Neurofuzzy Model Optimized for Integrating Explainability in the Prediction of Engine Performance Losses.

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ABSTRACT

The anticipation of automotive failures in general and the prediction of engine performance losses remain challenging for vehicle owners and automotive industry professionals. In this article, we start by analyzing the causes of engine performance loss to identify the significant parameters of this failure mode. These parameters are then identified as inputs for the implementation of Adaptive Neuro-Fuzzy Inference System (ANFIS) neurofuzzy models optimized by a Particle Swarm Optimization (PSO) algorithm that takes into account the four previous instants to predict the next instant. The model was used to predict the performance loss characteristic failures of engine overheating, air leakage, engine power loss, air-to-air heat exchanger fouling, and filter clogging. The proposed model is an Explainable solution that better compromises performance and complexity. The performance of the ANFIS-PSO algorithm was evaluated by comparing test data with actual data. Satisfactory results were obtained, with R^2 of the order of 0.99 for the test and training data, Root Mean Square Error (RMSE) of the order of 10^{-14}, Standard Deviation of prediction Errors (Error St. D) of the order of 10^{-15} and Mean Absolute Error of the order of 10^{-15} for a prediction horizon of 1800s. This is with a Central Processing Unit (CPU) time of 0.002s. It is clear that the ANFIS-PSO model, which considers the four previous time instants, is sufficiently performant to predict the phenomena associated with the loss of engine performance.

1. INTRODUCTION

Vehicles are the most visible and indispensable piece of industrial equipment in our societies, offering significant advantages in terms of mobility and transport (J. Pranav.P et al., 2023; Kim, 2023; R. S. Krishnan et al., 2023). Like all industrial equipment, vehicles are subject to faults during their operation, which can affect the safety of people and the asset itself. The ability to anticipate a vehicle's specific failures is of great value in ensuring its reliability (Shi et al., 2024).

Introducing an accurate model adapted to predict changes in the attitude of vehicle components during operation will make it possible to anticipate breakdowns while providing information on the ideal moment to intervene (Mohanty et al., 2020; Rao et al., 2022). Automotive prognostics is a major topical issue, making it possible to optimize vehicle reliability and durability while guaranteeing the safety of people and property (Pavlopoulos et al., 2024).

Over the years, several approaches have been developed for fault prediction: the physics-based model approach (Liu et al., 2023; X. Zhang et al., 2023), the knowledge-based approach (Li et al., 2023; Miraftabzadeh & Longo, 2023), and the data-based approach (Mueller et al., 2023; Yang et al., 2024). The data-driven approach is widely used in automotive maintenance because of its ability to exploit the degradation indicators provided by monitoring processes (Revanur et al., 2020; Vasavi et al., 2021; Y. Zhou et al., 2020). Research has been carried out to predict failures using

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this approach, using sensor data to predict powertrain faults (Revanur et al., 2020), shock absorber degradation rate (O'Donnell & Yoon, 2020), the useful life of each component of a fleet of vehicles (M. S. Punith et al., 2022), and engine performance losses (Gad & Alenany, 2024). These approaches improve repair planning and reduce maintenance costs by exploiting the data collected. However, this work does not allow us to have a plural look at failures by emphasizing characteristic failures.

The engine is the most critical component of industrial equipment (Pandey et al., 2021). It is also for the vehicle (Anjaneya et al., 2024). By optimizing faults engine prediction, we can anticipate improving these failures to prevent the vehicle from coming to a standstill, causing traffic accidents, and, more importantly, impeach performance losses. Several works were carried out to predict engine performance losses using machine learning methods (Addo et al., 2023; H. Wang et al., 2023) and artificial neural networks (Ağbulut et al., 2020; Shalahuddin et al., 2023). However, the failure prediction methods can be complex and challenging to interpret, limiting understanding of the underlying factors contributing to failure. As a result, there is a lack of adaptability and interpretability of the results of these predictions by engineers (Keneni et al., 2019a).

Explainable Artificial Intelligence (XAI) addresses the need for transparency and justification in decision-making processes (Keneni et al., 2019b; Pramod & Pillai, 2021; Singh et al., 2023). To achieve this, rule-based methods are considered the most advantageous and widely used (Casalino et al., 2023; Lughofer & Pratama, 2023; Peláez-Rodríguez et al., 2024; Sun et al., 2023). The Adaptive NeuroFuzzy Inference System (ANFIS) is particularly appreciated in this context, as it is capable of modeling and predicting complex phenomena in various domains such as industry (TJAHE et al., 2021a), environmental engineering (Duranoğlu et al., 2024), machining and manufacturing (Stephen & Sethuramalingam, 2024), nanofluid Technology and thermal Engineering (Z. Zhang et al., 2023) and especially the automotive sector (Machesa et al., 2023a). However, adjusting the ANFIS parameters remains necessary to find an optimal balance between the complexity of the model and its performance.

Alongside ANFIS combined with GA (Genetic Algorithm) (Ude et al., 2023) to DE (Differential Evolution) (Chen et al., 2017), PID(Proportional Integral Derivative) (Saraswathi & Vijayaraghavan, 2024) , PSO (Kontoni & Ahmadi, 2024; Oladipo et al., 2024) . ANFIS-PSO is widely used in the literature because it is the one that offers the best performance (Şener et al., 2024). This approach allows promising solutions to be found quickly by exploiting the particles' interactions, making it possible to obtain good performance for complex problems (Chaudhury et al., 2022; Oliaye et al., 2023; Samanataray & Sahoo, 2021; Sarkar et al., 2023). This paper presents a novel approach combining the ANFIS-PSO algorithm to predict engine performance losses. The main contribution of this paper is summarized in theorical, pratical contributions and contribution of this work compared to existing solutions in the literature.

❖ Theoretical contribution

- This work uses Failure Mode and Effect Analysis (FMEA) to identify and examine the key parameters contributing to engine performance losses. Five main failures were identified: engine overheating, filter clogging, air-to-air heat exchanger fouling, air leakage and power loss. These failures served as the basis for developing a predictive model capable of anticipating performance losses. Unlike many previous studies which focus on one-dimensional prediction methods, this research adopts a multi-faceted approach by analyzing several failures characteristic of engine performance loss;
- The proposed model offers a diversified perspective on performance loss prediction over multiple time horizons, enabling a more comprehensive and dynamic assessment of engine performance. This enables interventions to be tailored to the specific needs at each point in time;
- The model generates simple, self-explanatory fuzzy rules, making it easy for automotive maintenance engineers to understand. This transparency is essential for informed decision-making during maintenance operations;
- The article deals with the collection of data on a vehicle in Douala, Cameroon, using a locally manufactured acquisition system designed to collect engine parameters in real time. The aim is to create an automotive database adapted to African conditions, enabling improved failure prediction and vehicle maintenance. This approach aims to optimize vehicle reliability and safety in the specific context of sub-Saharan Africa.

❖ Practical contribution

- This work focuses on the prediction of engine performance losses, essential for vehicle maintenance. By anticipating these losses, we can improve vehicle reliability and durability, while reducing maintenance costs and downtime, enabling proactive and targeted interventions - all of which contributes to reducing air pollution levels;
- In this work, five failures responsible for performance loss were identified. This makes it possible to target maintenance interventions, optimize the use of resources and train technicians to recognize signs of failure, thereby improving reliability and safety;
- Integrating the values of the four instants preceding failure improves predictive accuracy without increasing model complexity. This helps to identify failure patterns and plan preventive interventions, making the model adaptable to each failure to be predicted;
- Multi-horizon prediction enables flexible planning of short, medium and long-term maintenance interventions,

optimizing resource allocation and reducing downtime. It also encourages preventive measures before major problems occur;

- The rules generated by ANFIS help engineers to understand the relationships between variables and results, facilitating informed decision-making on maintenance and necessary interventions.

❖ Overall contribution

To position our approach within the broader context of predictive maintenance and engine performance prediction, we conducted a comparison between our method and those found in the literature. Below, we highlight the strengths and weaknesses of each approach and demonstrate how our model stands out, particularly in terms of its pluralistic and contextualized approach, explainability, computational efficiency, real-time applicability, and its ability to predict across multiple horizons.

Table 1 provides a comprehensive comparison between the proposed approach and several recent studies in the field of engine performance prediction.

2. MATERIALS AND METHODS

This section begins by presenting the equipment used in this work. It consists of a Common Rail diesel engine and a black box that enabled us to collect engine data. Secondly, an analysis of the failure modes with significant parameters, the neuro-fuzzy network, and the optimization algorithm are presented.

2.1. Common rail engine

The Common Rail injection system of diesel engines is used to predict engine performance losses due to its precise control of fuel injection based on the load (Chen et al., 2021). The work undertaken in this article was carried out on a diesel engine shown in Figure 1, a 2.2-liter, four-cylinder, four-valve, and Direct-Injection (DI) engine fitted with a VGT (Variable Geometry Turbocharger) turbocharger.

Table 1. Comparative Evaluation of Predictive Maintenance Approaches in Engine Performance Prediction.

Citations	Data quality	Plural approach	Explainability	Computing efficiency	Real-time applicability	Multi-horizon prediction
(Machesa et al., 2023b)	Data set from a test on an existing Stirling engine	Two key indicators: power and torque	Less emphasis on the explainability of results.	No precise indication of the calculation time.	Not specified	Not specified
(Chaki & Biswas, 2023)	Data sets from experiments	Determination of performance parameters such as brake specific fuel consumption, brake thermal efficiency and exhaust temperature	No emphasis on the explainability of the results.	No precise indication of the calculation time.	Not specified	Not specified
(Yang et al., 2022)	Engine vibration signals from an engine cylinder block	Characteristics of vibration signals	No emphasis on the explainability of the results.	No precise indication of the calculation time.	Not specified	Not specified
(Asaad et al., 2024)	Literature review and previous studies on RSM in biodiesel.	Uses input and output parameters	No emphasis on the explainability of the results.	No precise indication of the calculation time.	Not specified	Not specified
(Y. Wang et al., 2023)	Dataset from the World Harmonized Transient Cycle (WHTC).	Predict transient emission characteristics of diesel engines and evaluate diesel engine performance.	No emphasis on the explainability of the results.	No precise indication of the calculation time.	Not specified, but the model is designed to perform well in an operational setting.	Not specified
(Zandie et al., 2023)	1800 samples from the World Harmonized Transient Cycle (WHTC)	are aimed at improving the understanding and prediction of engine performance focusing on fuel mixtures while your study addresses a broader range of engine failures.	No emphasis on the explainability of the results.	No precise indication of the calculation time.	Not specified, but the model is designed to perform well in an operational setting.	Not specified
(Y. Zhang et al., 2023)	Data sets from experimetns.	Predicting coolant pump performance	No emphasis on the explainability of the results.	Average training time of 226.9 s and real-time running time of about 5 ms.	Real-time operating time tailored to operational requirements.	Not specified

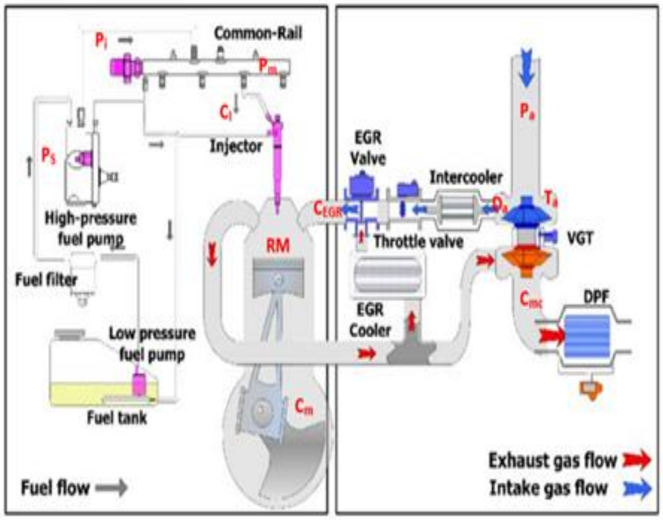

Figure 1.Common rail diesel engine model.

