SPECIAL FEATURE

Urban Planning using Prediction of Air Quality & Population

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Our Vision: "To become a center of excellence in the fields of technical education & research and create responsible citizens"

Message from the Vice-Chancellor

We, at Digital Digest, have been publishing articles of scientific and engineering interest over the past decade or more. We also publish feature articles reviewing the current status in new and exciting domains of technology, and pay homage to stalwarts who have made their mark in science. Recently, we have attained University Status, which is a commendable achievement and we are entitled to bask in the glory for a little while. However, along with the distinction comes challenges and responsibilities. We are about to embark on a new journey, explore new horizons and traverse uncharted territory; we hope to excel in our quest to meet and overcome any hurdle that may come our way.

A University is a higher educational institution where knowledge is created. The regular duties of content dissemination via lectures still constitute the primary delivery mechanism, but research and creativity now assume much greater proportions. This 'bringing into existence' new and pertinent knowledge is what separates a university from a college. As you are probably aware of, The Scientific Method is the basis for all the knowledge that we have in our possession today, accumulated over the past three hundred years from Newton's time on, in the form of journal articles, textbooks, reference books and encyclopedias. The method is based on keen observation, relevant enquiry and validation by experiments. Experiments are the cornerstone of the Scientific Method - no matter how elegant a hypothesis is, unless it is validated by experiments, it cannot be pursued further and an alternative investigation needs to be initiated.

Here our role will be to foster creativity among students and faculty members, encourage innovation and incubation, so that technical articles of quality commensurate with publications from a university press is produced. This will help setup an ecosystem where research and innovation will result from the ground up. Historically, the University Press of famous universities have played a dominant role in producing superior quality journal articles and textbooks; these have been the basis for knowledge-sharing throughout the world, and continue to do so. As a university it is our solemn responsibility to add to the body of knowledge and make a mark in the scientific and technical community.

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Urban Planning using Prediction of Air Quality and Population

Abstract *– Urban Planning, a multidimensional initiative employing advanced machine learning techniques for predicting air quality and population levels in urban environments. The imperative need for accurate predictions is crucial for informed and sustainable urban development. This work unfolds in two primary dimensions: Air Quality Prediction and Population Prediction. The former addresses the escalating concerns regarding air pollution, targeting precise forecasts for sulfur dioxide (SO_2), particulate matter (PM_{10}), and nitrogen dioxide (NO_2) levels. The later dimension focuses on anticipating population growth, an indispensable factor for effective infrastructure planning. The work's significance is understood by its potential to inform urban planners, policymakers, and environmentalists. Accurate predictions empower stakeholders to make proactive decisions for mitigating air pollution and adapting infrastructure to accommodate population growth.*

Keywords *– Prediction, Advanced Machine Learning, Urban Planning, Forecasts.*

I. INTRODUCTION

The relentless tide of urbanization sweeping across the globe underscores the urgent need for innovative and data-driven approaches to urban planning .As cities expand, diversify, and confront unprecedented challenges, the intersection of technology and urban development becomes crucial for sustainable growth. This work leverages advanced machine learning methodologies to address two pivotal facets of urban development: Air Quality and Population Prediction.

In the contemporary urban landscape, the quality of the air we breathe stands as a testament to the health and resilience of our cities. The escalating concerns surrounding air pollution, fueled by industrial activities and urban lifestyles, necessitate precise and predictive tools for monitoring and mitigating environmental risks. Simultaneously, the ebb and flow of population dynamics wield a profound impact on infrastructure demands, requiring foresight and adaptability from urban planners [1] [2].

This Work employs a symbiosis of environmental science, data analytics, and advanced machine learning techniques. For air quality prediction, Seasonal Autoregressive Integrated Moving Average (SARIMA) models take center stage, providing a nuanced understanding of pollutant levels over time. These models tailored for each pollutant, provide insights into the future trajectories of environmental factors.On a parallel track, the work addresses the intricate task of Population Prediction. Here, ensemble models, comprising random Forest and Gradient Boosting classifiers, venture into the realm of demographic forecasting. Trained on historical data, these models empower urban planners to anticipate population trends, steering the course of infrastructure development towards sustainability.

The synthesis of these endeavors finds its manifestation in an interactive Flask web application, democratizing access to predictions and insights. The user interface acts as a gateway for urban planners, policymakers, and researchers to navigate the intricate tapestry of urban data, fostering informed decision-making and collaborative city development.

Our work is driven by a set of clearly defined objectives, implementing personalized and adaptive models in urban planning, particularly using SARIMA and stacking ensemble models, are centered around improving the effectiveness, responsiveness, and user-centricity of urban planning practices.

India is experiencing rapid urbanization, leading to increased challenges in managing urban infrastructure, environmental quality, and public health. With a growing population and urban sprawl, there is a critical need for effective urban planning that considers both air quality and population dynamics. The deterioration of air quality poses severe health risks, and accurate population predictions are essential for developing sustainable infrastructure and services.

II. LITERATURE SURVEY

Thorough literature review for a work on urban planning using air quality and population prediction would entail examining a range of scholarly articles, reports, and studies related to urban development, environmental science, and predictive modeling. This review would seek to understand urban areas face significant challenges related to air quality and population growth, necessitating effective urban planning strategies that account for these interconnected factors.

Several studies have highlighted the importance of accurate air quality assessment in urban areas for informing planning decisions. For example, K. Kumar (2022) [3] utilized satellite-based remote sensing data to assess air pollution levels in urban centers, demonstrating the potential of such data for spatially explicit air quality mapping. Similarly, Rafia and Arslen (2023) [4] emphasized the role of ground-based monitoring stations in providing real-time air quality data, enabling planners to identify pollution hot spots and prioritize mitigation efforts.

Population prediction models play a crucial role in urban planning by forecasting future demographic trends that influence infrastructure development and resource allocation. Nichol. (2021) [5] proposed a novel approach using machine learning algorithms to predict population growth in urban areas based on historical demographic data and socio-economic indicators, achieving high accuracy in their predictions. In contrast, Carlos Borrego (2022) [1] employed agent-based modeling techniques to simulate population dynamics and their impact on urban land use patterns, providing insights into the spatial distribution of future population growth.

The integration of air quality and population prediction into urban planning has the potential to revolutionize the way cities are designed and managed. By leveraging AI-driven models, urban planners can develop more resilient and sustainable cities that prioritize the well-being of residents and the environment. The review also delves into the methodologies and tools used in urban planning research, such as GIS (Geographic Information Systems) [1][4], data analysis techniques, and modeling approaches

Identifies areas for future investigation, aiming to contribute to the advancement of knowledge in the field of urban planning.

III. PROPOSED METHOD

In response to the identified challenges, machine learning acts as catalysts for urban planning by transforming raw data into actionable knowledge. The work's utilization of diverse models and ensemble techniques reflects a commitment to overcome the intricacies of urban planning strategies. Here's how our proposed method unfolds:

Seasonal Auto Regressive Integrated Moving Average (SARIMA): Seasonal Auto Regressive Integrated Moving Average, commonly known as SARIMA, is a statistical time series forecasting method. It is an extension of the Auto Regressive Integrated Moving Average (ARIMA) model, designed to handle time series data with seasonal patterns. SARIMA is particularly useful for predicting future values in a time series dataset where observations exhibit both non-seasonal and seasonal trends.

Auto Regressive (AR): Represents the correlation between a time series and its past values. The AR component assesses how the current value of the time series is related to its own past values.

Integrated (I): Involves differencing the time series data to make it stationary, removing trends or seasonality. The integration order (d) indicates the number of differencing steps required.

Moving Average (MA) Component: The MA component captures the relationship between the current observation and a residual error from a moving average model applied to lag values.

Seasonal Components: SARIMA includes additional seasonal components to model periodic variations in the data. These components are denoted as SAR (Seasonal Auto Regressive) and SMA (Seasonal Moving Average). They capture the influence of past observations and past forecast errors on the current observation, respectively.

Seasonal Integration (SI) Component: The SI component represents the number of seasonal differences needed to make the seasonal part of the time series stationary.

