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Predictive Maintenance Strategies for HVAC Systems: Leveraging MPC, Dynamic Energy Performance Analysis, and ML Classification Models

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Abstract— This research explores the multifaceted challenges that can affect ventilation, air conditioning systems, and heating appliances, leading to reduced operational efficiency, heightened energy consumption, and increased maintenance expenses. Predictive maintenance, a progressive approach, is investigated as a pivotal strategy, complementing traditional HVAC equipment maintenance paradigms, including breakdown maintenance and preventative machine learning. Utilizing a diverse set of predictive models infused with machine learning techniques, this study employs the 'Semiconductor Manufacturing Process (SECOM) dataset' to simulate the manufacturing processes of HVAC systems, aligning with characteristics akin to semiconductor-based devices. The research undertakes a comparative analysis, contrasting the predictive capabilities of the Random Forest (RF) algorithm with the Support Vector Machine (SVM) in areas such as problem detection, diagnostics, and load monitoring. Notably, the RF model demonstrates superior prediction accuracy. The research aims to proactively detect potential HVAC system or component issues, discerning the nature of impending failures at their earliest stages to enable proactive maintenance strategies. Evaluation metrics such as the Receiver Operating Characteristic (ROC) curve and accuracy are employed for rigorous comparative analysis across various predictive machine learning classification models. Furthermore, a comprehensive 'dynamic energy performance benchmark' framework is meticulously developed for HVAC systems, facilitating real-time operational performance assessment and the identification of irregularities in power utilization at different operational stages. Additionally, Artificial Neural Network (ANN) models are employed to establish an administrative Model Predictive Control (MPC) system tailored for residential HVAC applications.

Indexed Terms—Predictive maintenance, supervised machine learning, MPC, Random Forest, Fault detection & diagnosis.

I. INTRODUCTION

The operation power utilization of HVAC appliances or components reports for approximately50% of overall building power utilization. Building HVAC systems are frequently plagued by device failures, incorrect control, and inadequate maintenance, which can result in considerable energy loss [1]. The device is made up of an exhaust fan and an intake fan that regulates air circulation in the HVAC system. Dampers control the airflow in the dampers by regulating the air velocity and opening and shutting the dampers. The system also includes filters that filter the air and cooling coils that modify the air if a cool down or calefaction is required. To obtain the desired temperature for the air channel, the coils in the system heat or cool the air as it passes by. A reheating coil is situated in each zone to provide a reasonable temperature level, and an outlet fan pumps air out of the space to keep the air moving. Typically, the bulk of the air drained from the room is mixed with incoming air from the outside, but the same quantity of air that enters the air channels is evacuated to the environment consequently. Huge volumes of information are produced & distributed every single epoch. Handling such a massive level of information in order to provide evocative findings is a difficult & time-consuming task. Nevertheless, other unsupervised or supervised machine learning methods, like SVM, LR, and RF, might be used to make superior predictions [2]. The used dataset is rather small, with just 1567 occurrences. Nonetheless, it has a high dimensionality. As an outcome, it may produce issues such as the curse of dimensionality. As a result, data pre-processing is vital to settle these concerns [3].Techniques like “Correlation”, “Feature Selection” & “Synthetic Minority Oversampling Technique (SMOTE) analysis”, might be used to surmount initial complications such as correlated features & class imbalance. After this, ML models are executed& tested to conclude the superlative probable prediction approach grounded on the demands.