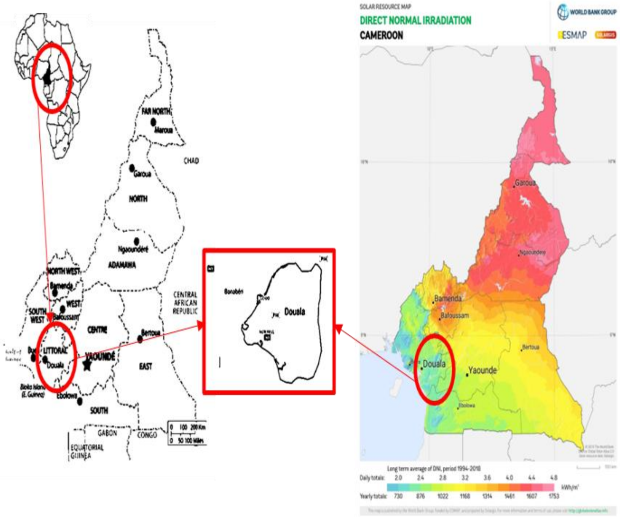

Figure 2. Study Area (Ndarwe et al., 2019).

2.2. Data collection

2.2.1. Data Collection Environment

Cameroon, located in Central Africa along the Gulf of Guinea, covers an area of approximately 475,650 km² and spans latitudes 1° 40′–13° 05′ N and longitudes 8° 30′–16° 10′ E. The country is divided into two climatic regions: a humid tropical zone in the south and a semi-arid region in the north. Douala, the economic capital situated at 9.7° E and 4.0° N on the Atlantic coast near the Wouri River, experiences an equatorial climate influenced by the West African monsoon. The presence of Mount Cameroon, located 60 km to the west and rising to 4,070 m, further impacts the local climate (Ndarwe et al., 2019).

Data collection in Douala revealed environmental conditions characterized by high solar irradiation, averaging 2.6 kWh/m²/day, and elevated ambient temperatures ranging from 25.6 °C in August to 28.9 °C in February. Humidity is significant, particularly during the rainy season from March to November, which influences air quality and thermal conditions. This warm, humid climate, coupled with a dense urban environment, provides a dynamic setting for data collection. Integrated sensors within vehicles allowed for the measurement of these parameters in real-world conditions, offering valuable insights into the interactions between solar irradiation, temperature, and humidity in this region.

2.2.1. Data Acquisition System

Predictive maintenance in the automotive industry faces unique challenges due to the lack of essential data to optimize fleet management and maintenance (Chinta et al., 2023). This project has developed a real-time data collection system to facilitate maintenance.

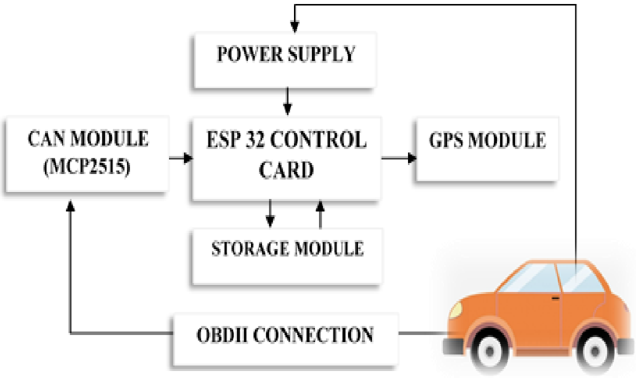

Figure 3. Schematic diagram of the black box.

When the black box is connected to the OBDII port and the ignition is turned on, the GPS transmits the position. The ESP32 microcontroller communicates with the ECU to retrieve the sensor data, which is then transmitted to the computer and recorded on the storage module.

The parameters collected are displayed in the table 2 below:

Table 2. Collected engine parameters.

Parameters	Designations	Unit	Min	Max
$\boldsymbol{C_{mc}}$	Motor load	kPa	0	100
$\mathrm{T_{LR}}$	Engine coolant temperature	°C	87	96.01
$\boldsymbol{P_a}$	Intake manifold absolute pressure	Pa	99	255
RM	Engine speed	rpm	0	4543
$\boldsymbol{T_a}$	Intake air temperature	°C	47	64
$\boldsymbol{D_a}$	Airflow from the mass flow sensor	g/s	0	156.91
$\boldsymbol{P_i}$	Fuel pressure in the rail	kPa	210	160210
$\boldsymbol{C_{EGR}}$	EGR control		5.9	100
$\boldsymbol{C_l}$	Fuel consumption measured in liters every 100km	l/km	0	428.10
$\boldsymbol{P_m}$	Engine power	kW	0	66
$\boldsymbol{C_m}$	Engine torque	Nm	0	178
$\boldsymbol{P_s}$	Boost pressure	kPa	-2.3	153.70

The collected parameters reveal a wide range of values, illustrating the different operating states of a common-rail engine. While these data are specific to a particular type of engine, they highlight essential characteristics that are not exclusively dependent on its design or architecture. These parameters represent fundamental aspects of engine operation, and the ability of sensors to provide relevant data, regardless of the configuration, demonstrates the universality of these measurements. Thus, these results emphasize that the information gathered is applicable to a variety of engines, enhancing the relevance and flexibility of our study model in various application contexts. It is important to note that this work was conducted using data from a single vehicle. For large fleets, the model can be deployed on a cloud platform where data from multiple vehicles is centralized (Dintén et al., 2023; P. Singh et al., 2019; Wang et al., 2021). In this case, the cloud platform can manage data aggregation, model execution, and predictive analysis, allowing the model to simultaneously process data from thousands of vehicles.

2.2.2. Data Processing

The data collected from the integrated sensors in the vehicles are directly generated by the vehicle's onboard computer, ensuring that the information is inherently filtered and processed. This system not only collects environmental parameters but also analyzes them in real-time to assess the state of the vehicle's equipment. As a result, the data is already refined, minimizing noise and enhancing reliability. Furthermore, normalization techniques are applied to standardize the data for consistency (Peng et al., 2023; Song et al., 2024), allowing for better comparison and analysis. By scaling the values to a common range, we ensure that variations in measurement units or magnitudes do not skew the results, facilitating a clearer understanding of the interactions between all the collected parameters. The formula used for Min-Max normalization (Mottahedi et al., 2018) is as follows:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where: X' is the normalized value. X is the original value of the parameter. X_{max} is the maximum value observed in the dataset. X_{min} is the minimum value observed in the dataset.

2.3. Analysis of significant engine degradation parameters

Table 3 shows the failure mode analysis and the associated parameters. This analysis combines the study of failure modes with an analysis characterizing the evolution of an engine component toward a failure mode.

Table 3. Analysis of failure modes and associated parameters.

Elements	Functions	Failure mode	Effect of failure	Parameters
Radiator	Contain cooling Liquid and facilitate its cooling	External leaks	Motor heating Decrease in the quantity of water	T_{LR}, Pa, D_a
Water pump	Suction and delivery of pressurized air	Low operating speed	Engine overheating	T_{LR}, P_a, D_a
Fan	Accelerate the speed at which air passes through the radiator	Irregular operation	Excessive motor heating	T_a
Water pipe	Run cooling water through the engine	External leaks, sealing	Cooling water losses	T_{LR}
Thermostat	Regulate the cooling water temperature	Does not open	Engine overheating	$T_{LR,}$ RM
Intercooler Air-air exchanger	Cool the charge air	Clogged, Blocked	Drop in air pressure in the circuit	T_a, P_s,
Air pressure sensor	Inform the air pressure computer	Irregular operation	Reduced engine performance	P_a
EGR control	Ensure exhaust gas recycling	Blocked		P_a, C_{EGR}
Turbocharger	Increase the air pressure in the circuit	Malfunction		P_m,P_s
Fuel filter	Retain impurities to protect the pump	Obstruction, clogging		P_m, P_i, C_l
Fuel pipe	Get diesel to the pump	Leaks		P_m, P_i
Injector	Spray diesel at high pressure into the combustion chamber	Blocked, Clogged		P_m, P_i
Rail pressure sensor	Measure the pressure in the rail and inform the ECU	Irregular operation		P_m, P_i
Air filter	Retain particles in the air	Clogging		P_a, D_a

We have found that the critical parameters required for our prediction models are coolant temperature, intake manifold absolute pressure, intake air temperature, engine power, and boost pressure. Abnormal variations in these parameters can lead to leaks, clogged filters, and clogged intercoolers. These failure modes affect engine performance. The engine parameter analysis aims to establish the interdependent relationships between the parameters to be predicted. We first observed and calculated the correlation coefficients between these parameters to do this. The rank Spearman correlation (Jiang et al., 2024) is calculated by applying Eq. (2):

$$\rho = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)}, \tag{2}$$

with *ρ:* Spearman rank correlation value; *d*: Margin of each pair value; *n*: Spearman rank pair values. Table 4 shows the Spearman correlation coefficients for the significant parameters;

Table 4. Spearman correlation coefficient.