Model Selection: SARIMA is a powerful tool for time series forecasting, especially in situations where both non-seasonal and seasonal components play a significant role in shaping the data patterns. Its effectiveness lies in its ability to capture complex temporal structures and provide accurate predictions for future time points.

Customization and Training of SARIMA Model for pollutant prediction: Customization and training of SARIMA (Seasonal Auto Regressive Integrated Moving Average) model involve specific steps tailored to the characteristics of the data and the objectives of the forecasting task. We fine-tuned this model using a specially curated dataset for different pollutants, population. This dataset includes data collected for hundred different cities. The training process involved examining the auto correlation function (ACF) and partial auto correlation function (PACF) to identify potential values for p, d, q, P, D, Q, and s (seasonal frequency) in the SARIMA (p, d, q)(P, D, Q)s model. Fit the SARIMA model to the training data using estimation techniques like maximum likelihood estimation. Evaluate the model's goodness of fit using diagnostic checks. Use the trained SARIMA model to make predictions on the future time points.

Customization and Training of Stacking Ensemble Model for population prediction and Air Quality Index classification: Choose diverse base models, each employing different algorithms or hyper parameters. Train each base model on the training data. Train a meta-model on the predictions of the base models. Evaluate the performance of the stacking ensemble model on the validation set. Fine-tune hyper parameters of both base models and the meta-model to optimize performance. Once hyper parameters are selected, train the final stacking ensemble model on the entire training dataset. Choose the best-performing model based on validation results. Consider metrics such as mean squared error criteria.

Platform Integration: The model will be embedded within an interactive, easy-to-use platform, where users can enter the city and year for which they want to predict the future values such as, population and the pollutants & the AQI based on the values of pollutants predicted.

SARIMA Model: The SARIMA model is a time series forecasting method represented by the equation:

$$Y[t] = \mu + \varphi_1 * Y[t-1] + \theta_1 * \mathcal{E}[t-1] + \cdots + \theta_p * \mathcal{E}[t-p] + \mathcal{E}[t] \quad (1)$$

Here, Y[t] represents the pollutant value at time t, φ1 represents the autoregressive parameter, θ1 represents the moving average parameter, and ε[t] represents the error term at time t.

Stacking Ensemble: The stacking ensemble combines predictions from multiple models using a meta-learner. The prediction can be represented as:

$$Y\ pred = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \ldots + \beta_n * X_n \quad (2)$$

Here, Y_ pred is the predicted population value, β0 is the intercept, β1 to βn are the coefficients, and X1 to Xn are the predictions from base models.

Base Models: Ensemble stacking involves training multiple diverse base models, each utilizing different algorithms, hyperparameters, or subsets of the training data. The diversity in base models is crucial for capturing different aspects of the underlying patterns in the data.

a) Linear Regression: Linear regression is a statistical method used to model the relationship between a dependent variable (often denoted as y) and one or more independent variables (often denoted as X). It assumes that the relationship between the variables is linear, meaning that a change in one variable is associated with a proportional change in the other(s).

The basic form of a linear regression model with one independent variable is:

$$y = \beta_0 + \beta_1 * X + \epsilon \quad (3)$$

Where y is the dependent (predicted) variable and X is the independent variable. β_0 is the intercept (the value of y when X is 0). β_1 is the slope (the change in y for a one-unit change in X). ϵ is the error term (the difference between the observed y and the predicted y).

b)Random Forest Regressor: A Random Forest Regressor is an ensemble learning method that can be used for regression tasks, such as predicting a continuous output variable. It works by constructing multiple decision trees during training and outputting the average prediction of the individual trees for regression tasks.

c) XGBoost Regressor: XGBoost stands for Extreme Gradient Boosting, which is an implementation of gradient boosting machines. Gradient boosting is an ensemble learning method that builds a strong model by combining multiple weak models (typically decision trees) sequentially.

d) CatBoost Regressor: CatBoost Regressor is a machine learning algorithm designed for regression tasks, where the goal is to predict a continuous output variable based on input features. CatBoost is a Categorical Feature Support that is a built-in support for categorical features without the need for extensive pre-processing. It can handle categorical features directly, which can be advantageous when dealing with datasets containing both numerical and categorical features. CatBoost is an open-source gradient boosting library. Like XGBoost, CatBoost is based on the gradient boosting framework, which builds an ensemble of weak learners (typically decision trees) in a sequential manner.

e) MLP Regressor (Neural Network): The MLP (Multi-layer Perceptron) Regressor is a type of neural network model used for regression tasks, where the goal is to predict continuous values. It is part of the scikit-learn library in Python and is based on the feed forward artificial neural network architecture.

IV. EXPERIMENTAL RESULTS

In parallel with traditional machine learning models, the experiment delved into the realm of time series analysis models. These models are particularly adept at handling sequences of data points ordered chronologically, making them well-suited for the time-centric nature of urban planning challenges.

Dataset Creation: The backbone of any models performance is the quality and diversity of its training data. The dataset for the Urban planning Work has been meticulously curated by collecting data from authoritative sources. The compilation includes demographic information spanning multiple years and air quality data for specific pollutants (NO_2, SO_2, and Pm_{10}[Particulate matter less then 10 μm size]) [9] [10].

Source and Composition: The dataset encompasses population figures from the census of India, offering a comprehensive overview of demographic statistics at the state level and from the department of drinking water and sanitation [7], ministry of jalshakti, providing insights into the current population status [7] [8].

Air quality data, including concentrations of pollutants such as sulfur dioxide (SO_2), particulate matter (PM_{10}), and nitrogen dioxide (NO_2), have been sourced from the Central Pollution Control Board and a dataset for AQI-bucket classification [10].

Quality Control: To ensure dataset's quality, data from different sources have been utilized to ensure comprehensive coverage [6] [7] [8].

System, Language and Library used: The sklearn package of python for different models and Flask are used to deploy the model. The html and CSS are used to create user-interactive pages. This platform is easy to interact with, where user only needs to enter city from the drop-down and year for which they want the results.

Table – 1. Accuracy of all models used for AQI bucket classification:

Models	Accuracy
Random forest	69.92
Gradient boosting	69.98
XGBoost	70.68
Logistic regression	63.40
SVM	68.18
KNN	68.38
Decision tree	61.68
Naïve Bayes	65.44
Ensemble (Random forest, XGBoost)	71.88

Table 1, shows accuracy of different models which are applied on AQI Bucket Classification (multi-class classification) dataset. In Ensemble, a combination of different models are tried but Ensemble of Random forest and XGBoost gave us optimal accuracy of 71.88.

Table – 2. Information of Ensemble Prediction:

Classes	F1 score	Precision	Recall
Good	0.66	0.41	0.51
Satisfactory	0.75	0.84	0.79
Moderate	0.73	0.76	0.74
Poor	0.48	0.39	0.43
Very poor	0.62	0.56	0.59
Severe	0.72	0.62	0.67

The ensemble prediction is made based on the output obtained from the individual pollutant models and as of here, for Bilaspur among the six class labels i.e., severe, very poor, poor, moderate, satisfactory, good, the ensemble prediction is 'Satisfactory'. Table 2 shows the F1Score, Precision and Recall of ensemble model for different AQI bucket class labels.

Table 3 shows the accuracy of different models which are used in Ensemble Stacking along with different models used, linear regression is used as final model.

Table – 3. Mean Square Error of base models (Ensemble stacking) on test data for Population dataset:

Models	MSE
Linear regression	0.32
Random Forest	0.66
XGBoost	0.25
CatBoost	0.74
Neural Network	0.65
Stacked Ensemble	0.35

Table – 4. Mean Square Error of SARIMA model's performance on different pollutant (SO_2, PM_{10}, and NO_2)

Pollutants	MSE
So_2	0.307
Pm_{10}	0.425
No_2	0.359

In the dynamic landscape of urban planning, the integration of machine learning models holds the promise of enhancing decision-making processes, predicting urban trends, and fostering sustainable development. Leveraging Flask, a web framework for Python, these models are deployed to provide real-time insights and facilitate user interaction. Table 4 shows mean square error of SARIMA models performance.