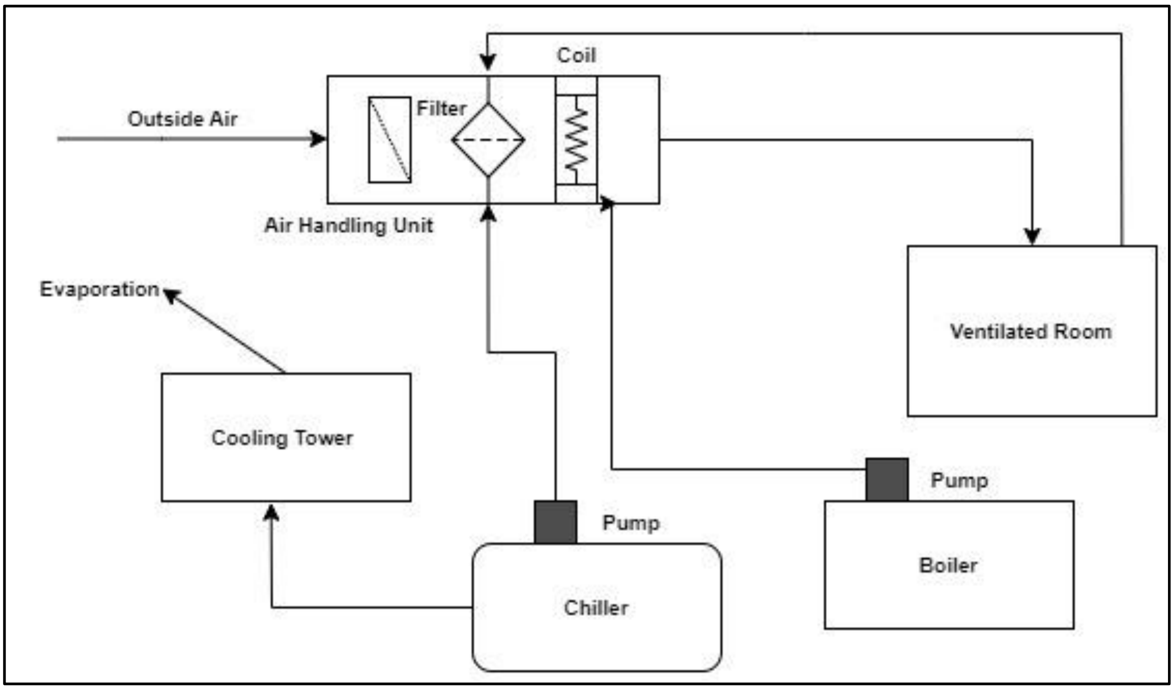

Fig 1: Basic HVAC system

Because of the communication of a huge amount of subsystems, (HVAC) systems are exceedingly nonlinear & complex systems. In order to compute the overall force utilized by the (HVAC system), every subsystem must be properly modelled [4]. Developing exact dynamic models of every subsystem via physics-based modeling or standard forward approaches is extremely challenging, & a large endeavour is necessary for a full grasp of system physics [5].

The limitations of forward modelling approaches become clear as soon as mock-ups for a range of HVAC system conformations must be constructed & refined, preventing their use in the actual world. Forward modelling approaches are beneficial for research-based study of larger classifications, but they do not meet the needs of industrial users. According to studies, accumulation of a managerial MPC controller to HVAC systems can outcome in a 8% to above than 50% decline in power usage & operational costs [6].

MPC techniques based on ANN are nonlinear because models produced using ANN are nonlinear. Via using procedures for optimization like the ‘interior point method’ or the ‘active set method’, the bare minimum of a rectilinear optimization delinquent could be identified easily. Non-linear optimization problems, might be non-convex & contain several local minima. There is currently no algorithm in the literature that promises‘ global minima of a nonlinear optimization problem’. Evolutionary algorithms & simulated annealing approaches of global optimization might resolve “non-linear optimization problems”, nevertheless they have challenges with convergence and computing complexity.

This paper's key goals and contributions are as follows:

i. Predictive maintenance of (HVAC) system using Machine Learning classification models.
ii. To detect Anomaly in (HVAC) systems & propose Dynamic energy performance for (HVAC) systems.

iii. Replication of the MPC controller (based on ANN) on the precisely standardized housing (HVAC) classification prototypical.
iv. Examination of cost reserves via MPC allied to the static set-points on a housing(HVAC) system.

II. LITERATURE STUDY

To increase speed and carry out global optimization, a novel approach known as particle swarm optimization is applied. The suggested technique's goal is to deplete the exploration interim of a problem in order to identify the parameters that maximize the desired objective. This program mimics the behavior of particles in a *swarm*. The location of a *"particle x in the kth step & its velocity in the (k+1)th step"* define its stand point. Ideal location might calculated using 'i/p constraints', like particle positions after a piece stage [7].

Several rapidk-NN search techniques have been developed to minimize computing stretch. For a data set made up of real photographs LAI algorithm is an excellent choice. If pre-processing time is critical & an information collection has a large quantity of dimensions, "the MPAT" approach is the finest option [8].

Table 1: Existing approaches based on Machine Learning

Existing Approach	ML Technique	Relevance
Zhou et.al [9]	SVM, kNN	Fault Classification
Carbery et.al [11]	BN	Diagnosing & Predicting Faults
Schmidt et.al [10]	RF, kNN, NB	Fault Classification
Ansari et.al [12]	DBN	Predicting failure events
Adhikari et.al [14]	SVM, NB, RF	Anomaly Detection
Calabrese et.al [13]	GBM, XGBoost	RUL

The existing studies that use neural networks(NN), indicating classifications & the job performed by the (NN) inside every study is listed in Table 1. Schmidt et al. [10] compared the functioning of Naive Bayesian (NB), k-Nearest Neighbour (kNN), Support Vector Machine (SVM), Decision Tree(DT)Random Forest(RF), in countless situations to find time series prediction for the finest grouping of procedures.