	C_{mc}	T_{LR}	Pa	RM	T_a	D_a	P_i	C_{EGR}	C_l	P_m	C_m	P_s
C_{mc}	1	0.18	0.49	0.37	0.04	0.39	0.41	-0.01	0.10	0.27	0.37	0.38
T_{LR}	0.18	1	0.17	0.16	0.08	0.17	0.22	0.03	0.07	0.20	0.22	0.13
P_a	0.49	0.17	1	0.74	0.07	0.79	0.57	-0.08	0.11	0.51	0.54	0.60
RM	0.37	0.16	0.74	1	0.16	0.81	0.57	-0.02	0.11	0.46	0.45	0.51
T_a	0.04	0.08	0.07	0.16	1	0.07	0.06	0.21	0.06	-0.02	0.02	0.04
D_a	0.39	0.17	0.79	0.81	0.07	1	0.64	-0.09	0.16	0.55	0.55	0.55
Pi	0.41	0.22	0.57	0.57	0.06	0.64	1	-0.02	0.34	0.63	0.63	0.66
C_{EGR}	-0.01	0.03	-0.08	-0.02	0.21	-0.09	-0.02	1	0.07	-0.15	-0.07	-0.11
C_l	0.10	0.07	0.11	0.11	0.06	0.16	0.34	0.07	1	0.18	0.15	0.284
P_m	0.27	0.20	0.51	0.46	-0.02	0.55	0.63	-0.15	0.18	1	0.72	0.65
C_m	0.37	0.22	0.54	0.45	0.02	0.55	0.63	-0.07	0.15	0.72	1	0.65
P_s	0.38	0.13	0.60	0.514	0.04	0.55	0.66	-0.11	0.28	0.65	0.65	1

Together with an analysis of engine operation and references from the literature, these coefficients enabled us to establish the interdependence between the parameters to be predicted, as described in Eq (3) :

$$\begin{cases} \dfrac{dT_{LR}}{dt} = f_1\left(T_{LR}, P_a, D_a, T_a, C_l\right) \\ \dfrac{dP_a}{dt} = f_2\left(P_a, D_a, T_a\right) \\ \dfrac{dT_a}{dt} = f_3\left(P_a, D_a, T_a, C_l\right) \\ \dfrac{dP_m}{dt} = f_4\left(P_m, C_{mc}, RM, P_i, C_m, P_s, P_a, C_{EGR}\right) \\ \dfrac{dP_S}{dt} = f_5\left(P_a, D_a, T_a\right) \end{cases} \tag{3}$$

2.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS system is widely implemented in the literature as part of the development of Explainable Artificial Intelligence solutions (Aghamohammadi et al., 2019; Chen et al., 2019; M. Querales et al., 2023; M. S. Kamal et al., 2022). The ANFIS model shown in Figure 3, proposed by (Jang et al., 1997), is utilized in this work due to its ability to combine the learning capacity of artificial neural networks with fuzzy inference systems, allowing it to effectively understand machine-learned information (Elymany et al., 2024). Additionally, ANFIS offers flexibility and noise management capabilities (E. Özer et al., 2024) while also reducing computation time (Bakare et al., 2024; TJAHE et al., 2021). Its adaptability to variable inputdata, particularly in evolving environments, enables real-time optimization of forecasts and enhances responsiveness to changes. Unlike traditional neural networks, ANFIS incorporates fuzzy rules, which makes it more interpretable and suitable for applications where transparency is essential (Bakare et al., 2024).

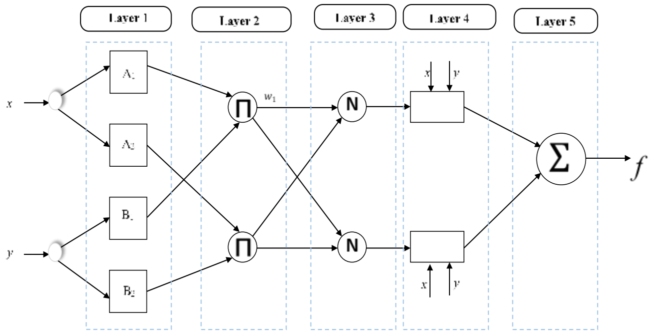

Figure 4 . Network structure of ANFIS model (Jang et al., 1997).

The model developed in Figure 4 is based on Takagi-Sugeno type fuzzy "if–then" rules, which consist of a premise part containing nonlinear parameters (the membership functions, or MFs) and a consequent part with adaptive linear parameters. A typical Takagi-Sugeno rule can be expressed as follows:

If (x is A) and (y is B) then $f_1=p_1x+q_1y+r_1$ (4)

In this equation p_1, q_1 and $r_1$represent the linear parameters of the consequent part, while A and B denote the fuzzy sets associated with the input variables.

The ANFIS architecture consists of five layers, each serving a specific function in processing inputs and generating outputs. This layered approach includes fuzzification, rule evaluation, normalization, defuzzification, and output summation, as described in detail by (TJAHE et al., 2021b)

- **First Layer (Fuzzification Layer):** Each node in this layer is adaptive and computes the membership degree for the inputs x and y. The outputs are defining as:

Here A and B represent fuzzy sets with linguistic labels such as Low, Medium, and High. Each output $O_{1,i}$ is then sent in to the next layer (figure 4).

$$\begin{aligned} O_{1,i} &= mA_i(x) \text{ for } i=1,2 \\ O_{2,i} &= mB_i(y) \text{ for } i=3,4 \end{aligned} \tag{5}$$

- **Second Layer (Product Layer):** In this layer, the weight associated with each node is calculated as the product of the membership degrees from the previous layer:

$$\omega_i = m_{A_i}(y) \times m_{B_i}(y) \text{ for i=1,2} \tag{6}$$

- **Third Layer (Normalization Layer):** This layer normalizes the weights calculated in the second layer using the following equation:

$$\overline{\omega}_i = \frac{\omega_i}{\sum_{j=1}^{2} \omega_j} \text{ for i= 1,2} \tag{7}$$

- **Fourth Layer (Defuzzification Layer):** In this layer, the consequent part of the fuzzy rules is executed.
- **Fifth Layer (Output Layer):** The final output of the ANFIS model is calculated by summing the outputs from the fourth layer, weighted by the normalized membership degrees from the third layer.

2.5. Particle Swarm Optimization (PSO) algorithm

Particle Swarm Optimization (PSO) developed by (J. Kennedy & R. Eberhart, 1995) is an optimization algorithm inspired by the collective behavior of animals in groups (Abdelilah et al., 2024). Particle Swarm Optimization (PSO) is an efficient optimization algorithm that offers rapid convergence to optimal solutions with low computational cost, making it particularly advantageous for complex systems, where quick parameter adjustment is essential for enhancing accuracy and efficiency (Oliaye et al., 2023). As a socially inspired algorithm, PSO enables each particle to leverage collective intelligence to navigate towards globally optimal solutions, thereby avoiding the common pitfall of local minima often encountered with other optimization methods (Şener et al., 2024). The algorithm's strength lies in its ability to balance exploration and exploitation, guiding particles toward promising regions of the search space while avoiding stagnation. Each particle's velocity and position are updated according to specific equations that incorporate both individual and collective knowledge. The equations used for these updates are as follows (Abdelilah et al., 2024).

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \left(p_{best} - x_i^t \right) + c_2 r_2 \left(g_{best} - x_i^t \right) \qquad (8)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (9)$$

Where r_1 and r_2 represent random numbers in the interval [0, 1]; c_1 and c_2 are the cognitive and social constants, respectively. The term ω term is called the weighting function.

2.1. Optimization algorithm (ANFIS-PSO)

Figure 4 illustrates the general structure of the proposed system. The ANFIS-PSO approach has been applied across various fields, including work accident prediction (Sarkar et al., 2023), energy(Banoqitah et al., 2023), materials engineering (Kontoni & Ahmadi, 2024), hydrology (Samanataray & Sahoo, 2021) and meteorology (Oliaye et al., 2023). It is especially prominent in engineering applications(Eladl et al., 2023) and has demonstrated versatility and effectiveness in optimizing complex systems across these diverse domains (Lazreg & Benamrane, 2022; Nguyen et al., 2023).

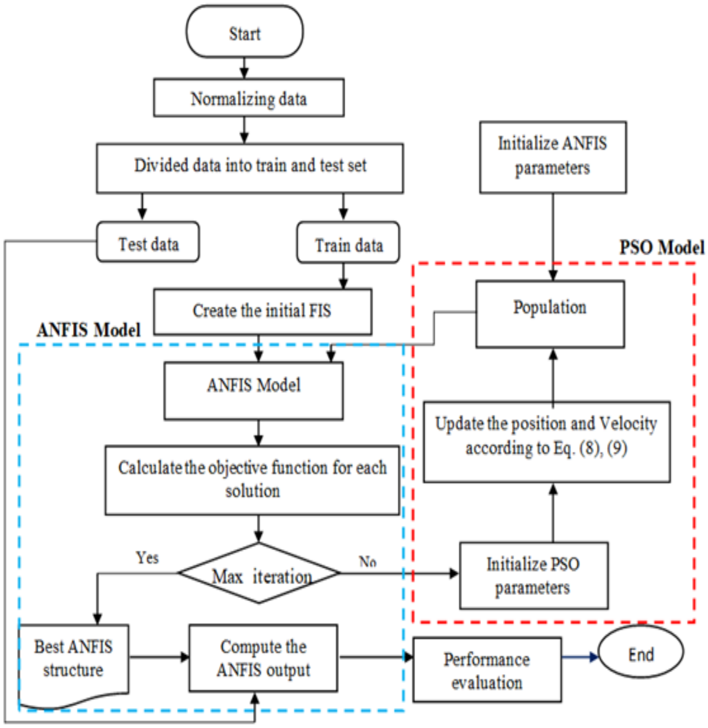

Figure 5 . ANFIS flowchart combined with PSO.

The ANFIS-PSO model used in this study demonstrates superior performance compared to other combinations (Şener et al., 2024). By integrating ANFIS with PSO, the model effectively captures the nonlinear behaviors of engines, such as power losses, overheating, and air leaks. PSO optimally adjusts ANFIS parameters, enhancing prediction accuracy for engine performance degradation.

As a group-inspired algorithm, PSO continuously optimizes ANFIS parameters, improving adaptability to dynamic data collected from operating engine sensors. This leads to increased reliability in predicting performance losses. Additionally, PSO accelerates convergence towards optimal solutions, reducing short- and long-term prediction errors, which is critical for accurate maintenance forecasting.

The ANFIS-PSO combination allows for flexible predictions in both short and long terms, adapting to various dynamics of engine systems. This capability enables proactive identification of potential failures, providing a broader window for engine maintenance and repairs.

3. RESULTS AND DISCUSSIONS

The ANFIS-PSO architecture was used in this study to analyze and evaluate the ability to predict failures related to loss of engine performance. The approach considered the four previous instants of data, control of the prediction error, and the ability to explain the decisions made. The challenge was to predict, throughout the 1800s, the failures associated with loss of engine performance, including engine overheating, air leaks, loss of engine power, clogging of the air-to-air heat exchanger, and clogging of the filters. This study was carried out to achieve this objective using a sample of 3,912 data sets collected from an operating vehicle, 70% of which were used for training and the remaining 30% for testing (Afshin Gholamy et al., 2018). This article tests the ability of the combination of ANFIS and PSO to predict the values of significant engine degradation parameters such as T_{LR}, P_a, T_a, P_S, and P_m at two different prediction horizons.

This article used various performance measures to evaluate the effectiveness of the ANFIS-PSO approach.