User Interaction

The script takes user input for the city name and the year to predict as shown in Figure 1. It then displays the predicted population, pollutant levels, and air quality index for the specified city and year. It also plots the graph to show the trend in change of population and pollutant levels.

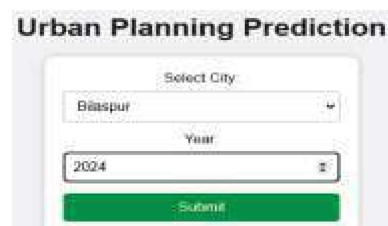

Fig.1.User can enter the city name and year for which they want to predict the results

Visualization

The script generates plots to visualize the actual and predicted population, pollutant levels, and air quality trends over the years in Fig. 2 and Fig. 3.

In the Fig. 2, y-axis represents the pollutant level in ppm and x-axis represents the year-wise prediction of different pollutants namely, PM_{10}, SO_2, NO_2. In Fig. 3, y-axis represents population prediction and x-axis represents different years for which prediction is made.

Fig.2.Result obtained for air quality i.e., for different pollutants along with AQI bucket prediction

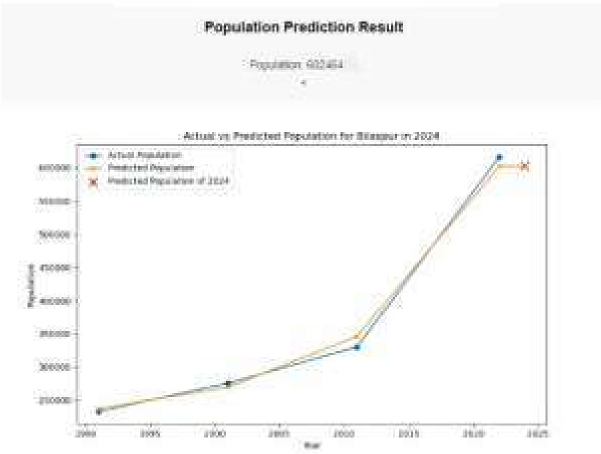

Fig.3.Result obtained for population prediction, graph showing results obtained for actual vs. predicted value

The goal is to integrate this model into a user-friendly platform accessible to different users and urban planner. This platform will not only serve as a tool to predict the future values of different pollutants and population for different cities, but also as a resource for urban planners to enhance their knowledge about the area.

V. CONCLUSION & FUTURE SCOPE

The integration of air quality and population prediction into urban planning processes holds significant promise for creating healthier and more sustainable cities. By leveraging advanced data analytics and predictive modeling techniques, this approach enables city planners to anticipate future population trends and the corresponding impact on air quality. This foresight empowers decision-makers to proactively design and implement policies, infrastructure, and green spaces that can mitigate potential environmental risks, improve overall air quality, and enhance the well-being of urban residents. Moreover, by factoring in population growth projections, cities can better allocate resources, optimize land use, and develop more efficient transportation networks, fostering a more livable and resilient urban environment for current and future generations.

VI. REFERENCES

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Investigating Extraterrestrial Organic Matter in the Winchcombe Meteorite: A Profound Exploration

INTRODUCTION

The Winchcombe Meteorite fell in Gloucestershire, UK on Feb. 28, 2021. It presents an opportunity to carefully examine a space rock. The Winchcombe meteorite which is categorized as a geological type 2 MigheiCM2 carbon-rich chondrite, has recently emerged as a focal point of scientific study, shedding light on the organic constituents present in extraterrestrial bodies. The meticulous examination of this meteorite provides an unprecedented opportunity to unravel the mysteries of the early solar system and the potential building blocks of life on Earth.

DETECTION OF NITROGEN-CONTAINING COMPUNDS

In the pursuit of understanding the organic composition of the Winchcombe meteorite, researchers employed cutting-edge high-spatial resolution spectroscopy techniques. Despite the meteorite's relatively low nitrogen content (N/C~1–3%), the application of sophisticated methods, including a low-noise direct electron detector, proved instrumental in identifying nitrogen-containing compounds. Among these compounds were amino acids and N-heterocycles—biologically relevant molecules that enhance the scientific significance of Winchcombe, expanding the repertoire of carbonaceous chondrites in preserving extraterrestrial organic matter in an exceptionally pristine state.

ANALYSIS METHODS

Departing from conventional chemical extraction methods, the research team opted for innovative approaches such as hyperspectral electron microscopy in high resolution and synchrotron spectral analysis with minimal processing of the sample. This strategy enabled localized measurements of both soluble and insoluble organic matter while maintaining the crucial petrographic context. The emphasis on minimally processed samples provides a unique opportunity to explore extraterrestrial organic matter with unprecedented detail.

ORGANIC MATTER TEXTURES AND FUNCTIONAL CHEMISTRY

The examination of organic matter textures within the Winchcombe meteorite unveiled a captivating complexity. Irregular boundaries and diffuse textures, ranging from nanometers to micrometers, were observed, distinguishing two primary types of organic matter. Larger, compact grains (>200 nm) with irregular boundaries and smaller, diffused matter (<200 nm) intermixed with sheet silicates (phyllosilicates) provided a nuanced perspective. Spectroscopic analyses at the carbon ionization K-edge revealed a homogeneous functional chemistry dominated by aromatic hydrocarbons and nitrile-bonded materials. Quantifying aromaticity content further underscored the pristine nature of specific organic matter grains, hinting at the presence of extraterrestrial prebiotic molecules.

VARIABILITY AND FINE-SCALE ANALYSIS

The study illuminated localized variability in carbon functional chemistry, emphasizing the need for fine-scale analysis. While synchrotron beam analyses targeted larger regions, the higher-spatial resolution electron beam provided crucial insights into smaller, more diffuse organic matter areas. This approach uncovered subtle features, such as a weak but distinct aliphatic bonding peak in one sample, showcasing the versatility and effectiveness of the employed techniques.

CONCLUSION

In conclusion, the Winchcombe meteorite stands as a remarkable specimen for the comprehensive study of extraterrestrial organic matter. The identification of nitrogen-containing compounds and the detailed analysis of organic matter textures and functional chemistry contribute significantly to our understanding of the cosmic origins of life. As scientific exploration continues to unfold the mysteries concealed within meteorites, each discovery brings humanity closer to unlocking the secrets of our celestial origins.

Source: physics.org

Source: https://www.ncbi.nlm.nih.gov/

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AI-powered Humanoid Robot Can Serve You Food, Stack the Dishes — and have a Conversation with You

Source: https://www.livescience.com

A self-correcting humanoid robot that learned to make a cup of coffee just by watching footage of a human doing it can now answer questions thanks to an integration with OpenAI's technology.

In the new promotional video, a technician asks Figure 01 to perform a range of simple tasks in a minimalist test environment resembling a kitchen. He first asks the robot for something to eat and is handed an apple. Next, he asked Figure 01 to explain why it handed him an apple while it was picking up some trash. The robot answers all the questions in a robotic but friendly voice.

Realtime Fingerprint Identification Under Noisy Conditions using FLANN

Abstract *– We have conducted a study on utilizing optimized FLANN to classify noisy fingerprints as a biometric classifier. The database was obtained in real-time from ten distinct individuals, and the Gabor Filter bank was utilized to extract features of five distinct categories of fingerprints. The findings show that this approach can classify fingerprints with a high degree of accuracy. To achieve the classification of distorted fingerprint images, we utilized Biogeography-based optimized Functional Link Artificial Neural Networks (BBO-FLANN).*

Keywords *– Fingerprint, ANN, BBO- FLANN*

I. INTRODUCTION

Fingerprints are distinctive, flow-like patterns found on human fingers that are widely used for biometric identification due to their uniqueness, security, durability, and convenience. These patterns, which consist of lines and ridges on the fingertips, reveal various types of features at different levels of scrutiny, including global and local features. In this study, we have utilized a Filter Bank approach to extract unique global features from real-time, noisy, and distorted fingerprints collected from a database. We collected the features in the form of feature vectors for each individual fingerprint, stored them in a feature sheet, and then classified them using a novel Biogeography-based Optimized Functional Link Artificial Neural Network (FLANN). The FLANN, which is a plane network, does not require a hidden layer, making the learning algorithm easy to implement. Furthermore, the functional expansion efficiently increases the dimensionality of the input vector, and the hyperplanes generated by the FLANN, in combination with BBO optimization, improve classification accuracy in the input pattern space. Artificial Neural Networks (ANN) are a powerful tool for many complex applications, such as functional implementation, nonlinear system recognition and management, unsupervised categorization, and optimization. In this study, we have employed a Functional Link Artificial Neural Network to solve the categorization difficulty, which is capable of generating complex plots and forming random, complex, nonlinear decision boundaries.

