factor and plays a major role in affecting the tensile strength and hardness of the friction stir welded joints.

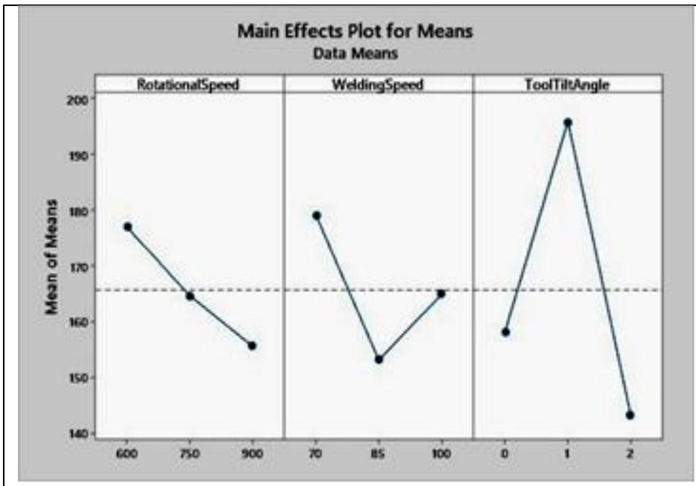

Figure 3.a: Means Plot.

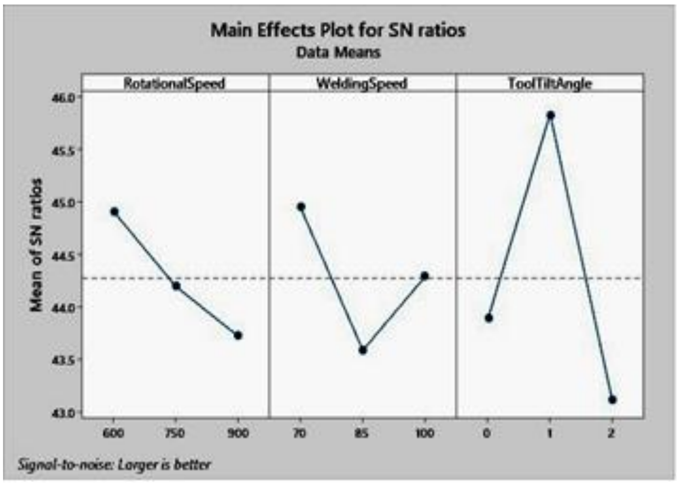

Figure 3.b: S/N Ratio Plot.

Figure 3.a & 3.b: Main effect plots on Tensile Strength.

Source: Authors, (2023).

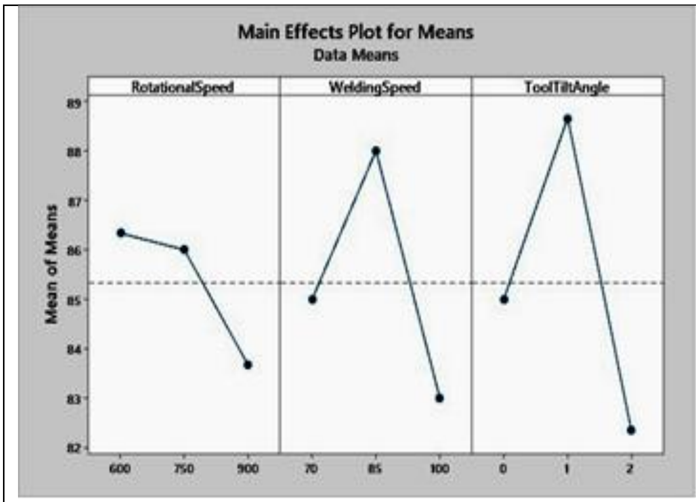

Figure 4.a: Means Plot.

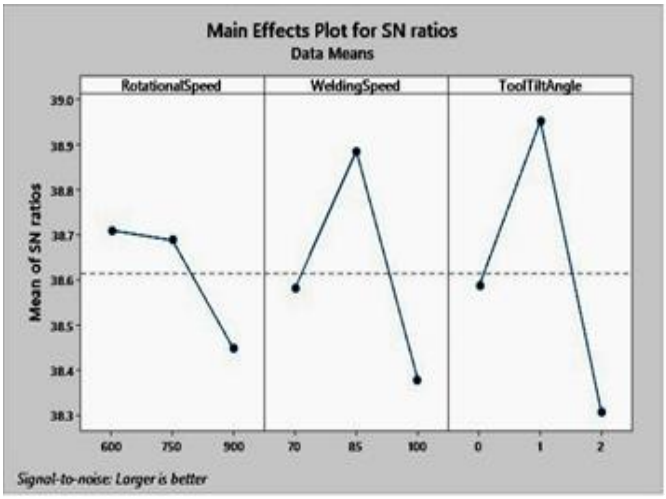

Figure 4.b: S/N Ratio Plot.