- Computational time refers to the amount of time taken by a computer or algorithm to perform a specific task or run a series of operations (E. Shulga et al., 2023; M. G. K. Machesa et al., 2019; TJAHE et al., 2021).
- RMSE(Root Mean Square Error) (Birim et al., 2022), is a commonly used metric for measuring the accuracy of a predictive model. It quantifies the difference between predicted values and actual observed values. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (10)$$

- Error Standard Deviation (Robati & Iranmanesh, 2020) is a statistical measure that quantifies the variability or spread of the errors between predicted values and actual observed values. It shows how much the errors deviate from the mean error. The formula for calculating the Standard Deviation of Errors is:

$$Error\ St.D = \sqrt{\frac{1}{N-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{11}$$

- MAE (Mean Absolute Error) (Nagar et al., 2024) is a statistical measure used to evaluate the accuracy of a predictive model by calculating the average absolute differences between predicted values and actual observed values. It provides a straightforward interpretation of the average error in the same units as the original data.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{12}$$

- R^2 (R-squared) (Şener et al., 2024) is a statistical measure that indicates the proportion of variance in the dependent variable that can be explained by the independent variable(s) in a regression model. It provides insight into the goodness of fit of the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{13}$$

Where n denotes data points, y_i is the predicted values of y, $\bar{\hat{y}}$ and y represents the mean values of y.

3.1. Optimization of ANFIS-PSO Parameters through Sensitivity Analysis

To determine the optimal parameters for the ANFIS-PSO model, we conducted a sensitivity analysis within a MATLAB framework by systematically varying the parameter values. Instead of isolating each parameter, this analysis evaluated their collective impacts on the model's performance. The key parameters examined included population size (nPop), personal learning coefficient (C_1), global learning coefficient (C_2), inertia weight (w), and maximum number of iterations (MaxIt). We explored a range of values for these parameters using nested loops, with each combination evaluated using the Particle Swarm Optimization (PSO) algorithm, which updates the velocities and positions of the particles based on the best personal and global solutions identified during the optimization process. At the end of this analysis, we compiled in table 5 the parameters that would be used for model prediction, focusing on those that yielded the best cost.

Table 5. Configuration of algorithm parameter.

Algorithm	Model Parameter and value
ANFIS	Number of clusters= auto, Max.epoch=100, Max.improvment=1e-5, Initial step=0.001, FIS structure =Sugeno-type
ANFIS-PSO	C_1 =1, C_2 =2, V_{max} =0.9, V_{min} =0.2, *W=1*, *Wdamp* =0.99, Max_it=100, *npop* = 25

To enhance the performance of the ANFIS-PSO model in high-frequency data environments, several optimizations can be implemented. First, parallelization of the PSO algorithm (Zhuo et al., 2023) can significantly improve the speed of parameter optimization, especially with large datasets, by distributing the evaluation of particle positions across multiple processors or cores to accelerate convergence. Additionally, adopting an incremental learning approach (A. Gupta et al., 2016) allows the model to continuously update its parameters as new data arrives, eliminating the need for retraining from scratch. This strategy is particularly beneficial in high frequency environments, ensuring that the model remains responsive and accurate in real-time applications.

3.1. Prediction of failure parameter at two horizons of prediction

The figure above presents the proposed hybrid model that exploits the initial conditions of the system to generate predictions at two distinct time horizons (t+600s and t+1800s) for the five failures to be predicted, thus allowing to capture the future dynamics of the system in the short, medium and long term. The integrated fuzzy logic (Ali et al., 2023) within the ANFIS model allows it to handle uncertain or imprecise.

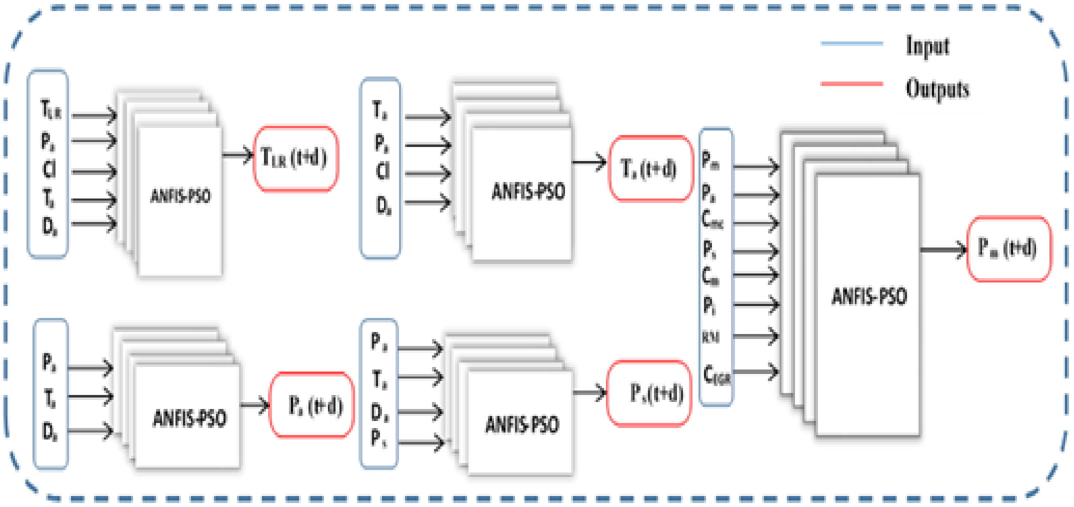

Figure 6. ANFIS-PSO model for failure prediction at different forecast horizons

Figures 7, 8, 9, 10 and 11 visually compare the actual and predicted values during the ANFIS-PSO model test phase. They also include a graph of the errors for each sample followed by a histogram of the error characteristic of each error value. The results of these predictions are obtained using MATLAB software on a DELL core i5 computer with a 64-bit configuration and 16 GB of Intel (R) dual-core RAM.

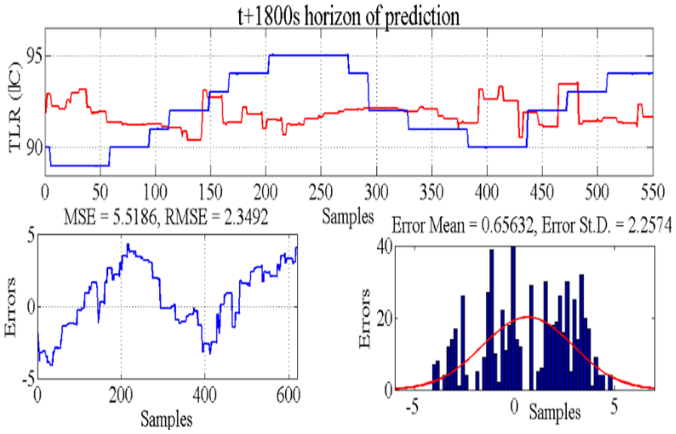

Figure 7. Results of prediction of T_{LR} via ANFIS-PSO.

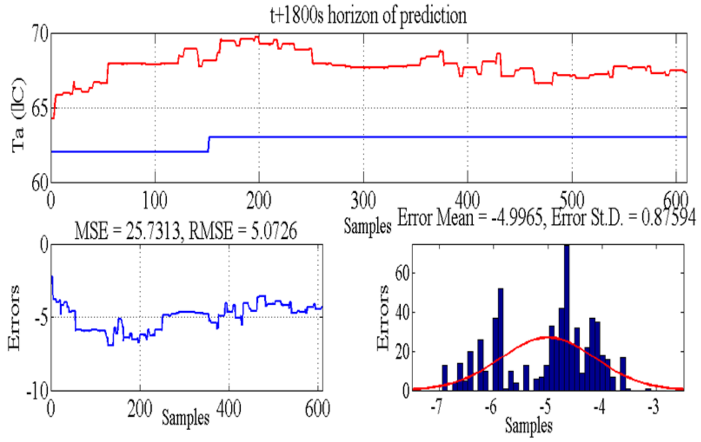

Figure 8. Results of prediction of T_a via ANFIS-PSO.

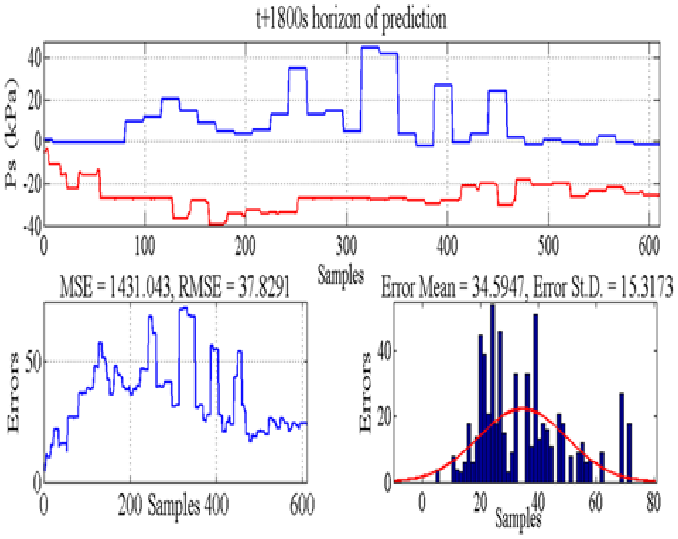

Figure 9. Results of prediction of P_s via ANFIS-PSO.

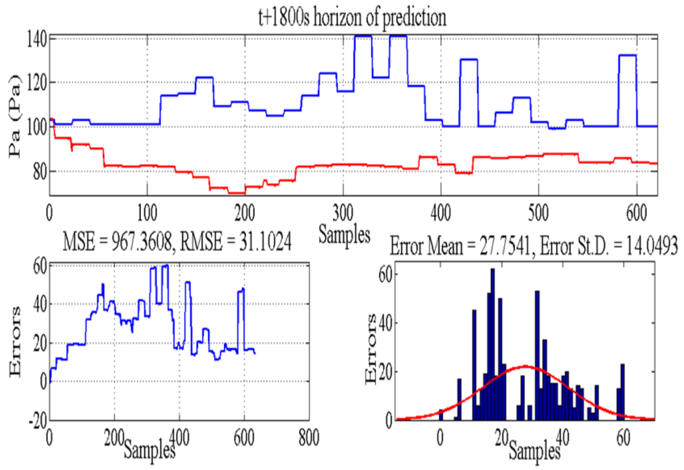

Figure 10. Results of prediction of P_a via ANFIS-PSO.

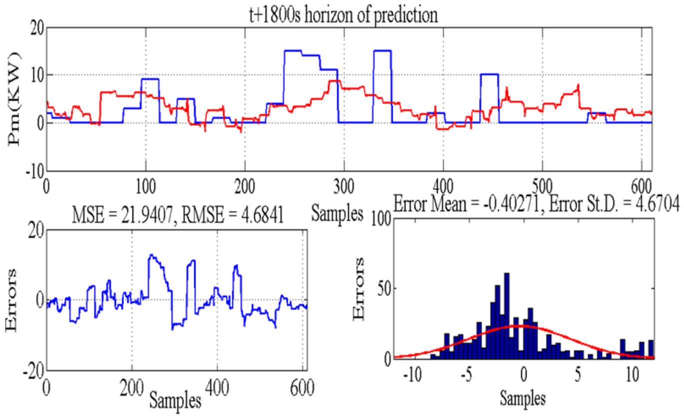

Figure 11. Results of prediction of P_m via ANFIS-PSO.