II. PROBLEM STATEMENT

Fingerprints are widely used for detecting and identifying criminals. However, when capturing real-time fingerprints, the presence of dust particles can lead to the addition of noise and distortion in the fingerprint image. Gaussian Noise is present when the image becomes hazy, and Salt & Pepper Noise is present when dust particles are present. To classify the fingerprint image with ease, a system can be built to train the noisy fingerprint. The primary objective of this project is to add noise to the fingerprint, extract the features, and then use FLANN to train the noisy fingerprint image and classify it into different classes. Fingerprint classification involves grouping fingerprints in a consistent and reliable manner so that different impressions of the same finger fall into the same group. This process is essential for pre-matching and expediting the query fingerprint's comparison with a smaller subset of fingerprints in the database belonging to the same group. To speed up the database search, it is often necessary to integrate a classification module into a fingerprint identification system.

III. REAL-TIME DATABASE COLLECTION AND FEATURE EXTRACTION

The process of Fingerprint Classification involves two steps, namely feature extraction and classification. To extract features, a group of sample fingerprint images called the database image is required. While frequently used standard databases are NIST 9 and DB, we have collected 50 real-time fingerprint images to create our database. This collection comprises 50 fingerprint sample images belonging to five different classes, including four classes obtained by combining Arch and Tented Arch into one. To proceed with pre-processing and feature extraction, we used the database. However, not all sample images were noisy; therefore, we introduced Gaussian noise in varying percentages to make them noisy. The noisy database created in this manner was then used for feature extraction via Gabor filter bank, and the resulting features were stored in an Excel sheet and processed for classification.

IV. PRE-PROCESSING STEPS

Improvement of the fingerprint is the operation involving the adjustment of digital image of fingerprint so that the outcomes are more satisfactory for display or for additional image investigation. It is primarily done to enhance the image standards and to make it simpler for further operations as shown in Fig.1. Often fingerprint images from different origins falls short of adequate disparity and simplicity. Hence image improvisation is a necessity [10]. It increases the disparities between corrugations and furrows and joins some of the erroneous broken points of corrugations due to inadequate quantity of ink or degraded standard of sensor input.

Fig.1. Pre-processing steps

Segmentation: Segmentation is the process of partitioning a digital image into multiple segments. Normalization: Normalization is a process of standardizing the intensity values in an image.

Orientation Field Estimation: It defines the orientation of ridges.

Binarization: Binarization is the process of converting a 8-bit grey fingerprint image to a binary image. Thinning: This operation is used to remove selected foreground pixels from the binary images as shown in Fig.1.

V. FLANN AS A CLASSIFIER

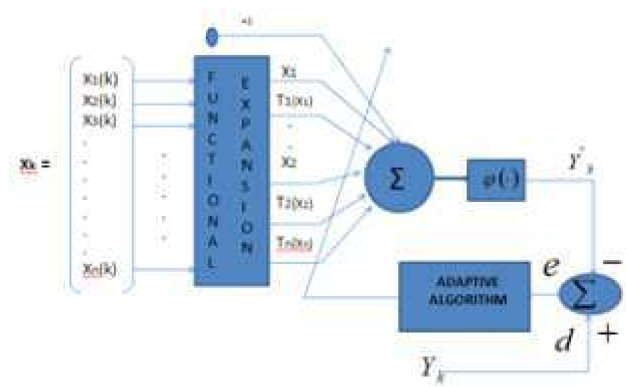

Fig 2. FLANN Architecture

A Functional Link Artificial Neural Network (FLANN) is a type of artificial neural network (ANN) that is designed to solve complex pattern recognition problems. FLANNs are composed of a single layer of neurons, which are connected to the input layer of the network. Each neuron in the FLANN consists of a set of input weights and a single output value. The input weights in each neuron are multiplied by the input values, and the resulting products are passed through a non-linear activation function to produce the neuron's output. The activation function can be a sigmoid function, a hyperbolic tangent function, or any other suitable non-linear function. The output values of the neurons in the FLANN are combined using a weighted sum to produce the final output of the network as shown in Fig 2. The weights used to combine the output values of the neurons are learned during the training process, which involves presenting the network with a set of input-output pairs and adjusting the weights to minimize the difference between the network's output and the desired output for each input. FLANNs have been used successfully in a variety of applications, including image recognition, speech recognition, and control systems. They are particularly well-suited to problems in which the input data is high-dimensional and the relationship between the input and output is complex and non-linear. [2,5]

The FLANN architecture in this study takes a 152-dimensional feature matrix called Feature Code as input. Each input is expanded into several individual expansions (seven in this case) through trigonometric expansion. A set of expansion weights is randomly introduced for each expansion in the range of -1 to 1, and the input is multiplied with the random weight, which is further passed to the adder unit to generate the cumulative output. The output is then fed to the threshold unit to produce the actual output of the network. The FLANN is an adaptive process that updates the weights by calculating the error, which is obtained by subtracting the actual output from the desired output. The weight updating continues until the error is minimized, and the optimum output of the network is obtained.

VI. FEATURE EXTRACTION

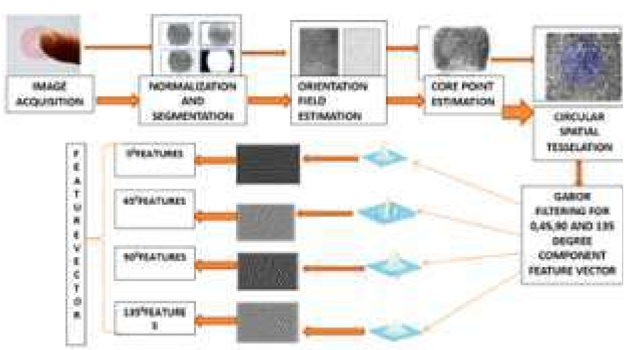

Fig 3. Feature extraction

Global features such as corrugation and furrow formations play a significant role in determining the category of a fingerprint. For accurate fingerprint categorization, it is necessary to have a suitable set of characteristics that can efficiently encapsulate this global information. The filter bank-based fingerprint representation is a well-established method for capturing the smallest attributes as well as the global features of a fingerprint. To use this representation for fingerprint categorization, some adjustments need to be made to make it more effective in representing the global features while remaining robust to individual small attributes. Our approach convolves a fingerprint image with four Gabor filters at different orientations (0°, 45°, 90°, and 135°) to generate four component images. The resulting characteristic vector is 152-dimensional (38 × 4) as shown in Figure 2. Our experiments show that the four component images capture most of the spatial information about the corrugation in a fingerprint image, resulting in an authentic representation. This is demonstrated by reconstructing a fingerprint image by adding together all four filtered images, which yields an image that is nearly identical to the original image without any significant loss of data. The feature extraction is shown in Fig. 3.

VII. FINGERPRINT CLASSIFICATION

Biogeography based optimization (BBO) is a global optimization algorithm inspired by the principles of biogeography, which is the study of the distribution of biological organisms in different geographic regions. In BBO, candidate solutions to an optimization problem are represented as islands, and their features are treated as the attributes of the biogeography of the island.

Initially, the population of candidate solutions is randomly generated. Each candidate solution is then evaluated, and its feature vector is used to represent an island in a habitat matrix. In the next step, immigration and emigration operations are performed to exchange the features of different islands.