Figure 4.a & 4.b: Main effect plots on hardness.

Source: Authors, (2023).

Table 8: Analysis of Variance for tensile strength.

Source	DoF	Adjusted Sum of Squares	Adjusted Mean Squares	F Value	P Value	Percentage of contribution
Rotational Speed of the Tool (RPM) (R)	2	690.4	345.2	2.62	0.27	10.81
Welding Speed (mm/min) (S)	2	1014.0	507.0	3.84	0.20	15.88
Tilting angle of the Tool (Θ) (T)	2	4415.8	2207.9	16.74	0.05	69.17
Error	2	263.8	131.9			4.13
Total	8	6383.9				

Source: Authors, (2023).

Table 9: Analysis of Variance for hardness.

Source	DoF	Adjusted Sum of Squares	Adjusted Mean Squares	F Value	P Value	Percentage of contribution
Rotational Speed of the Tool (RPM) (R)	2	14.89	7.44	0.74	0.576	11.85
Welding Speed (mm/min) (S)	2	46.89	23.44	2.32	0.301	37.34
Tilting angle of the Tool (Θ) (T)	2	43.56	21.77	2.15	0.317	34.69
Error	2	20.22	10.11			16.10
Total	8	125.56				

Source: Authors, (2023).

Based on the experimentations, the optimum level setting was identified for the responses of tensile strength are R-1S-1T-2 and hardness is R-1S-2T-2. At certain levels of key parameters, the maximum value of ultimate tensile strength was projected. Significant FSW process parameters and their optimum levels have already been selected as rotational speed (level 1) of 600 rpm and Welding Speed (level 1) of 70 mm/min and tool tilt angle (level 2) 1 degree in Table 6.

Also, the optimum value of hardness was predicted at selected levels of significant parameters. Significant FSW process parameters and their optimum levels have already been selected as rotational speed (level 1) of 600 rpm and Welding Speed (level 1) of 85mm/min and tool tilt angle (level 2) 1 degree in Table 7. Confirmation tests were carried out with a cylindrical threaded pin profile and other process parameters were set at their predicted optimal levels. Three tensile and hardness specimens were subjected to tensile and hardness testes, and the average value of the friction stir welded AA5083 was 216 MPa and 97HV.

IV.3 MICROSTRUCTURE OF FRICTION STIR WELDED AA5083 OPTIMUM JOINT

The microstructure of the base metal and welded material was characterized using optical microscopy (OM) and scanning electron microscopy (SEM). The examined specimens cut from the transverse cross section of optimum weld were ground and polished according to the standard procedures and then etched with Keller's reagent for Observation. Fig.5 shows the microstructure of base metal AA5083 where Mg2Si eutectic constituents in the same direction in primary aluminum solid solution.

This is affected by the effect of the shoulder of the tool, which is much wider than the tool itself. When it touches the plate, the shoulder produces a stirring effect, which spreads down into the plate. On the top side, a small ridge can be seen where the travel and the rotation directions of the shoulder coincide. Fig. 6 also shows the friction stir welded Thermo Mechanically Affected Zone (TMAZ) close to the nugget zone. Several Mg2Si particles dissolved into the metal matrix, and the grains exhibit part re-crystallization.