Zhou et al. [9] evaluated a diagnostics and prognostics framework using kNN and DT, as well as Multi-layer Perceptron (MLP)& SVM. Carbery et al. [11] sought to forecast failures by dealing with vast volumes of data. The authors employed a Bayesian Network to do this (BN). This strategy was chosen since BN is recognised for performing effectively in the face of uncertainty. Furthermore, utilising conditional probabilities, this method can break difficult issues into more manageable ones. Ansari et al. [12] propose a new BN termed the Dynamical Bayesian Network (DBN).

The idea is part of a framework meant to forecast failures and assess their influence on the eminence of fabrication forecasting procedures &conservation expenses. Adhikari et al. [14] introduced" auto-regressive integrated moving average (ARIMA)", a form of ARMA, in order to forecast the residual usable lifespan of components in a predictive maintenance framework. ARIMA was chosen because of its capability to forecast future behaviour using previous data. In addition to RUL estimation, Adhikari et al. [14] propose using SVM to discover potential anomalies and characterize algorithmic failures. Calabrese et al. [13] offer an architecture that employs 3 separate methods in order to identify computers with 30 days or fewer of RUL by using 'tree-based' techniques in order to forecast risk of breakdown. As soon as associated to Extreme Gradient Boosting (XGBoost) models produced the best classification results.

The 'data-based dynamic energy benchmark evaluation' approach is gaining popularity because it may give precise power assessment by evaluating present power operation to previous data [15]. This technique assesses energy-saving possibilities and gives recommendations for improving building energy performance [16]. To target the typical power usage & fabricating parameters. The estimation findings were further validated by evaluating the model standardization to the beak of measures [17].

A [dynamic energy benchmark] of workplace edifice was constructed by Liu et. al in Energy Plus, using which the office building's operating performance over several months was assessed [18]. Yan et al. suggested a technique for diagnosing multilayer energy performance. To represent the relative difference between existing & predictable functioning & to quantify the power hoarding latent of entire parts of the power system [19]. It could do hourly, daily &weekly, power assessments in the overall component layer, system layer, &building layer [20].

Modern dynamic energy performance evaluation research frequently relies on current operational data to generate direct dynamic energy benchmarks. Yet, irregular energy consumption happens often in the real functioning of a building energy system due to different problems. The errors in the operating data must first be addressed, especially when evaluating individual structures. Data pre-processing can fix certain aberrant data. Unfortunately, certain aberrant circumstances are more concealed, and finding a generic data pre-processing approach is challenging, resulting in variances in the 'dynamic energy benchmark'. In certain research, power replications/w is utilized in order to create a house power regularity prototypical& anticipate system's power utilization over course of a year in order to generate a 'dynamic energy breakdown'. It is difficult to assess the discrepancy between simulation results and actual operating outcomes, resulting in unclear reliability. As a result, this research offers a ML & ANN -grounded dynamic energy performance& anomaly detection assessment approach for an (HVAC system).

III. METHODOLOGY

The HVAC is monitored in real-time using sensors, & the information obtained is processed in the microcontroller. The processed data is used to produce a dataset. The classifier architecture was trained using 9521 training observations with a 20% validation split and 1520 testing observations. The algorithm was also tested on IAWE with an accuracy of 92%.The dataset may also be visualized using Matplotlib. As shown in Table II, the accuracy of the training dataset was [94.5%] and the accuracy of the validation dataset was [93.2%]. This study introduces random forest approach & was compared to a coarse decision tree& support vector machines.

Table 2: Reflections of Random Forest Algorithm

Dataset	Accuracy	Opinions
Training	94.5%	6000 of datasets formed
Testing	93.1%	1520 of datasets formed
Validation	93.2%	2001 IAWE dataset

Yet, a basic model like Decision Tree has poor predictive power. Improved approaches, like as random forests and boosting, produce better outcomes, but at the expense of interpretability and prediction accuracy. Via Random Forests [RF]& diversifying the training dataset improves model performance by 4-5%.

There is no consistent approach to designing a PdM platform or digital program. But, as an example, a PdM design has four primary levels.