According to the results, the ANFIS-PSO model used to predict various system parameters shows mixed performance. For the prediction of the coolant temperature (T_{LR}), an increase in the variability of the predictions over time is observed, with an increase in RMSE from 1.59 to 2.34 and a standard deviation from 1.47 to 2.25. Compared to the literature (Addo et al., 2023), these results may need to be improved. The prediction of the parameter P_a indicates low accuracy and model instability, with high RMSE, Mean Error, and Standard Deviation values. For the parameter P_m, the performance is generally acceptable compared to that of P_a, with reasonable gaps between predictions and actual values, although higher than in other studies (Machesa et al., 2023a). The prediction of the parameter T_a shows good short-term performance but a degradation of the metrics in the longer term, remaining to be improved compared to the literature (Hosseini et al., 2022). The prediction of the filter clogging (parameter P_s), for which the results suggest low accuracy and inconsistent performance, still needs to be improved compared to the literature work (Tancredi & Vignali, 2024). These mixed results show that improvements are necessary for more stable and accurate performance across all the studied parameters. The variability in performance across these parameters underscores the need for comprehensive testing and additional modeling efforts. To optimize the predictive capabilities of the ANFIS-PSO algorithm, future work should focus on refining the model architecture, enhancing data preprocessing techniques, and exploring hybrid approaches that may integrate other machine learning algorithms for improved robustness and accuracy.

3.2. Prediction of the failure parameter using the four previous moments

However, to further improve the accuracy and performance of our results, it is necessary to find an alternative approach. With this in mind, we propose a New ANFIS-PSO model, which considers the four previous moments to predict the next moment (TJAHE et al., 2021a). Referring to the indication in Figure 5, the parameters P_a^*, D_a^*, $and\ T_a^*$ are input functions that depend on parameters P_a, D_a, and T_a of the previous, but taken at four previous time instants. Equations relating the input parameters of output $P_a\,(t+d)$ of are given

$$P_a^* = [\ P_a\,(t-3)\ \ P_a\,(t-2)\ P_a\,(t-1)\ P_a\,(t)\ ]^T$$
$$D_a^* = [\ D_a\,(t-3)\ \ D_a\,(t-2)\ D_a\,(t-1)\ D_a\,(t)\ ]^T$$
$$T_a^* = [\ T_a\,(t-3)\ \ T_a\,(t-2)\ T_a\,(t-1)\ T_a\,(t)\ ]^T \qquad (16)$$

Table 6. Comparison of the optimal parameters of ANFIS-PSO and the New ANFIS-PSO.

Algorithms		**ANFIS-PSO**		**New ANFIS-PSO**	
Parameters	Performance	t+600s	t+1800s	t+600s	t+1800s
$\mathbf{T_{LR}}$	RMSE (°C)	2.02	2.34	2.38×10^{-14}	3.85×10^{-14}
	MAE	1.66	2.015	1.01×10^{-14}	3.45×10^{-14}
	Error St.D	1.96	2.25	$1.92\ 10^{-14}$	1.73×10^{-14}
	CPU (s)	0.0013	0.0012	0.0024	0.0022
Pm	RMSE (kW)	6.37	4.68	5.07×10^{-15}	3.6×10^{-14}
	MAE	5.4699	3.60	2.59×10^{-15}	2.24×10^{-14}
	Error St.D	5.41	4.67	2.14×10^{-15}	2.82×10^{-14}
	CPU (s)	0.00155	0.0014	0.0020	0.0021
$\mathbf{P_a}$	RMSE (Pa)	20.12	31.10	1.81×10^{-13}	9.09×10^{-14}
	MAE	18.54	27.76	1.05×10^{-13}	6.40×10^{-14}
	Error St.D	16.85	14.04	4.43×10^{-14}	3.49×10^{-14}
	CPU (s)	0.0012	0.0011	0.0028	0.0020
Ta	RMSE (°C)	4.29	5.07	6.22×10^{-14}	3.36×10^{-14}
	MAE	4.06	4.99	2.03×10^{-14}	3.28×10^{-14}
	Error St.D	1.38	0.87	$1.07\ 10^{-14}$	7.15×10^{-15}
	CPU (s)	0.0011	0.0014	0.0025	0.0022
Ps	RMSE (kPa)	20.35	34.82	1.7×10^{-14}	2.15×10^{-14}
	MAE	19.10	34.59	2.01×10^{-15}	1.65×10^{-14}
	Error St.D	12.39	15.31	1.72×10^{-14}	1.07×10^{-14}
	CPU (s)	0.0012	0.0025	0.0020	0.0028

This principle extends to all other parameters, ensuring that the model can utilize the temporal progression of data to improve predictions. By incorporating these historical influences, we anticipate a reduction in prediction errors and increased model stability, particularly for parameters that previously exhibited high variability and low accuracy. Further testing and optimization will be essential to validate the efficacy of this approach and refine its predictive capabilities.The table above presents a comparative study between the performance metrics of ANFIS-PSO and New ANFIS-PSO at the last two prediction horizons.

Table 6 presents a comparative performance analysis between the conventional ANFIS-PSO model and the proposed New ANFIS-PSO model across five critical engine parameters (T_{LR}, P_m, P_a, T_a, P_s) and two prediction horizons (t+600s and t+1800s). The results demonstrate a significant leap in predictive accuracy; while the standard ANFIS-PSO shows non-negligible residuals, the New ANFIS-PSO reduces error metrics to near-zero levels (magnitudes of 10^{-14} to 10^{-15}. This drastic reduction in RMSE, MAE, and Error Standard Deviation confirms that integrating a multi-step temporal window (t to t-3) allows the model to capture the complex, non-linear dynamics of engine degradation much more effectively. Such high numerical precision, combined with the PSO's global search capability, ensures that the proposed model provides a highly reliable foundation for proactive maintenance decisions.

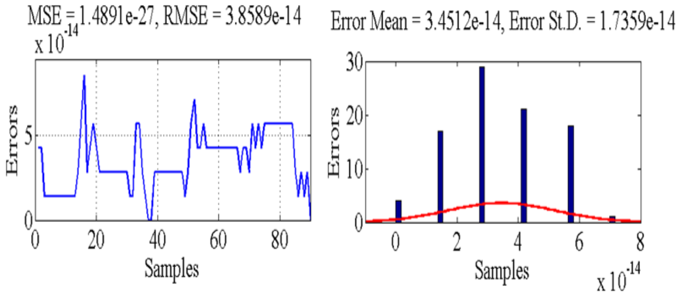

Figure 12. Results of prediction of T_{LR} via New ANFIS-PSO, which considers the four previous moments

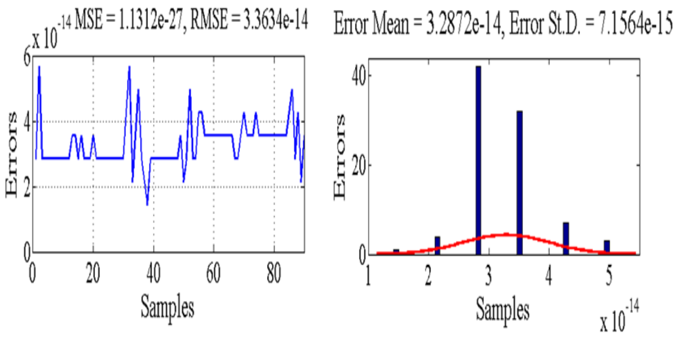

Figure 13.Results of prediction of Ta via New ANFIS-PSO, which considers the four previous moments

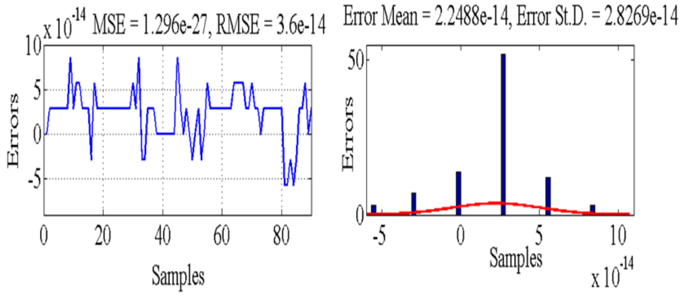

Figure 14. Results of prediction of Pa via New ANFIS-PSO, which considers the four previous moments

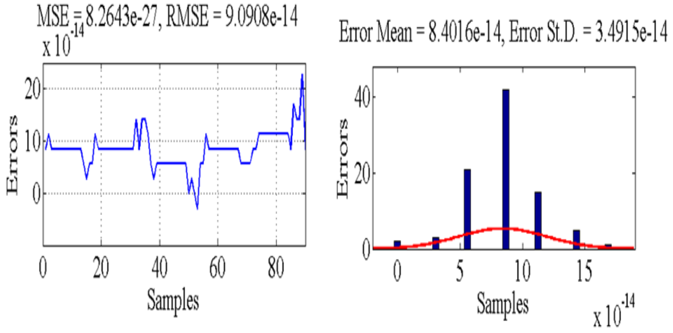

Figure 15. Results of prediction of Pm via New ANFIS-PSO, which considers the four previous moments

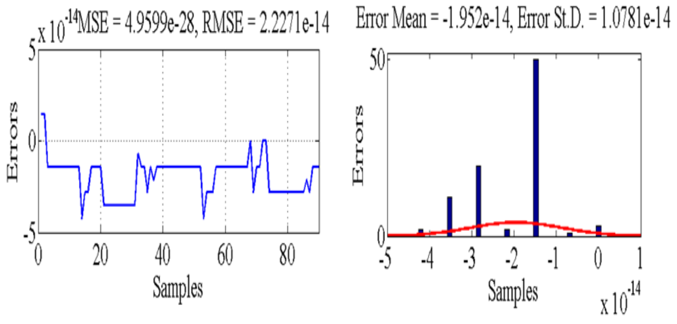

Figure 16.Results of prediction of Pm via New ANFIS-PSO, which considers the four previous moments

The prediction performance illustrated in Figures 12-16 shows extremely low MSE values, reaching magnitudes on the order of 10^{-28}. Although these values may appear close to zero, they result from the combined effect of Min–Max normalization (scaling the dataset to the [0,1] range) and the use of squared-error metrics. In this normalized domain, the residual prediction errors produced by the optimized New ANFIS-PSO model are already very small (approximately 10^{-14}). When these residuals are squared during the computation of the MSE, the resulting values naturally decrease to the order of 10^{-28}.

Therefore, these extremely small values should not be interpreted as exact zero error, but rather as a numerical consequence of normalization combined with the high precision of double-precision floating-point computation. The integration of four previous time instants (t, t–1, t–2, t–3) enables the model to effectively capture the temporal dynamics of engine degradation, which significantly reduces the prediction residuals. Similar observations of very small residual errors in optimized neuro-fuzzy predictive models have been reported in the literature (Bakare et al., 2024; Şener et al., 2024; Y. Zhang et al., 2023), where normalization and high-precision numerical computation can produce extremely small error magnitudes. Consequently, these results indicate that the proposed model provides stable predictions with minimal numerical residuals, supporting its suitability for reliable real-time predictive maintenance applications.