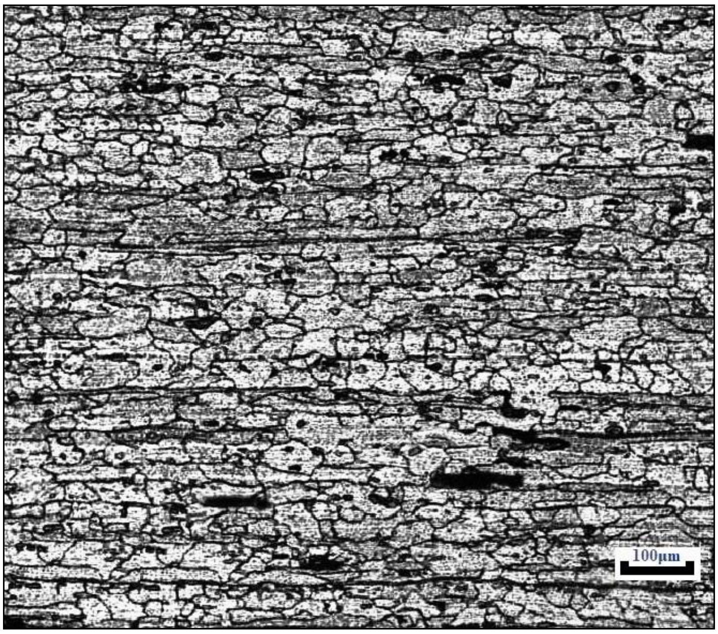

Figure 5: Microstructure of the base metal AA5083.
Source: Authors, (2023).

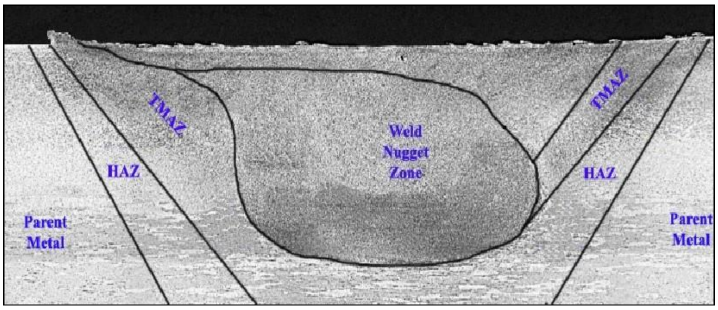

Figure 6: Microstructure of Friction Stir Welding Area of Metal AA5083.
Source: Authors, (2023).

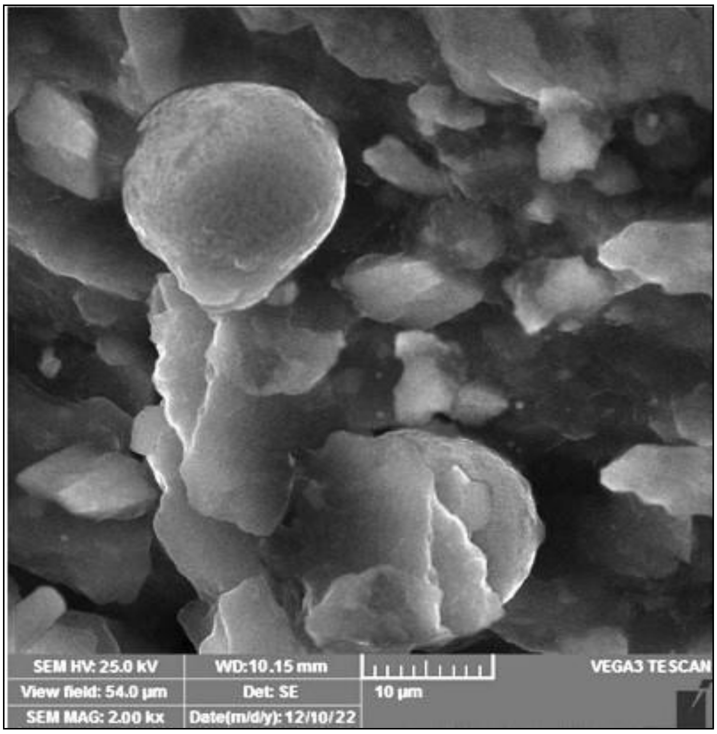

Figure 7: SEM Micrograph of Friction Stir WNZ.
Source: Authors, (2023).