Immigration occurs when the biogeography of an island is influenced by the biogeography of other islands with better features. Emigration happens when the features of an island are exported to other islands with lower biogeography.

After a predefined number of iterations, the algorithm terminates, and the island with the best features is selected as the solution. BBO is an effective optimization algorithm that has been successfully applied to a variety of problems, including function optimization, feature selection, and machine learning.[1,2]

The Biogeography-based Optimization (BBO) [1] algorithm aims to improve candidate solutions or habitats within a population, with each habitat characterized by a Habitat Suitability Index (HSI). The HSI indicates the number of species and the adaptability of the habitats and can range from high to low. BBO, similar to Genetic Algorithms, utilizes two key operations: Migration and Mutation. Migration helps to provide high HSI habitats, and the selection of habitats is determined by a probabilistic operator. The migration process involves two operations: Immigration and Emigration, which are quantified by the emigration rate (μ) and immigration rate (λ), respectively. These rates also determine the migration rate for the subsequent generation, as shown in equation 1. The number of species in the habitat, denoted by k, is directly related to the values of μ and λ.

$$\mu_k = E_k S_{max}$$
$$\text{And } \lambda_k = I\,(1\ \mu_k) \quad ....(1)$$

where, E is the maximum emigration rate, I is the maximum immigration rate, and S max is the largest achievable number of species that the habitat can support. The second operation in BBO is mutation which modifies the randomly selected SIV of a population as per the mutation rate.

BBO-FLANN Hybrid Network:

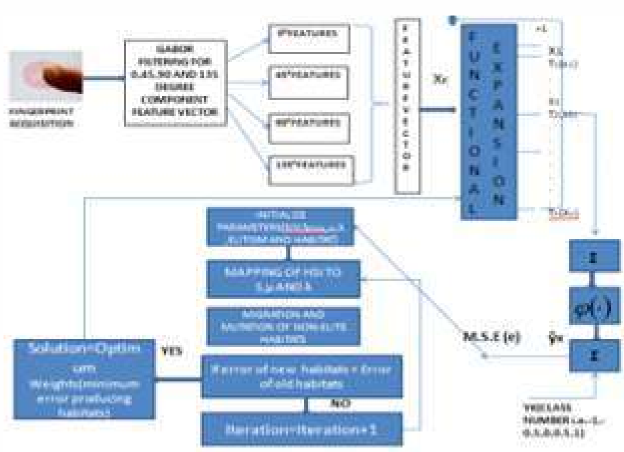

Fig 4. Structure of the proposed BBO - FLANN hybrid method

In our study, we incorporated the BBO algorithm as an optimizer for optimizing the FLANN network, as depicted in Fig 3. The process involves creating a network with a fixed number of habitats that meet the network requirements. The weights and biases for each habitat are initially set randomly, and the fitness value is generated based on these fixed values. The Mean Squared Error (MSE) is used as the cost function, and our goal is to minimize this value. The network then undergoes various probabilistic operations, such as migration and mutation, to enhance the solution. These operations are repeated until the desired MSE goal is reached which is represented in Fig 4. [8,11]

Fingerprint Classification comprises of two main steps: feature extraction and classification. Feature extraction is performed on a collection of sample fingerprint images, known as the database image. We used a total of 50 fingerprints, representing all five classes (four classes when Arch and Tented Arch are combined as one), to create the database. Some of the sample images were not noisy, so we added Gaussian noise to different percentages to simulate noisy conditions. The created noisy database is used for feature extraction using a Gabor filter bank, which captures the fingerprint image as four component images, forming an authentic representation. We demonstrate this by reconstructing a fingerprint image through the addition of all four filtered images, resulting in an image equivalent to the original image with minimal data loss.

VIII. CONCLUSION

The authors have developed a method for classifying noisy fingerprints in real time using a multichannel filter bank approach with BBO-FLANN. The method employs 152-dimensional feature vectors and achieves an accuracy of 60% with a short execution time. The classifier performs well for lower percentages of added Gaussian 8 noise, but increasing the noise percentage may decrease accuracy. The method classifies noisy fingerprints into four categories using a multichannel filter-based feature extraction algorithm and BBO, resulting in higher accuracy than other algorithms in the NIST database. The algorithm achieves an accuracy of 78% for normal fingerprint data without rejection. To reduce the overall computational time, the authors suggest using special-purpose hardware for convolution as it takes up 90% of the total computational time.

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Perovskite Mineral Supports Solar-Energy Sustainability

When it comes to the future of solar energy cells, say farewell to silicon, and hello to calcium titanium oxide—the compound mineral better known as perovskite.

Cornell engineers have found that photovoltaic wafers in solar panels with all-perovskite structures outperform photovoltaic cells made from state-of-the-art crystalline silicon, as well as perovskite-silicon tandem (stacked pancake-style cells that absorb light better) cells.

In addition to offering a faster return on the initial energy investment than silicon-based solar panels, all-perovskite solar cells mitigate climate change because they consume less energy in the manufacturing process, according to Cornell research published in Science Advances.

Source: *https://techxplore.com/news/2020-08-perovskite-mineral-solar-energy-sustainability.html*

Comparison of Multi-Carrier PWM Techniques in a Seven-Level Asymmetrical Cascaded Multilevel Inverter

***Abstract** – The multilevel inverters (MLIs) are classified into three topologies namely Diode Clamped, Flying Capacitor and Cascade Multilevel Inverter (CMLI). CMLI topologies include two kinds of structure that is named symmetric and asymmetric topologies. Asymmetric Cascade MLI (ACMLI) topologies consist of unequal DC sources. Many modulation techniques have been used in ACMLI topology such as Multi-Carrier PWM (MC-PWM), Space Vector PWM and Selective Harmonic PWM. The MC-PWM technique is achieved by four different types. In this study, MC-PWM techniques which are named Phase Disposition PWM, Phase Opposition Disposition PWM, Alternate Phase Opposition Disposition PWM and Phase Shifted PWM have been compared. It is uncovered that Phase Opposition Disposition PWM technique is more convenient in terms of Total Harmonic Distortion of output voltage and current signals and in terms of the quality of power factor in ACMLI which is performed in this study.*

***Keywords** – Asymmetric cascade multilevel inverter; multi carrier PWM; THD; frequency index; power factor*

I. INTRODUCTION

In recent years, MLIs have a wide range of application in high power applications and power electronics. The advantages of MLIs are lower switching loss, better electromagnetic compatibility and lower harmonics. Several topologies such as Diode Clamped, Flying Capacitor and Cascade MLI (CMLI) are widely used in dc-ac power conversion where the CMLI topology includes H-Bridges with serial connections. The CMLIs can be constituted in two ways of structure as symmetric and asymmetric topologies. The asymmetric structure involves unequal DC sources that the voltage ratios of sources increase as a power of two or three in Asymmetric Cascade MLI (ACMLI). The ACMLI topologies provide to increase the output level while keeping the number of switching device. The symmetric CMLI and ACMLI topologies are shown in Fig. 1[1-4].

Besides the topologies, there are also many modulation techniques are used in MLI topologies which are classified into some categories as given in Fig. 2. The modulation techniques are categorized into two basic categories as Low Switching Frequency (Fundamental Switching Frequency) and High Switching Frequency. Space Vector PWM (SVPWM), Selective Harmonic PWM (SHE-PWM) and MC-PWM have been mostly used in MLI topologies. A sinusoidal modulation signal is compared with a few triangular signals in MC-PWM method. The ACMLI topology can be realized with four different ways of MC-PWM method: Phase Disposition PWM (PD-PWM), Phase Opposition Disposition PWM (POD-PWM), Alternate Phase Opposition Disposition PWM (APOD-PWM) and Phase Shifted PWM (PS-PWM) methods [5-9].