We remark that the New ANFIS-PSO model demonstrates its ability to optimally and quickly predict the significant parameters due to the engine performance loss, using a relatively low MAE, characteristic of the model's performance, and a very low Error St.D, also characteristic of the model's consistency.

Although integrating the four previous moments before failure improves the performance of the ANFIS-PSO model, mixed results still persist in long-term predictions. To enhance the stability and accuracy of the model, strategies such as adaptive learning (Dass et al., 2023), periodic recalibration(Axenie et al., 2024), and the incorporation of feedback loops(Wang et al., 2020) can be implemented. These approaches will allow the model to adjust to new data and correct the drift of input variables.

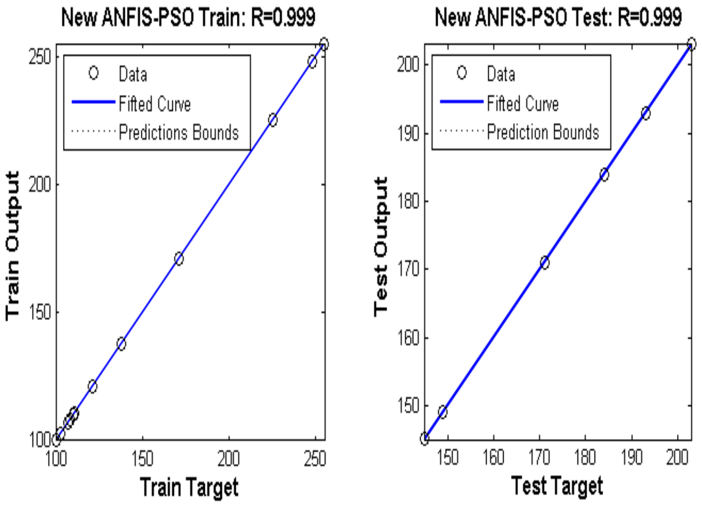

Figure 17.New ANFIS-PSO algorithm training, testing R values fitted curve and prediction bounds.

3.2. Sensitivity

To conduct a sensitivity analysis aimed at predicting engine performance losses, we evaluated the significant parameters associated with each predicted failure. This analysis aimed to identify the key factors influencing the accuracy of our predictions regarding performance degradation in the engine. By examining these parameters, we can better understand their impact on the overall predictive model and enhance the reliability of our assessments. To determine the most effective parameters influencing the phenomenon, sensitivity analysis was conducted using the Cosine Amplitude (CAM) method.

The strength of this relationship, denoted as r_{ij}, is calculated by the following formula:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{Jk}^2}} \tag{17}$$

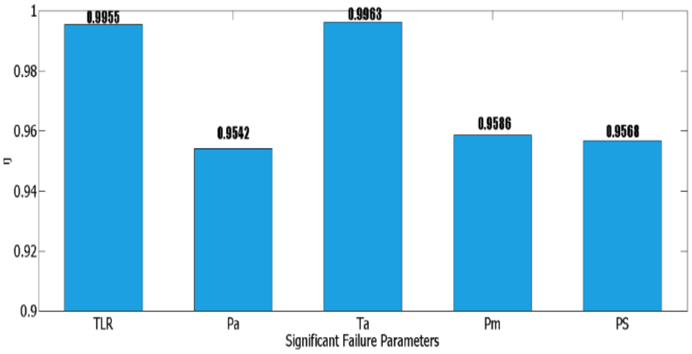

Figure 18.New ANFIS-PSO algorithm training, testing R values fitted curve and prediction bounds.

The sensitivity analysis results shown in Figure 18 indicate that fouling of air-to-air heat exchangers is the most significant parameter affecting engine performance, closely followed by engine overheating. Addressing fouling can lead to substantial performance improvements, while monitoring overheating underscores the need for effective cooling systems and preventive maintenance. Overall, focusing on these critical parameters in predictive models will enhance the accuracy of engine performance loss forecasts, aiding vehicle owners and automotive professionals in proactive maintenance and decision-making.

3.3. Extraction of fuzzy rules

Each input parameter is associated with a specific number of membership functions in this section. According to an engineer's interpretation, each membership function is defined with a specific form and an appropriate range of values to construct relevant fuzzy sets. Then, each variable is fuzzified using the fuzzy terms S (small), M (medium), and L (large). The same membership functions generated fuzzy rules for each database, as shown in Table 7.

Table 7. Explainable fuzzy rules generated by the ANFIS model for failure prediction.

Parameters	**Fuzzy Rules**
T_{LR}	If T_{LR} is S, then P_a is S, D_a is S, C_l is S, and P_a is S. If T_{LR} is M, then P_a is M, D_a is M, C_l is M, and P_a is M. If T_{LR} is L, then P_a is L, D_a is L, C_l is L, and P_a is L.
T_a	If T_a is S, then P_a is S, D_a is S, C_l is S, and Ta is S. If T_a is M, then P_a a is M, D_a is M, C_l is M, and Ta is M. If T_a is L, then P_a is L, D_a is L, C_l is L, and Ta is L.
P_a	If P_a is S, then P_a is S, D_a is S, and T_a is S. If P_a is M, then P_a is M, D_a is M, and T_a is M. If P_a is L, then P_a is L, D_a is L, and T_a is L.
P_m	If P_m is S, then P_a is S, P_s is S, C_m is S, P_i is S, RM is S, C_{EGR} is S C_{mc} is S, and P_m is S. If P_m is M, then P_a is M, P_s is M, Cm is M, P_i is M, RM is M, C_{EGR} is M, C_{mc} is M, and P_m is M. If P_m is L, then P_a is L, P_s is L, C_m is L, P_i is L, RM is L, C_{EGR} is L C_{mc} is L, and P_m is L.
P_s	If P_s is S, then P_a is S, D_a is S, T_a is S, and P_s is S. If P_s is M, then P_a is M, D_a is M, T_a is M, and P_s is M. If P_s is L, then P_a is L, D_a is L, T_a is L, and P_s is L.

The ANFIS-PSO model generates fuzzy rules that are easily interpretable by maintenance engineers, providing actionable insights for proactively addressing issues such as low air intake or engine overheating. These rules guide decision-making by identifying components to check or replace during preventive maintenance. Here are some examples illustrating the impact of these rules on engineers' decisions in the context of predicting air leaks:

- Fuzzy Rule 1: "If Pa is S, then Pa is S, Da is S, and Ta is S."

Impact: This rule indicates that when the air pressure is low (S), both the air density and temperature are also low. This could suggest a significant issue, such as a potential leak or an obstruction in the air intake system. Engineers can prioritize inspections to identify the root cause of these conditions.

- Fuzzy Rule 2: "If Pa is M, then Pa is M, Da is M, and Ta is M."

Impact: This rule signifies that when the air pressure is medium (M), the air density and temperature are also at medium levels. This indicates that the system is likely functioning normally. Engineers can use this information to establish a baseline for regular operations and schedule routine maintenance checks.

- Fuzzy Rule 3: "If Pa is L, then Pa is L, Da is L, and Ta is L."

Impact: When the air pressure is high (L), alongside high density and temperature, this may indicate a risk of overpressure in the system. Engineers can take proactive measures to inspect and adjust valves or other control mechanisms to prevent potential system failures.

We have not conducted a direct comparative analysis with other Explainable Artificial Intelligence (XAI) techniques such as SHAP or LIME. However, the main advantage of the ANFIS-PSO model lies in its ability to generate human-interpretable rules, unlike SHAP or LIME, which provide local explanations without offering a global interpretability (Aldrees et al., 2024). While SHAP and LIME are powerful tools for explainability, they do not intrinsically produce rule-based logic as ANFIS does. For real-time applications, ANFIS-PSO also has the advantage of a lower computational load, making it more suitable for resource-constrained environments, such as vehicle diagnostics.

3. CONCLUSION

This study has effectively demonstrated the potential of utilizing an ANFIS model combined with the Particle Swarm Optimization (PSO) algorithm to predict the performance degradation of automotive engines. By analyzing the primary causes of engine performance issues, we identified critical parameters that were employed as inputs in both the ANFIS-PSO and New ANFIS-PSO models. These models incorporated a range of parameters such as engine load, coolant temperature, intake manifold absolute pressure, engine speed, intake air temperature, air flow rate, fuel pressure, EGR control, fuel consumption, engine power, engine torque, and boost pressure. Key output parameters included intake manifold absolute pressure, coolant temperature, intake air temperature, engine power, and boost pressure. The data collected from sensors on operating engines allowed us to train and evaluate the ANFIS-PSO model effectively. This approach facilitated accurate predictions of characteristic failures associated with performance degradation, including engine overheating, air leaks, power loss, air-to-air heat exchanger fouling, and filter clogging. The results were highly satisfactory, with coefficient of determination (R^2) values around 0.99 for the test data, an RMSE in the range of 10^{-14}, an Error Standard Deviation around 10^{-15}, and a Mean Absolute Error around 10^{-15} for a prediction horizon of 1800 seconds. A significant focus of this study has been on the explainability of the ANFIS model, a crucial feature in automotive engineering where minimizing downtime and ensuring safety are paramount. The proposed ANFIS-PSO model provides a reliable, accurate, and explainable solution essential for preventive maintenance of automotive systems. Our research stands out due to its pluralistic approach, enabling a multifaceted analysis of failures and enhancing our understanding of the underlying factors. By employing Failure Modes and Effects Analysis (FMEA), we identified key parameters influencing performance losses, facilitating the optimization of maintenance interventions. Furthermore, the model's transparency, bolstered by explicit fuzzy rules, supports engineers in making informed decisions. This study lays a solid foundation for significant advancements in vehicle reliability and durability while reducing maintenance costs. By integrating localized data specific to the African environment, our model is not only relevant on a global scale but also tailored to local realities. The ongoing optimization of these predictive systems could revolutionize automotive maintenance, fostering a proactive approach that anticipates failures before they occur. Looking ahead, while our focus has been on a specific set of parameters, future research will explore expanding the parameter set and comparing our model with other Explainable Artificial Intelligence (XAI) methodologies. We will also investigate the integration of localized data to enhance adaptability and examine the model's potential incorporation with IoT technologies for real-time monitoring. Additionally, we propose long-term studies and real-world testing to validate the model's effectiveness. Importantly, we plan to employ machine learning techniques to ensure the long-term stability and performance of the algorithm. Overall, this research sets the stage for substantial improvements in vehicle reliability and maintenance efficiency, particularly in diverse operational contexts.