The microstructure shows the weld interface between AA5083 and the nugget zone with fusion line at the center. The fusion is complete without any discontinuities. The TMAZ revealed that some Mg2Si particles had partially dissolved. The WNZ revealed Mg2Si fragments in a matrix of aluminium as seen in Fig. 7. The agitation zone had significantly and equalized grains. This structure was produced by dynamic recrystallization and static grain growth after welding [20]. The micrographs were taken at the center and at the bottom of the nugget zone. The microstructure shows fine fragmented particles of eutectic Mg_2Si and the matrix undergone dynamic re-crystallization due to the rapid process of FSW with heat and stress. The assortments of particles were categorized by qualitative EDS (energy dispersive spectroscopy) analysis. The AA5083 has an Mg and Fe-rich phase or a multidimensional phase with Mg, Si and O_2-rich regions. They were noticed in the WNZ zone that was optimized. The other variations, such as Si and O_2 rich particles, were also seen. [21]. Tiny particles, which are primarily Mg and Si-rich, proved challenging to examine.

IV.4 MICROHARDNESS

The friction stir welded AA5083 alloy optimum joint were taken for the microhardness analysis. Microhardness test results are exposed in Fig.8 which demonstrates the hardness profile of the similar FSW'ed AA5083 Aluminum alloys at a rotational speed of tool 600 rpm, welding speed of 85 mm/min and tilting angle of the tool 1 degree. The meager microhardness levels found at TMAZ have been marked by the dotted lines. The base metal matrix that was not harmed had a 93 $HV_{0.5}$ value, indicating that it was harder, and this pattern decreased as it moved towards the weld location. The minimum hardness value was found at TMAZ of 74 $HV_{0.5}$ comparing with base metal and WNZ [22]. It can be noticed that the WNZ resulting higher hardness values than TMAZ where a maximum value of 83 $HV_{0.5}$ was found at the optimum weld joint.

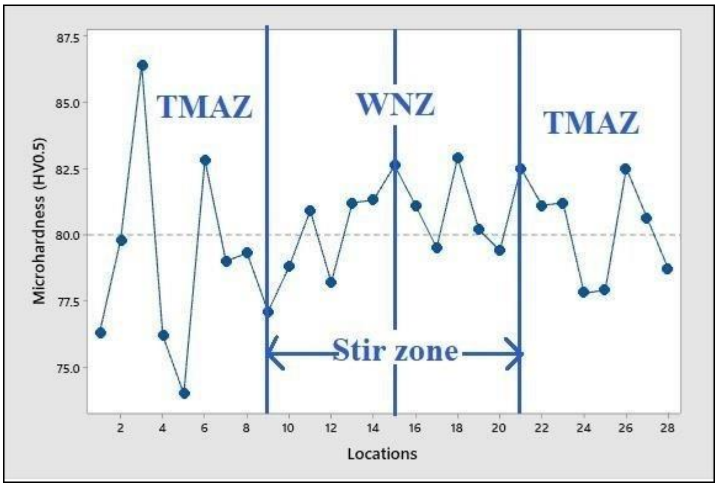

Figure 8: Microhardness analysis of FSW'ed Optimum Joint.
Source: Authors, (2023).

V. CONCLUSIONS

In this study, the welding process parameters of a Friction Stir welded AA5083 aluminium alloy have been optimized to maximize the tensile and hardness of the joints by using with Taguchi L_9 orthogonal array. The optimal combination of FSW parameters was a tool rotational speed of 600rpm, welding speed of 85 mm/min and tool tilt angle of 1 degree. The influence of FSW process parameters was tool tilt angle followed by welding speed. The most significant process parameter was the tool tilt angle with a contribution of 69.17 percent. All fractures of the joints in the tensile testing occurred in the TMAZ near to the SZ. The finer grain size in the WNZ led to a higher hardness, which caused in greater fracture strength for the joints. The microstructure of the Welded Nugget Zone consists of tiny shredded eutectic Mg_2Si particles. The matrix had undergone re-crystallization due to the rapid process of FSW with heat and stress. Some Mg_2Si particles were dissolved into the metal matrix, and partial re-crystallization of the grains was perceived in the TMAZ. Successful microhardness testing revealed that, when compared to the base metals of AA5083 and WNZ, WNZ had a greater hardness value while TMAZ had a lower microhardness value.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Kathiresan G, Ragunathan S and Prabakaran M P.
Methodology: Kathiresan G and Prabakaran M P.
Investigation: Prabakaran M P.
Discussion of results: Kathiresan G and Prabakaran M P.
Writing – Original Draft: Kathiresan G.
Writing – Review and Editing: Prabakaran M P.
Resources: Ragunathan S.
Supervision: Ragunathan S.
Approval of the final text: Kathiresan G, Ragunathan S and Prabakaran M P.

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