(i) *Sensing layer*: is combined with existing h/w objects in order to recognize the standings of objects.
(ii) *Network layer*: is the substructure that permits wireless or wired connection amongst the factors for allocation & swapping.
(iii) *Service layer*: is to generate & accomplish amenities vital by applications or users.
(iv) *Interface layer*: is the collaboration approach with application/users.

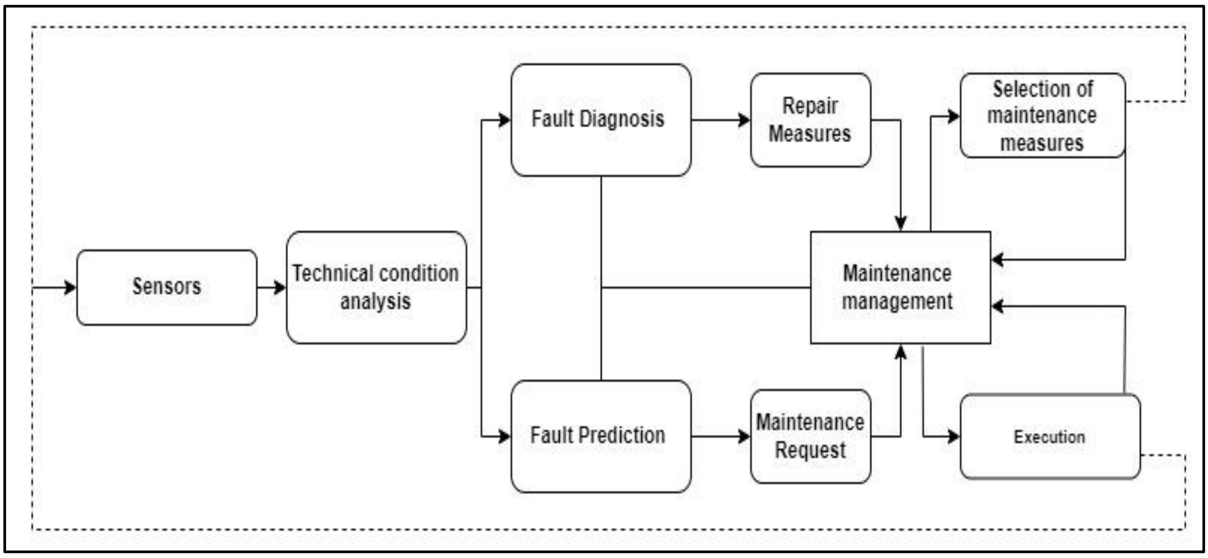

Fig 2: Structure of PdM with its main elements

The PdM structure seen in fig. 2 is made up of seven linked parts. Initially, "Sensing" emphases on sensor placement& sensor modality technique. Assignment of sensors are critical responsibilities establishing the furthermost accurate image of benefit state. Incidental sensing systems are frequently fewer expensive & less complicated, & they allow for continuous monitoring without halting procedure [40].Secondly, "Condition status assessment" refers to evaluating the obtained data in order to identify the resource well-being status, serves as a basis for defining present standing of the asset condition. The indication might be viewed as a traffic light, offering a quick and easy overview[40].Third, "fault diagnosis" (which comprises fault detection, fault isolation, fault location, & fault recovery) and "fault prediction" are difficult errands with a variety of approaches grounded on data-driven methods, analytical models, & qualitative empirical knowledge.

Recognition of breakdown modes is the basis of RUL prediction, &'RUL of a fabricating system' might be described as [41]: "the period of steady production of high-quality goods." ANN might viewed AI approach in this context. "Fault diagnosis" and "Fault prediction" are cohering components that give a foundation for the best "Repair measures,"&stretch for carrying out the "Maintenance activities," elements. Moreover, there should be a relationship amongst operations management& maintenance management, since information from procedures may advance PdM competences, but PdM could also assist speedy & data-driven throughout maneuvers.

Logistic regression [LR] is most basic &well-organized procedures for dealing with '*binary dependent variable issues'.* Algorithm 1 explains how it is arithmetical technique by the foremost purpose of computing the weights (w)connected with the variable quantity.

Algorithm 1: Logistic Regression

1. generate *w= (w [0], w[1],.....w[n-1],1)*
2.while$\nabla E_{in} > \epsilon$
3. for$i \leftarrow$ 0,1,2, ...
4. Compute Gradient
5. $\nabla E_{in} = -\frac{1}{N\sum_{n=1}^{N} y_n x_n} \div 1 + e^{yn} w^T(t)x^n$
6. Compute Gradient
7. w(t+1) ←w(t)$-n\nabla E_{in}$
8. end
9. return w

In Algorithm 2, a (Rf) random forest is a category of ensemble learning that employs strategy concurrently founding numerous trees &appointed for the finest precise tree classification.