REFERENCES

A. Gupta, K. Gusain, & D. Kumar. (2016). Novel approach for incremental learning using ensemble of SVMs with particle swarm optimization. *2016 11th International Conference on Industrial and Information Systems (ICIIS)*, 426-430. https://doi.org/10.1109/ICIINFS.2016.8262978

Abdelilah, H., Makhad, M., El marghichi, M., Ouanjli, N. E., & Loulijat, A. (2024). Towards sustainable water pumping systems : Integration of particle swarm optimization and direct torque control PSO-DTC. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, *7*, 100480. https://doi.org/10.1016/j.prime.2024.100480

Addo, K. D., Davis, F., Fiagbe, Y. A. K., & Andrews, A. (2023). Machine learning for predictive modelling of the performance of automobile engine operating without coolant thermostat. *Scientific African*, *21*, e01802. https://doi.org/10.1016/j.sciaf.2023.e01802

Afshin Gholamy, Vladik Kreinovich, & Olga Kosheleva. (2018). Why 70/30 or 80/20 Relation Between Training and Testing Sets : A Pedagogical Explanation. *International Journal of Intelligent Technologies and Applied Statistics*, *11*(2), 105-111. https://doi.org/10.6148/IJITAS.201806_11(2).0003

Ağbulut, Ü., Ayyıldız, M., & Sarıdemir, S. (2020). Prediction of performance, combustion and emission characteristics for a CI engine at varying injection pressures. *Energy*, *197*, 117257. https://doi.org/10.1016/j.energy.2020.117257

Aghamohammadi, M., Madan, M., Hong, J. K., & Watson, I. (2019). Predicting Heart Attack Through Explainable Artificial Intelligence. In J. M. F. Rodrigues, P. J. S. Cardoso, J. Monteiro, R. Lam, V. V. Krzhizhanovskaya, M. H. Lees, J. J. Dongarra, & P. M. A. Sloot (Éds.), *Computational Science – ICCS 2019* (p. 633-645). Springer International Publishing.

Aldrees, A., Khan, M., Taha, A. T. B., & Ali, M. (2024). Evaluation of water quality indexes with novel machine learning and SHapley Additive ExPlanation (SHAP) approaches. *Journal of Water Process Engineering*, *58*, 104789. https://doi.org/10.1016/j.jwpe.2024.104789

Ali, A., Abu-Elkheir, M., Atwan, A., & Elmogy, M. (2023). Missing values imputation using Fuzzy K-Top Matching Value. *Journal of King Saud University - Computer and Information Sciences*, *35*(1), 426-437. https://doi.org/10.1016/j.jksuci.2022.12.011

Anjaneya, G., Sunil, S., Rao K, S., Manjunatha, N. K., Giri, J., Al-Lohedan, H. A., Sathish, T., & Prasad, C. D. (2024). Performance analysis and optimization of thermal barrier coated piston diesel engine fuelled with biodiesel using RSM. *Case Studies in Thermal Engineering*, *57*, 104351. https://doi.org/10.1016/j.csite.2024.104351

Asaad, S. M., Inayat, A., Ghenai, C., & Shanableh, A. (2024). Response Surface Methodology in Biodiesel Production and Engine Performance Assessment. *International Journal of Thermofluids*, *21*, 100551. https://doi.org/10.1016/j.ijft.2023.100551

Axenie, C., Scherr, W., Wieder, A., Torres, A. S., Meng, Z., Du, X., Sottovia, P., Foroni, D., Grossi, M., Bortoli, S., & Brasche, G. (2024). Fuzzy modelling and inference for physics-aware road vehicle driver behaviour model calibration. *Expert Systems with Applications*, *241*, 122590. https://doi.org/10.1016/j.eswa.2023.122590

Bakare, M. S., Abdulkarim, A., Shuaibu, A. N., & Muhamad, M. M. (2024). A hybrid long-term industrial electrical load forecasting model using optimized ANFIS with gene expression programming. *Energy Reports*, *11*, 5831-5844. https://doi.org/10.1016/j.egyr.2024.05.045

Banoqitah, E., Sathyamurthy, R., Moustafa, E. B., Fujii, M., Sudalaimuthu, P., Djouider, F., & H. Elsheikh, A. (2023). Enhancement and prediction of a stepped solar still productivity integrated with paraffin wax enriched with nano-additives. *Case Studies in Thermal Engineering*, *49*, 103215. https://doi.org/10.1016/j.csite.2023.103215

Birim, Ş. Ö., Sönmez, F. E., & Liman, Y. S. (2022). Estimating Return Rate of Blockchain Financial Product by ANFIS-PSO Method. In C. Kahraman, A. C. Tolga, S. Cevik Onar, S. Cebi, B. Oztaysi, & I. U. Sari (Éds.), *Intelligent and Fuzzy Systems* (p. 802-809). Springer International Publishing.

Casalino, G., Castellano, G., & Zaza, G. (2023). Interpretable Neuro-Fuzzy Models for Stress Prediction. In S. Massanet, S. Montes, D. Ruiz-Aguilera, & M. González-Hidalgo (Éds.), *Fuzzy Logic and Technology, and Aggregation Operators* (p. 630-641). Springer Nature Switzerland.

Chaki, S., & Biswas, T. K. (2023). An ANN-entropy-FA model for prediction and optimization of biodiesel-based engine performance. *Applied Soft Computing*, *133*, 109929. https://doi.org/10.1016/j.asoc.2022.109929

Chaudhury, S., Samantaray, S., Sahoo, A., Bhagat, B., Biswakalyani, C., & Satapathy, D. P. (2022). Hybrid ANFIS-PSO Model for Monthly Precipitation Forecasting. In V. Bhateja, J. Tang, S. C. Satapathy, P. Peer, & R. Das (Éds.), *Evolution in Computational Intelligence* (p. 349-359). Springer Nature Singapore.

Chen, H.-Y., Lee, C.-H., & Huang, B.-M. (2019). *Electricity Consumption Forecasting of Buildings Using Hierarchical ANFIS and GRA* (p. 7). https://doi.org/10.1109/ICMLC48188.2019.8949177

Chen, W., Panahi, M., & Pourghasemi, H. R. (2017). Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. *CATENA*, *157*, 310-324. https://doi.org/10.1016/j.catena.2017.05.034

Chen, Z., He, J., Chen, H., Geng, L., & Zhang, P. (2021). Comparative study on the combustion and emissions of dual-fuel common rail engines fueled with diesel/methanol, diesel/ethanol, and diesel/n-butanol. *Fuel*, *304*, 121360. https://doi.org/10.1016/j.fuel.2021.121360

Chinta, V. S., Kethi Reddi, S., & Yarramsetty, N. (2023). Optimal feature selection on Serial Cascaded deep learning for predictive maintenance system in automotive industry with fused optimization algorithm. *Advanced Engineering Informatics*, *57*, 102105. https://doi.org/10.1016/j.aei.2023.102105

Dass, A., Srivastava, S., & Kumar, R. (2023). A novel Lyapunov-stability-based recurrent-fuzzy system for the Identification and adaptive control of nonlinear systems. *Applied Soft Computing*, *137*, 110161. https://doi.org/10.1016/j.asoc.2023.110161

Dintén, R., García, S., & Zorrilla, M. (2023). Fleet management systems in Logistics 4.0 era : A real time distributed and scalable architectural proposal. *4th International Conference on Industry 4.0 and Smart Manufacturing*, *217*, 806-815. https://doi.org/10.1016/j.procs.2022.12.277

Duranoğlu, D., Sinan Altın, E., & Küçük, İ. (2024). Optimization of adaptive neuro–fuzzy inference system (ANFIS) parameters via Box-Behnken experimental design approach : The prediction of chromium adsorption. *Heliyon*, *10*(3), e25813. https://doi.org/10.1016/j.heliyon.2024.e25813

E. Özer, N. Sevinçkan, & E. Demiroğlu. (2024). Comparative Analysis of Computational Intelligence Techniques in Financial Forecasting : A Case Study on ANN and ANFIS Models. *2024 32nd Signal Processing and Communications Applications Conference (SIU)*, 1-4. https://doi.org/10.1109/SIU61531.2024.10600769

E. Shulga, S. Maurel, T. -B. Airimitoaie, & P. Lanusse. (2023). Optimal CRONE control of the intake manifold pressure of a spark ignition internal combustion engine. *2023 International Conference on Fractional Differentiation and Its Applications (ICFDA)*, 1-6. https://doi.org/10.1109/ICFDA58234.2023.10153274

Eladl, A. A., Saeed, M. A., Sedhom, B. E., Abdelaziz, A. Y., & Bureš, V. (2023). LoRaWAN-based IoT protocol for three levels central protection scheme in MT-HVDC networks with ANFIS-PSO restoration algorithm. *Energy Reports*, *10*, 4556-4573. https://doi.org/10.1016/j.egyr.2023.11.013

Elymany, M. M., Enany, M. A., & Elsonbaty, N. A. (2024). Hybrid optimized-ANFIS based MPPT for hybrid microgrid using zebra optimization algorithm and artificial gorilla troops optimizer. *Energy Conversion and Management*, *299*, 117809. https://doi.org/10.1016/j.enconman.2023.117809

Gad, M. S., & Alenany, A. (2024). Comparative diesel engine performance and emission forecasting using extreme learning and quadratic regression techniques burning waste cooking biodiesel. *International Journal of Hydrogen Energy*, *60*, 94-106. https://doi.org/10.1016/j.ijhydene.2024.02.099

Hosseini, S., Khandakar, A., Chowdhury, M. E. H., Ayari, M. A., Rahman, T., Chowdhury, M. H., & Vaferi, B. (2022). Novel and robust machine learning approach for estimating the fouling factor in heat exchangers. *Energy Reports*, *8*, 8767-8776. https://doi.org/10.1016/j.egyr.2022.06.123

J. Kennedy & R. Eberhart. (1995). Particle swarm optimization. *Proceedings of ICNN'95 - International*

Conference on Neural Networks, *4*, 1942-1948 vol.4. https://doi.org/10.1109/ICNN.1995.488968

J. Pranav.P, A. Jenifer.J, S. Janish.A, N. K, & J. Ernest.C. (2023). Smart Fleet : An Advanced Web-Based Solution for Fleet Management and Security. *2023 International Conference on Circuit Power and Computing Technologies (ICCPCT)*, 530-535. https://doi.org/10.1109/ICCPCT58313.2023.10245993

Jang, J.-S., Sun, C.-T., & Mizutani, E. (1997). Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence [Book Review]. *Automatic Control, IEEE Transactions on*, *42*, 1482-1484. https://doi.org/10.1109/TAC.1997.633847

Jiang, J., Zhang, X., & Yuan, Z. (2024). Feature selection for classification with Spearman's rank correlation coefficient-based self-information in divergence-based fuzzy rough sets. *Expert Systems with Applications*, *249*, 123633. https://doi.org/10.1016/j.eswa.2024.123633

Keneni, B., Kaur, D., Al Bataineh, A., Devabhaktuni, V., Javaid, A., Zaientz, J., & Marinier III, R. (2019a). Evolving Rule Based Explainable Artificial Intelligence for Unmanned Aerial Vehicles. *IEEE Access*, *PP*, 1-1. https://doi.org/10.1109/ACCESS.2019.2893141