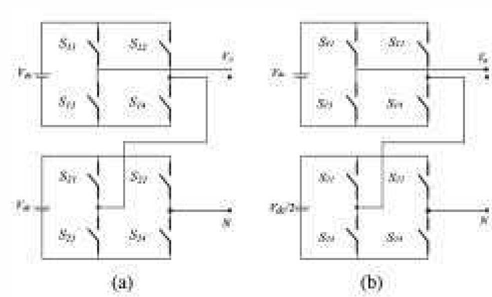


Fig – 1. CMLI topologies a) Symmetric b) Asymmetric

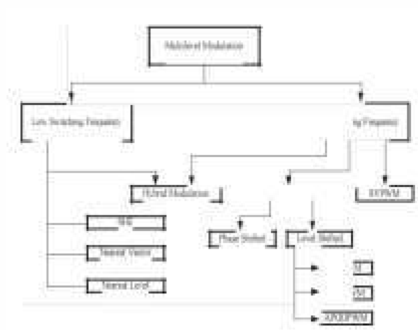


Fig – 2. Modulation techniques

This paper presents ACMLI topology with MC-PWM modulation techniques and shows the variation of Total Harmonic Distortion (THD) between the frequency index and modulation index changing.

II. ASYMMETRIC CASCADE MULTILEVEL INVERTER (ACMLI)

The Asymmetric topologies have two different types namely ACMLI and Asymmetric Hybrid MLI (AHMLI). The main difference of AHMLI with respect to the ACMLI is the switching devices. H-Bridge cells are formed using same semiconductors in ACMLI such as IGBT and MOSFET. On the other hand, in AHMLI topology, cells are formed with different semiconductors such as GTO, IGBT and MOSFET [1, 7, 10].

If the ratio of DC sources in any asymmetric topologies arranged as the twice of previous one, the topology is named binary structure; if it is three times greater according to previous, the topology is named as trinary structure. The calculation of output voltage level is given in (1) for binary structure and in (2) for trinary structure. "N" is the output voltage level and "n" is the cell number in (1) and (2), where the "k" parameter is an integer [10, 11].

$$N_{binary} = 2^{n+1} - 1 \quad V_{dc} = V / 2^{k-1},\ k = 1, 2, ..., n \qquad (1)$$

$$N_{trinary} = 3^{n} \quad V_{dc} = V / 3^{k-1},\ k = 1, 2, ..., n \qquad (2)$$

A seven-level ACMLI topology is performed with binary structure in this study. There are two serial connected H-bridge cells that the supply voltages are applied as V_{dc} and $V_{dc}/2$. In this case, the output levels are $+3V_{dc}/2$, $+V_{dc}$, $+V_{dc}/2$, 0, $-V_{dc}/2$, $-V_{dc}$, $-3V_{dc}/2$. While the dc sources are V_1=70V and V_2=140 V, the output values of levels are "0, +70, +140, +210, -70, -140, -210" as depicted in Fig. 3 [10]. The block diagram of seven-level ACMLI is given in Fig. 4. R-L values are 5 Ÿ and 5 mH, respectively and they are connected to the output of the inverter. The module structure of H-Bridge cell is shown in Fig. 5.

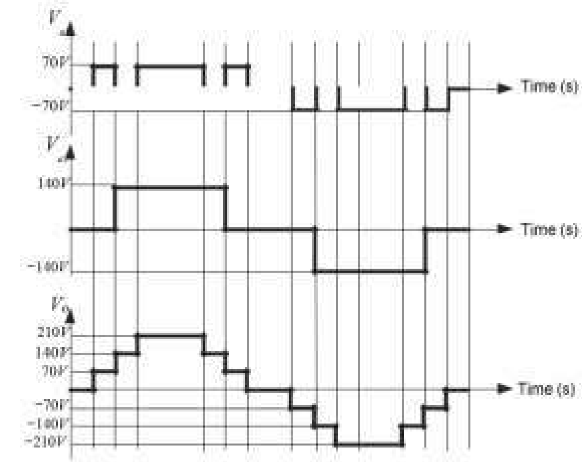


Fig – 3. The output voltages of H-Bridge cells and the output of Seven-Level ACMLI

III. MODULATION TECHNIQUES

In MC-PWM, (n-l) carriers are used to compare with the modulation signal in an n-level inverter [1]. There are six triangular carrier signals for seven-level ACMLI inverter in the MC-PWM modulation. The phases of triangular carrier signals are changed and these signals are placed vertically in PD-PWM, POD-PWM and APOD-PWM. The triangular waves are compared with one sinusoidal signal at different amplitude. The APOD-PWM circuit is depicted in Fig. 6. Another MC-PWM technique is known as PS-PWM. Carrier signals are placed horizontally in different phases. PS-PWM circuit is illustrated in Fig. 7. PS-PWM has also n-1 carriers and phase difference of each phase is calculated with 1800/n for n-level output [9, 12-15, 17, 18, 20].

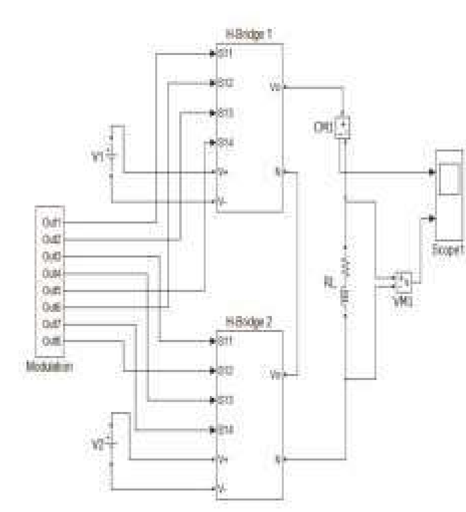


Figure 4.The block diagram of seven-level ACMLI

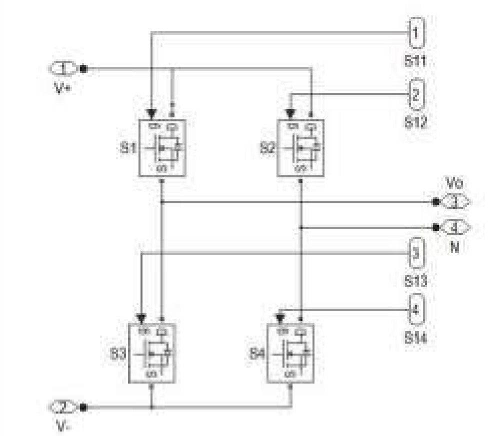


Figure 5. H-Bridge cell module

In PD-PWM, POD-PWM and APOD-PWM, the modulation output signals are defined by the modulation index and the frequency index. The modulation index (m_a) is determined in (3) and frequency index (m_f) is determined in (4). In addition, the calculation of modulation index in PS-PWM is defined (5). In these equations, V_m is the amplitude of modulation signal and V_c is the amplitude of one carrier wave.

Carrier frequency is f_c and the frequency of modulation signal is f_m [1, 4, 16].