Algorithm 2: Random Forest

1. for i← 0 $to\ number\ of\ trees,\ n$
2. for i← 0 $to\ number\ of\ nodes, l$
3. Select k out of m features
4. Calculate the node d
5.Split the nodes into daughter nodes
6. for i← 0 $to\ n$
7. Use generated rules to predict output
8. Calculate votes for each predicted output
9. end for

10. return highest predicted target as the final prediction

OPTIMIZATION METHOD: In contrast to *linear systems*, attaining optimum resolutions for *nonlinear systems* is a tough undertaking subsequently logical solutions are rarely available. As a result, numerical approaches such as gradient methods& dynamic programming must be used for *nonlinear systems*. Because of the equality restrictions utilised in the issue formulation, the Lagrange multiplier techniques didn't execute well, & the generalised approach delivers reliable consequences solitary if it begins with a plausible result [22].

During ANN-MPC research, the subsequent 'nonlinear optimization' approaches are used:

- Newton-Raphson method [23],
- Interior-point method [24],
- Particle swarm optimization (PSO) algorithm [25],

The Newton-Raphson technique, a convergence algorithm, was employed in [23]. As compared to other approaches, it converges in less rounds and is a quicker &various effective solution for 'real-time controller appliances.' The interior-point technique resolves unceasingly "differentiable cost function (cf)" while constraining & ensuring the best answer [24].

PSO is a proportionate technique for improving & adapting to local& global examination issues. PSO excels in resolving 'single-objective optimization' problems via high convergence rates. [25] compared harmony search to [PSO]&[SPEA]. In comparison to SPEA, PSO and Harmony searches took less time and had a greater computational frequency. As a result, SPEA is unsuitable for online optimization.

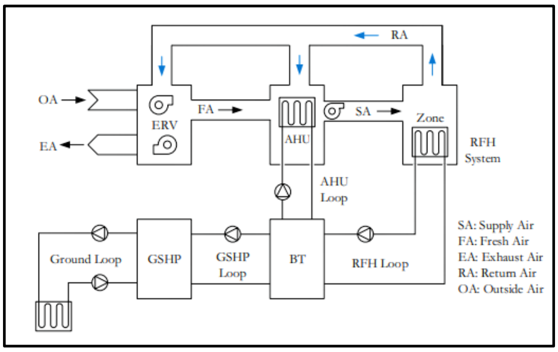

Fig 3: Illustration of residential HVAC system

[29] introduced an 'ANN-MPC controller' to manage the interior air temperature & attempted to advance on the controller concept described in [26]. Unlike most previous techniques, the research in [29] looked at the cost function indicating the cost of running an HVAC system rather than power usage. As compared to the technique in [26], which solely reduced energy usage, employing the cost function (cf) occasioned in [13.5%] depleted power use and [7.8%] larger cost savings. MLP ensemble was used in [27] to predict an office building's AHU supply air temperature, IAQ, AHU energy usage, AHU static pressure. The 'MLP ensemble-based controller' employed to forecast appropriate 'supply air set-point' settings even though diminishing power usage and optimising thermal comfort. The multiple goal nonlinear optimization issue was solved using an evolutionary computing approach based on modified PSO. [28] also reported creation of "MLP type ANN-MPC" where scholars evaluated the usage of a 'meta-heuristic search method' through optimization as an alternative of Particle swarm optimization (PSO).

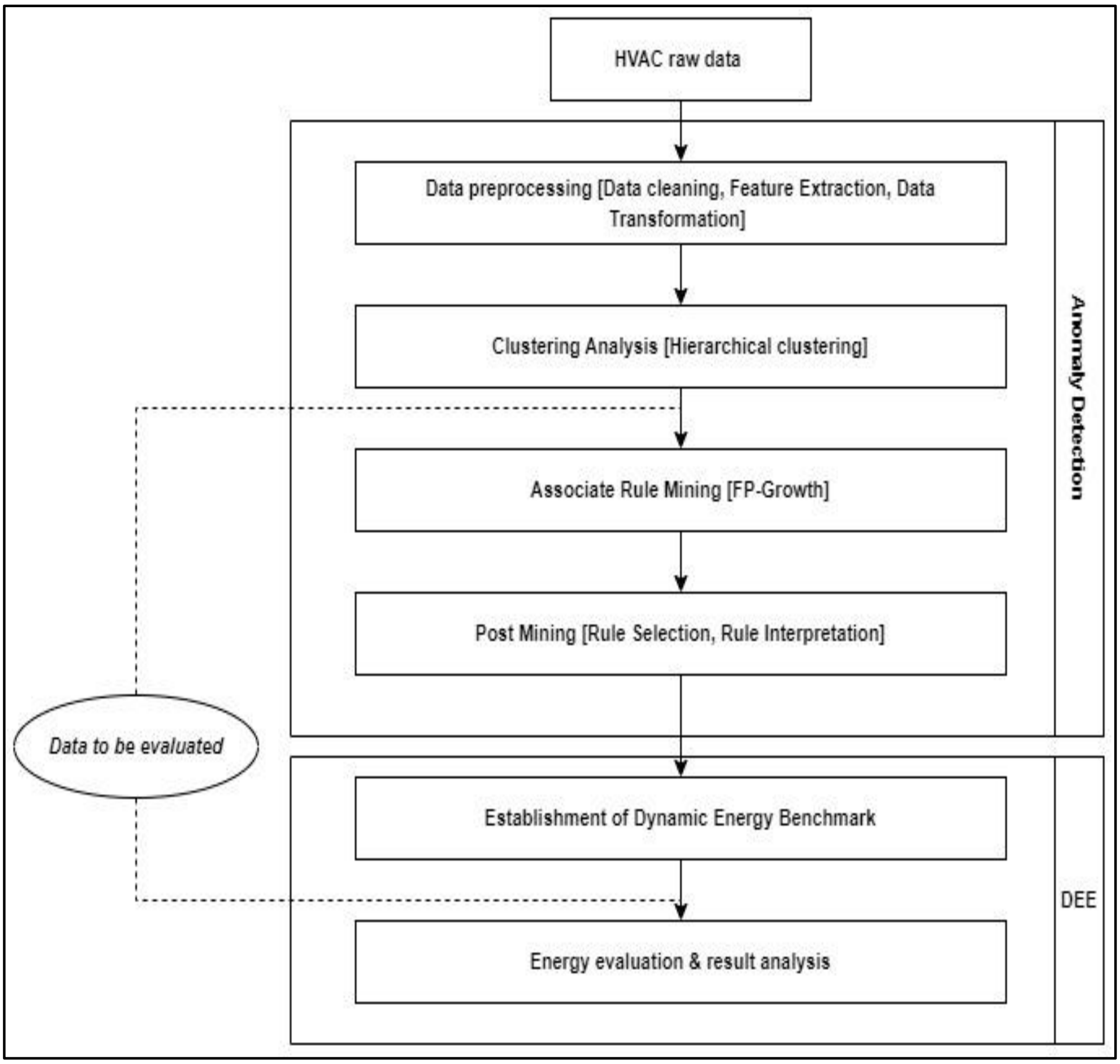

Fig 4: Framework for Anomaly detection & the dynamic energy performance evaluation method

Figure 4 depicts the suggested method's framework, which is separated into 2 processes: dynamic energy performance& anomaly detection assessment. The uncharacteristic power utilization is repaired in the procedure of dynamic energy performance & anomaly detection estimation grounded on the operating faults that are detected. The suggested method's detailed implementation processes are depicted below.

Formation of the 'dynamic energy benchmark', developing power assessment criteria, & power estimation & consequences investigation are three major components. An (HVAC system) might be separated to multiple power outlines after association rule mining, anomalous operation,& clustering analysis, incidences in diverse power outlines could be discovered. When establishing the 'dynamic energy benchmark', incorrect energy consumption values induced by aberrant operation must be corrected. The entire structure& each substructure may then define based on different energy patterns. The power standard is a typical number which indicate pattern's 'avg. quantity of power' usage underneath entirely scenarios. As a result, in this study, the average value is employed to calculate the energy benchmark.

IV. IMPLEMENTATION & RESULTS

Diverse ML algorithms, incorporating random forest& logistic regression, have been applied to the dataset. Univariate analysis is also available. Ad a Boost and other boosting algorithms have been constructed, and their accuracy ratings are compared to others. The (ROC curves) of the representations might cast-off in order to evaluate efficacy. Random forest, Ad a Boost, decision trees, k-NN, MLP, logistic regression are among the models that have been applied. Approaches of dimensionality reduction such as PCA and LDA are employed. Table 3 shows the proportion of precision records that have been observed &linked at the equivalent time. In terms of accuracy, "Random Forest with 'False Discovery Rate' is the finest functioning algo.," whereas Logistic Regression with LDA is the worst-functioning.