$$m_a = 2V_m/(N-1) \times V_c \qquad (3)$$

$$m_f = f_c / f_m \qquad (4)$$

$$m_a = V_m / V_c \qquad (5)$$

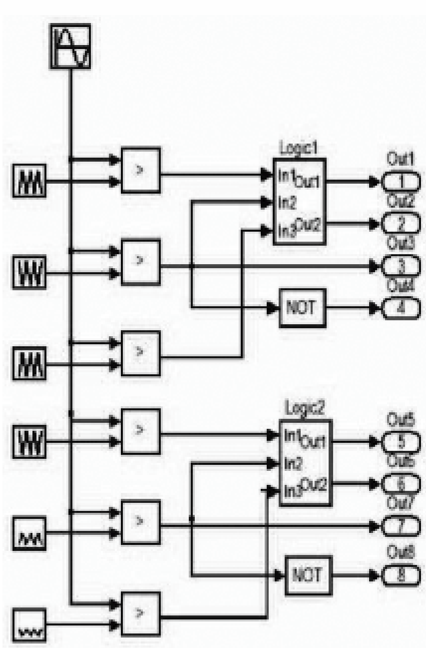


Figure 6.PD-PWM, POD-PWM, APOD-PWM modulation

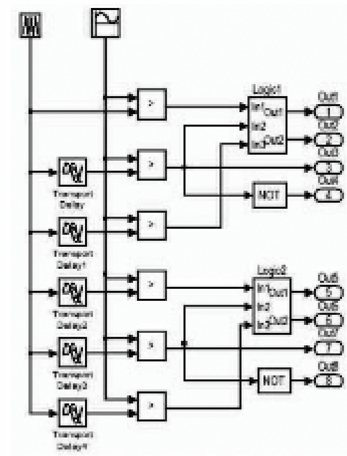


Figure 7.PS-PWM

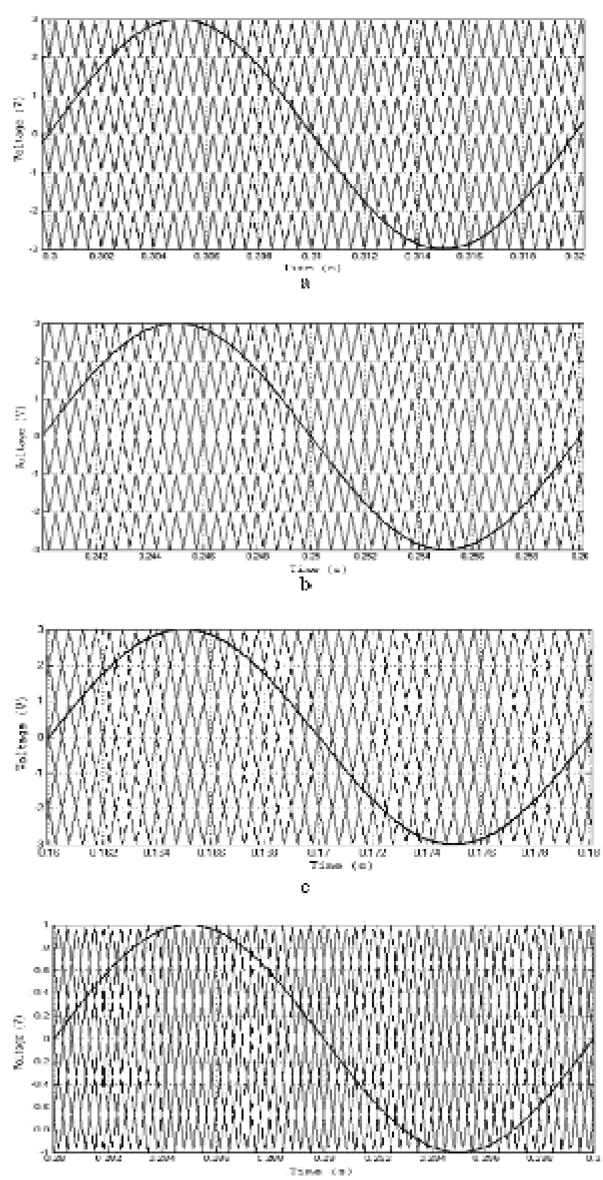


Figure 8.MC-PWM compilation signals a) PD-PWM b)POD-PWM c)APOD-PWM d)PS-PWM

The comparison output has six levels as shown in Fig. 8. The seven-level ACMLI has six voltage levels and one zero level. After comparison, some of the outputs must be processed with the logic operations for switching the semiconductors. Fig. 9 illustrates the inside of the logic module. The XOR logic gates are located in logic cells and used to generate switching signals of lower voltage cell.

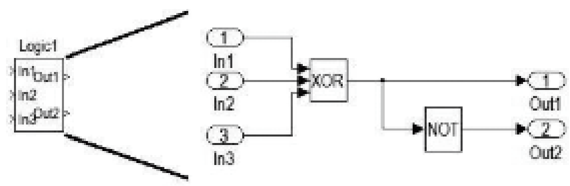


Figure 9.Logic module in modulation block

IV. MODULATION INDEX AND FREQUENCY INDEX

The frequency index, m_f is determined in (4). Modulation signal is a constant (50 Hz) for setting the ACMLI output to 50 Hz. The significant harmonic energy is dominated on the carrier frequency with m_f. THD of output waveforms is varied with m_f. Frequency index must be integer. While $m_f<21$, the m_f must be an odd number; when $m_f>21$, it can be either odd or even number. The change of modulation indexes is another parameter of the simulation. It has been performed with three modulation indexes as 0.8, 1 and 1.2 [1, 19].

Table I. THD variation of THDv & THDi belong to the changing of Frequency Index & Modulation Index changing.

fc (Hz)	m_a	PD-PWM		POD-PWM		APOD-PWM		PS-PWM	
		THD_v	THD_i	THD_v	THD_i	THD_v	THD_i	THD_v	THD_i
950	0.8	23.95	4.09	23.83	3.99	23.86	3.94	56.20	6.46
	1	16.77	3.32	17.66	3.78	17.67	3.31	32.55	7.52
	1.2	15.62	5.98	15.93	6.46	15.88	6.53	26.20	4.14
2000	0.8	22.90	2.27	21.50	2.29	22.72	2.15	44.84	4.09
	1	17.02	1.69	17.52	1.68	17.04	1.67	24.08	7.27
	1.2	15.23	5.99	14.64	5.77	15.15	5.75	20.48	5.69
3000	0.8	21.20	1.87	21.16	1.75	21.63	1.85	51.78	9.94
	1	16.49	1.59	16.77	1.74	16.54	1.5	30.49	7.14
	1.2	14.64	5.90	14.67	6.21	14.60	5.94	23.08	5.59
4000	0.8	21.02	2.94	20.62	3.36	20.39	2.65	48.53	6.48
	1	15.70	1.54	14.83	1.12	15.20	1.05	25.83	6.77
	1.2	14.62	5.85	14.23	5.93	14.37	5.94	21.78	6.22
5000	0.8	22.21	2.30	23.04	2.32	21.21	2.39	32.37	4.72
	1	17.81	2.68	17.73	2.83	17.26	3.15	29.27	6.21
	1.2	15.07	6.0	14.53	5.98	14.89	5.92	19.79	5.83

In this study, the effects of different mf and ma values have been investigated for ACMLIs which is given in Table I. Analysis results show that the better solution about the THDi is achieved when ma=1 in vertical techniques of MC-PWM from Table I. However, PS-PWM technique is not convenient and usable for ACMLIs. Output voltages and currents are shown in Fig. 10, while ma=1. ma is not preferred less than “1” or greater than “1” in ACMLI with MC-PWM modulation techniques. When the modulation index decreases or increases from ma=1, THDi increases. The best THDi values of PD-PWM, POD-PWM, and APOD-PWM are 1.54%, 1.12% and 1.05%, respectively at 4 kHz carrier frequency as illustrated Fig. 11. POD-PWM and APOD-PWM techniques are so close to each other, as well as, APOD-PWM has the lowest one.

At the same time, while vertical MC-PWM techniques have more number of harmonics at output voltage, the harmonic numbers of PS-PWM are less than the THDi of others as shown Fig. 11.