SMOTE analysis solves the hindrance of "class imbalance." Table 3 displays the accuracy formerly & afterwards' SMOTE sampling'. The accuracy numbers are all in percentages. The cv has a value of '5'.

Table 3: Assessment of mean cross-validation scores & accuracy scores in various methods following SMOTE sampling.

Algorithm	Mean cross validation score	Using SMOTE
Random Forest	93.40	94.87
Logistic Regression	81.80	84.73
k-NN	92.47	56.73
MLP	78.91	88.93

4ML models have 'ROC curves' integrated. "The Area Under the ROC Curve (AUC)"dimensions reflect in what way fine specific constraint can differentiate b/w2 clusters. Originally, the ROC curve was built for the most basic algorithms, such as logistic regression& random forest. Figures 5,6 illustrate the outcomes.

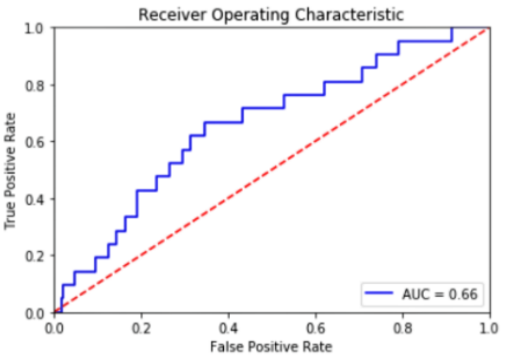

Fig 5: Logistic Regression's ROC Curve

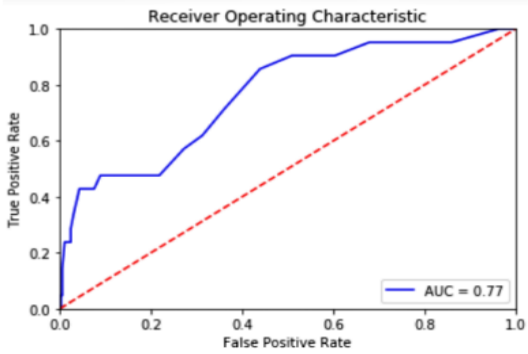

Fig 6: Random Forest's ROC Curve

Table 3 shows the proportion of accuracy scores that have been observed & evaluated on spot. Random Forest with False Discovery Rate is the finest executing algo., whereas Logistic Regression with LDA is the worst functioning method in terms of accuracy. The ROC curves of the models might be used to evaluate their efficacy.

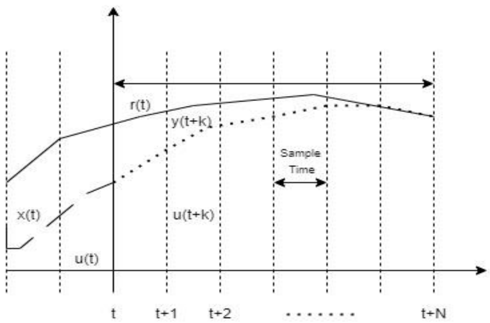

Fig 7: I/p & O/p of MPC-based controller.

- Estimated o/p *{y (t + k)}*, Measured o/p *{x(t)}*,Projected switch i/p *{u (t + k)}*, Previous switch i/p *{u (t)}*.
- Take new measurements at '*time t + 1*'& continue the optimization procedure.

In the aforementioned formulation, the cost function is sum of control effect &tracking error. In the occurrence of system i/p& o/p limitations, the optimization attempts to decrease control effect & tracking error throughout the upgradation prospect & provides the optimum regulator trajectory. MPC was proficient to conserve b/w 6% & 73% on operational costs as associated to the "fixed set-point (FSP)", depending on the season. Anomaly detection is divided into four steps: data pre-processing, mining, post-mining, association rule, & clustering analysis. The development of the power assessment criteria, & the power assessment & outcomes investigation are three components of dynamic energy performance evaluation.

Table 4: Dynamic energy benchmark of the overall system & subsystems

Cluster Number	Dynamic energy benchmark heating appliances (kWh)	Dynamic energy benchmark of A.C (kWh)	Dynamic energy benchmark of Ventilation appliances (kWh)	Dynamic energy benchmark of cooling system (kWh)	Dynamic energy benchmark of chiller (kWh)
1	594.75	67.99	13.88	71.26	444.61
2	814.56	93.23	35.38	74.41	614.54
3	1232.50	98.34	61.00	139.85	936.34

Table 4 displays the results of dynamic energy benchmark. Furthermore, establishing an power baseline for the entire system aids in the inclusive assessment of the HVAC system's functioning. The energy benchmark is a typical number which indicate pattern's median height of power usage underneath scenarios. As a result, in this study, the average value is employed to calculate the energy benchmark.