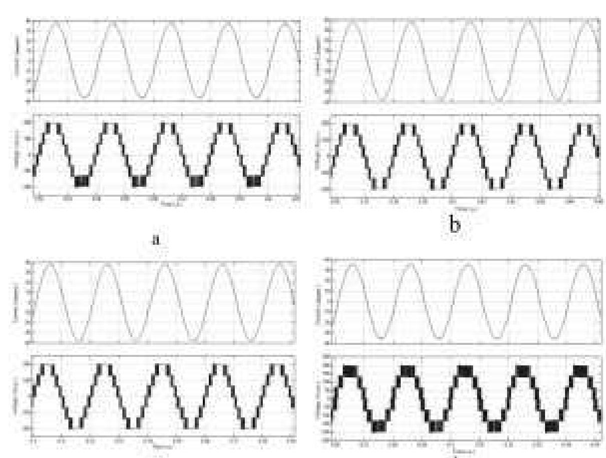
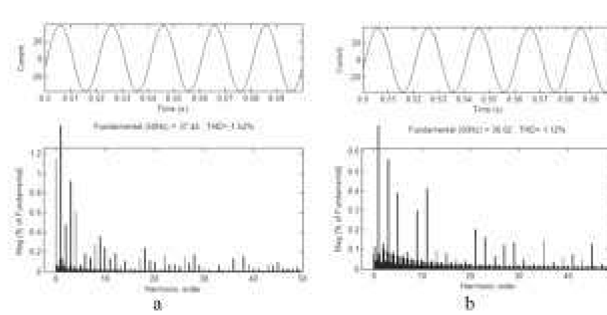


Figure 10. Seven-Level ACMLI output current and voltage a) PD-PWM, fc=4000 b)POD-PWM,fc=4000 c)APOD-PWM, fc=4000 d)PS-PWM, fc=5000



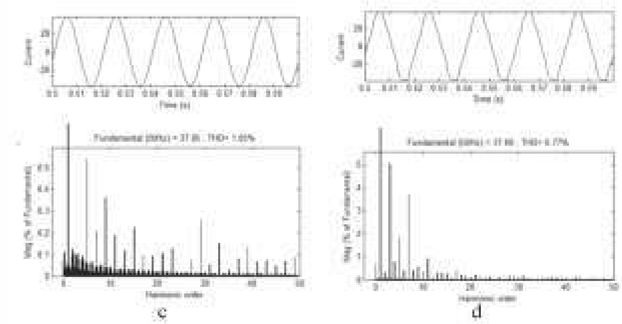


Figure 11. Output current THD (fc=4000)a) PD-PWM, b)POD-PWM, c)APOD-PWM, d)PS-PWM

V. POWER FACTOR ANALYSIS

The power quality includes both voltage and current qualities [20]. Power factor (PF) calculation includes the values of voltage and current signals. t_v and t_i are zero point crossing time of voltage and current in one period and T is the period of the output signal in (6). PF calculations are depicted in Table II. PF analysis is done with different modulation index and frequency indexes. t_v and t_i values are taken from the output signal as shown in Fig. 12. In Table II, the highest PF values were obtained in PD-PWM and POD-PWM. In PD-PWM, it is achieved as 0.997 for the m_a value of 0.8 and 1.2 in the carrier frequency of 1 kHz. In POD-PWM, it is worked out as 0.998 for the m_a value of 0.8 in the carrier frequency of 5 kHz.

$$PF = cos\left(\frac{(t_v - t_i) \times 360}{T}\right) \qquad (6)$$

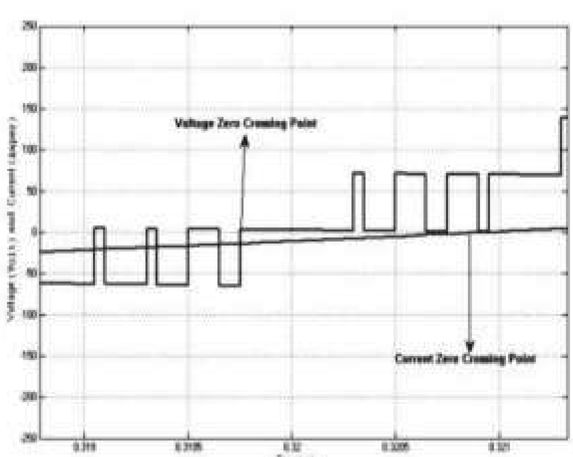


Figure 12. PF analysis of voltage and current zero crossing point

Table II. Power factor in different Frequency Index and Modulation Index

fc (Hz)	m_a	PD-PWM	POD-PWM	APOD-PWM	PS-PWM
		PF	*PF*	*PF*	*PF*
950	0.8	0.873	0.685	0.685	0,581
	1	0.498	0.685	0,864	0.881
	1.2	0,873	0.864	0,864	0.660
2000	0.8	0.924	0.873	0.881	0.881
	1	0.581	0.997	0.924	0.660
	1.2	0.924	0.997	0.924	0.660
3000	0.8	0.873	0.660	0.581	0.660
	1	0.581	0.924	0.924	0.581
	1.2	0.581	0.873	0.924	0.581
4000	0.8	0.581	0.581	0.660	0.660
	1	0.917	0.924	0.581	0.660
	1.2	0.916	0.581	0.881	0.581
5000	0.8	0.660	0.998	0.660	0.881
	1	0.660	0.660	0.917	0.881
	1.2	0.917	0.581	0.924	0.660

VI. CONCLUSION

In this paper, a seven-level ACMLI topology was analyzed with different modulation techniques of MC-PWM. In order to realize the seven-level inverter with multi carrier techniques, six carriers must be used. PD-PWM, POD-PWM, APOD-PWM and PS-PWM techniques were compared in terms of THD on the output voltage and the output current and in terms of PF in different modulation indexes and frequency indexes. It is concluded that the modulation index must be preferred as "1" for lower THDi. In case of comparing all of MC-PWM techniques in terms of THDi and PF, it is evident that the most appropriate multi carrier PWM technique is POD-PWM since it provides the highest PF value corresponding to the lowest THDi value.

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Jeff Bezos: Visionary Entrepreneur and Founder of Amazon

Jeffrey Preston Bezos, born on January 12, 1964, in Albuquerque, New Mexico, is an American entrepreneur, investor, and philanthropist. He is best known as the founder and former CEO of Amazon, the world's largest online retailer and one of the most influential technology companies.

Bezos demonstrated an early fascination with technology and innovation. After earning degrees in electrical engineering and computer science from Princeton University, he embarked on a successful career on Wall Street. However, his passion for e-commerce led him to establish Amazon in 1994 in a garage in Seattle. Originally an online bookstore, Amazon quickly diversified its offerings to include a vast array of products.

Under Bezos's leadership, Amazon transformed the retail landscape and became synonymous with e-commerce. The company's customer-centric approach, epitomized by its commitment to speedy and reliable deliveries, played a pivotal role in its success. Amazon's innovative ventures expanded beyond retail to include cloud computing services (Amazon Web Services), streaming services (Amazon Prime Video), and hardware (Kindle e-readers and Echo devices).

Bezos's entrepreneurial journey has been marked by a relentless pursuit of innovation and a willingness to take bold risks. Amazon's focus on long-term growth over short-term profits became a hallmark of Bezos's leadership style. Despite facing skepticism in the early years and enduring challenges, Bezos's vision for Amazon as an "everything store" and a tech powerhouse has been undeniably realized.

In 2021, Bezos stepped down as the CEO of Amazon, passing the reins to Andy Jassy, the former head of Amazon Web Services. Bezos, however, retained an active role in the company as the Executive Chairman, allowing him to focus on his other ventures, such as his space exploration company, Blue Origin.

Beyond his impact on the business world, Jeff Bezos is recognized for his philanthropy. In 2018, he and his then-wife, MacKenzie Scott, announced the "Bezos Day One Fund," a $2 billion initiative to address homelessness and support education in underserved communities.

Jeff Bezos's legacy extends beyond the success of Amazon; he has become an emblematic figure in the tech industry, embodying the spirit of innovation, risk-taking, and the transformative power of entrepreneurial vision.

Green & Sustainable Living

By 2050, the world's population may reach a whopping 10 billion and with more people there will be more demand for food, fashion, travel, housing and related aspirations. An increasing number of people will likely be unable to meet basic needs while two to three billion new urban consumers and youth will receive the majority of their information from social media. In a world stretched thin for resources and under the threat of global biodiversity loss and climate change, our lifestyle decisions are putting the planet at risk. We need targeted action & need to turn towards Green & Sustainable Living. Sustainable living and lifestyles for the first time appear in the Sustainable Development Goals. Green living is a lifestyle that strives to create balance in preserving and protecting earth's natural resources, habitats, human civilization and biodiversity. Green living is a means of developing sustainable habits in one's daily life so that their daily routines work alongside the resources of nature, instead of depleting them, or doing more long-term damage to the environment or ecological system. Sustainable Lifestyles can be considered as ways of living, social behaviours and choices, that minimize environmental degradation (use of natural resources, CO_2 emissions, waste and pollution) while supporting equitable socio-economic development and better quality of life for all.

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