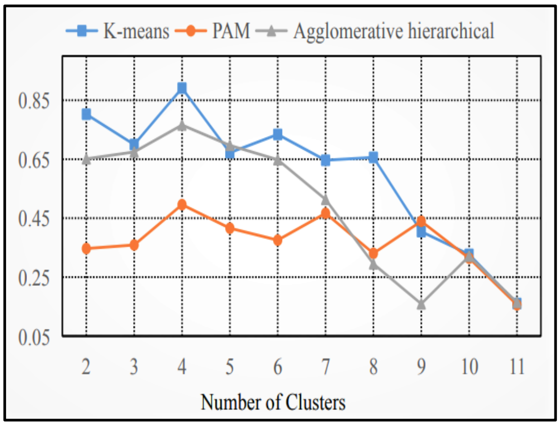

Fig. 8: Clustering validation results by month

In order to identify energy patterns, three prominent clustering techniques were used: agglomerative hierarchical, k-means, agglomerative &hierarchical. The outcome of clustering was examined comprising the 'silhouette index' to identify appropriate number of clusters. The 'silhouette width' is calculated by taking the avg. of a piece opinion's 'silhouette value', that shows self-assurance of certain inspection collection. The width of silhouette ranged from ['1 to 1'].Greater breadth of the silhouette, the greater the 'clustering outcome. Through evaluating widths of the 3 techniques (clustering number assortment was chosen from 2 to 11), the best clustering number by month was determined to be 4, as shown in Fig. 3. This technique is adaptable & expandable, and its components may be chosen or altered based on actual demands anticipate energy consumption of (HVAC system), diagnose & optimise system, and achieve other goals. MPC was capable to conserve b/w 7% & 83% on operational costs as contrasted to the 'fixed set-point (FSP)' depending on the season.

CONCLUSION

Based on the broad comparison investigation, it is possible to infer that random forest(rf)executes badly on the [SECOM-dataset]due to 'class imbalance problem.'(LR)Logistic regression executes significantly improved. Random Forest with 'False Positive Rate' that mounts dataset the finest. Some algorithms does not execute fine imputable to the above-stated problem, therefore definite hybrid algo. Like advanced ML might be implemented. The (SMOTE) method assisted for improving accuracy of Logistic Regression. As soon as the 'cross-validation' approach is used amid Random Forest, mean cross-validation score is the greatest. Based on supervised machine learning, a model for predictive maintenance of HVAC systems is developed. It has been demonstrated through experimentation & simulation that the random forest method outperforms the SVM and other approaches. The Random Forest method produced the best results for load identification& defect detection, with prediction accuracy of 94.5% & 93.1%, correspondingly. The proposed model might be used for 'real-time ailment scrutinizing' of (HVAC systems), particularly industrial & viable edifices wherever supervising a huge no. of HVACs critical in decreasing maintenance costs& energy consumption. The preventive maintenance algorithm's efficacy is determined by the underlying dataset. The next step would be to collect additional measurements to enrich the dataset. Moreover, to study increases in prediction accuracy, the programme might be modified using

Genetic Algorithms and Particle Swarm Optimization approaches.

Building HVAC systems need a systematic technique for automatically identifying and correcting different aberrant operation data, followed by the establishment of an acceptable energy benchmark to assess power operation. This research offered a technique for detecting anomalies and dynamically evaluating HVAC systems based on dynamic energy performance. The approach is distributed into 2 stages: dynamic energy performance evaluation& anomaly identification. Data pre-processing, association rule mining, clustering analysis& post processing are all steps in the anomaly detection process. It can efficiently recognise abnormal operation from an (HVAC system's) past operation data & analyse details following the same. The progression of ‘dynamic energy performance’ assessment establishing power estimation rules, evaluating energy, & analysing the results. An HVAC system's operation data may be examined in real-time& with various layers, & anomalous power utilization in the function procedure could be detected to analyze the causes of excessive power utilization. The method's dependability was demonstrated using the instance of a commercial cooling system. A dynamic multilayer power utilization assessment of an HVAC system was performed after modifying the aberrant power utilization in the previous operating data. This technique is adaptable and expandable, and its components may be chosen or altered based on actual demands to anticipate energy consumption of (HVAC system), diagnose &optimize system, and achieve other goals. MPC was capable of conserving b/w 7% & 83% on operational costs as contrasted to (FSP) depending on the season.

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