Keneni, B., Kaur, D., Al Bataineh, A., Devabhaktuni, V., Javaid, A., Zaientz, J., & Marinier III, R. (2019b). Evolving Rule Based Explainable Artificial Intelligence for Unmanned Aerial Vehicles. *IEEE Access*, *PP*, 1-1. https://doi.org/10.1109/ACCESS.2019.2893141

Kim, S. (2023). Innovating knowledge and information for a firm-level automobile demand forecast system : A machine learning perspective. *Journal of Innovation & Knowledge*, *8*(2), 100355. https://doi.org/10.1016/j.jik.2023.100355

Kontoni, D.-P. N., & Ahmadi, M. (2024). 8—Practical prediction of ultimate axial strain and peak axial stress of FRP-confined concrete using hybrid ANFIS-PSO models. In M. L. Nehdi, H. C. Arora, K. Kumar, R. Damaševičius, & A. Kumar (Éds.), *Artificial Intelligence Applications for Sustainable Construction* (p. 225-255). Woodhead Publishing. https://doi.org/10.1016/B978-0-443-13191-2.00015-8

Lazreg, M., & Benamrane, N. (2022). Hybrid system for optimizing the robot mobile navigation using ANFIS and PSO. *Robotics and Autonomous Systems*, *153*, 104114. https://doi.org/10.1016/j.robot.2022.104114

Li, X., Teng, W., Peng, D., Ma, T., Wu, X., & Liu, Y. (2023). Feature fusion model based health indicator construction and self-constraint state-space estimator for remaining useful life prediction of bearings in wind turbines. *Reliability Engineering & System Safety*, *233*, 109124. https://doi.org/10.1016/j.ress.2023.109124

Liu, Q., Liu, W., Dong, M., Li, Z., & Zheng, Y. (2023). Residual useful life prognosis of equipment based on modified hidden semi-Markov model with a co-evolutional optimization method. *Computers & Industrial Engineering*, *182*, 109433. https://doi.org/10.1016/j.cie.2023.109433

Lughofer, E., & Pratama, M. (2023). Evolving multi-user fuzzy classifier system with advanced explainability and interpretability aspects. *Information Fusion*, *91*, 458-476. https://doi.org/10.1016/j.inffus.2022.10.027

M. G. K. Machesa, L. K. Tartibu, F. K. Tekweme, & M. O. Okwu. (2019). Evaluation of the Stirling Heat Engine Performance Prediction Using ANN-PSO and ANFIS Models. *2019 6th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, 217-222. https://doi.org/10.1109/ISCMI47871.2019.9004406

M. Querales, R. Salas, R. Torres, A. Aguilera, & Y. Morales. (2023). Explainability of Machine Learning Models for Hydrological Time Series Forecasting : The Case of Neuro-Fuzzy Approaches. *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 1-6. https://doi.org/10.1109/ICECCME57830.2023.10252284

M. S. Kamal, N. Dey, L. Chowdhury, S. I. Hasan, & K. Santosh. (2022). Explainable AI for Glaucoma Prediction Analysis to Understand Risk Factors in Treatment Planning. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-9. https://doi.org/10.1109/TIM.2022.3171613

M. S. Punith, M. Nithya, & K. Deepa. (2022). IoT Enabled Smart Fleet Management. *2022 IEEE 4th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA)*, 256-260. https://doi.org/10.1109/ICCCMLA56841.2022.9989097

Machesa, M. G. K., Tartibu, L. K., & Okwu, M. O. (2023a). Performance analysis of stirling engine using computational intelligence techniques (ANN & Fuzzy Mamdani Model) and hybrid algorithms (ANN-PSO & ANFIS). *Neural Computing and Applications*, *35*(2), 1225-1245. https://doi.org/10.1007/s00521-022-07385-0

Machesa, M. G. K., Tartibu, L. K., & Okwu, M. O. (2023b). Performance analysis of stirling engine using computational intelligence techniques (ANN & Fuzzy Mamdani Model) and hybrid algorithms (ANN-PSO & ANFIS). *Neural Computing and Applications*, *35*(2), 1225-1245. https://doi.org/10.1007/s00521-022-07385-0

Miraftabzadeh, S. M., & Longo, M. (2023). High-resolution PV power prediction model based on the deep learning and attention mechanism. *Sustainable Energy, Grids and Networks*, *34*, 101025. https://doi.org/10.1016/j.segan.2023.101025

Mohanty, S., Hazra, S., & Paul, S. (2020). Intelligent prediction of engine failure through computational image analysis of wear particle. *Engineering Failure Analysis*, *116*, 104731. https://doi.org/10.1016/j.engfailanal.2020.104731

Mottahedi, A., Sereshki, F., & Ataei, M. (2018). Overbreak prediction in underground excavations using hybrid ANFIS-PSO model. *Tunnelling and Underground Space Technology*, *80*, 1-9. https://doi.org/10.1016/j.tust.2018.05.023

Mueller, P. N., Woelfl, L., & Can, S. (2023). Bridging the gap between AI and the industry—A study on bearing fault detection in PMSM-driven systems using CNN and inverter measurement. *Engineering Applications of Artificial Intelligence*, *126*, 106834. https://doi.org/10.1016/j.engappai.2023.106834

Nagar, H., Machavaram, R., Kulkarni, P., & Soni, P. (2024). AI-based engine performance prediction cum advisory system to maximise fuel efficiency and field performance of the tractor for optimum tillage. *Systems Science & Control Engineering*, *12*(1), 2347936. https://doi.org/10.1080/21642583.2024.2347936

Ndarwe, D., Bongue, D., Monkam, D., Moudi, P., Philippon, N., & KenfacK, C. A. (2019). Analysis of the diurnal to seasonal variability of solar radiation in Douala, Cameroon. *Theoretical and Applied Climatology*, *138*(1), 249-261. https://doi.org/10.1007/s00704-019-02821-z

Nguyen, M. D., Nguyen, D. D., Nguyen Hai, H., Ho Sy, A., Nguyen Quang, P., Nguyen Thai, L., Nguyen Cong, D., Prakash, I., Le, H. V., & Pham, B. T. (2023). Estimation of recompression coefficient of soil using a hybrid ANFIS-PSO machine learning model. *Journal of Engineering Research*. https://doi.org/10.1016/j.jer.2023.10.018

O'Donnell, J., & Yoon, H.-S. (2020). Determination of Time-to-Failure for Automotive System Components Using Machine Learning. *Journal of Computing and Information Science in Engineering*, *20*(061003). https://doi.org/10.1115/1.4046818

Oladipo, S., Sun, Y., & Amole, A. O. (2024). Investigating the influence of clustering techniques and parameters on a hybrid PSO-driven ANFIS model for electricity prediction. *Discover Applied Sciences*, *6*(5), 265. https://doi.org/10.1007/s42452-024-05922-1

Oliaye, A., Kim, S.-H., & Bae, D.-H. (2023). A new approach to weather radar adjustment for heavy rainfall events using ANFIS-PSO. *Journal of Hydrology*, *617*, 128956. https://doi.org/10.1016/j.jhydrol.2022.128956

P. Singh, M. S. Suryawanshi, & D. Tak. (2019). Smart Fleet Management System Using IoT, Computer Vision, Cloud Computing and Machine Learning Technologies. *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, 1-8. https://doi.org/10.1109/I2CT45611.2019.9033578

Pandey, N., Bhatnagar, M., & Ghosh, D. (2021). An analysis of critical success factors towards sustainable supply chain management – in the context of an engine manufacturing industry. *International Journal of Sustainable Engineering*, *14*(6), 1496-1508. https://doi.org/10.1080/19397038.2021.1966128

Pavlopoulos, J., Romell, A., Curman, J., Steinert, O., Lindgren, T., Borg, M., & Randl, K. (2024). Automotive fault nowcasting with machine learning and natural language processing. *Machine Learning*, *113*(2), 843-861. https://doi.org/10.1007/s10994-023-06398-7

Peláez-Rodríguez, C., Pérez-Aracil, J., Marina, C. M., Prieto-Godino, L., Casanova-Mateo, C., Gutiérrez, P. A., & Salcedo-Sanz, S. (2024). A general explicable forecasting framework for weather events based on ordinal classification and inductive rules combined with fuzzy logic. *Knowledge-Based Systems*, *291*, 111556. https://doi.org/10.1016/j.knosys.2024.111556

Peng, Z., Song, X., Song, S., & Stojanovic, V. (2023). Hysteresis quantified control for switched reaction–diffusion systems and its application. *Complex & Intelligent Systems*, *9*(6), 7451-7460. https://doi.org/10.1007/s40747-023-01135-y

Pramod, C. P., & Pillai, G. N. (2021). K-Means clustering based Extreme Learning ANFIS with improved interpretability for regression problems. *Knowledge-Based Systems*, *215*, 106750. https://doi.org/10.1016/j.knosys.2021.106750

R. S. Krishnan, U. Narmatha, N. Preethi, G. Subhashini, J. R. Francis Raj, & K. L. Narayanan. (2023). IoT Powered Smart Cars (ISC). *2023 International Conference on Inventive Computation Technologies (ICICT)*, 1351-1356. https://doi.org/10.1109/ICICT57646.2023.10134084

Rao, X., Sheng, C., Guo, Z., & Yuan, C. (2022). A review of online condition monitoring and maintenance strategy for cylinder liner-piston rings of diesel engines. *Mechanical Systems and Signal Processing*, *165*, 108385. https://doi.org/10.1016/j.ymssp.2021.108385

Revanur, V., Ayibiowu, A., Rahat, M., & Khoshkangini, R. (2020). Embeddings Based Parallel Stacked Autoencoder Approach for Dimensionality Reduction and Predictive Maintenance of Vehicles. In J. Gama, S. Pashami, A. Bifet, M. Sayed-Mouchawe, H. Fröning, F. Pernkopf, G. Schiele, & M. Blott (Éds.), *IoT Streams for Data-Driven Predictive Maintenance and IoT, Edge, and Mobile for Embedded Machine Learning* (p. 127-141). Springer International Publishing.

Robati, F. N., & Iranmanesh, S. (2020). Inflation rate modeling : Adaptive neuro-fuzzy inference system approach and particle swarm optimization algorithm (ANFIS-PSO). *MethodsX*, *7*, 101062. https://doi.org/10.1016/j.mex.2020.101062

Samanataray, S., & Sahoo, A. (2021). A Comparative Study on Prediction of Monthly Streamflow Using Hybrid ANFIS-PSO Approaches. *KSCE Journal of Civil Engineering*, *25*(10), 4032-4043. https://doi.org/10.1007/s12205-021-2223-y

Saraswathi, K., & Vijayaraghavan, S. (2024). Design of TITO system using ANFIS-PID controller for polymerization industry. *Measurement: Sensors*, *31*, 100996. https://doi.org/10.1016/j.measen.2023.100996

Sarkar, S., Pramanik, A., & Maiti, J. (2023). An integrated approach using rough set theory, ANFIS, and Z-number in occupational risk prediction. *Engineering Applications of Artificial Intelligence*, *117*, 105515. https://doi.org/10.1016/j.engappai.2022.105515

Şener, R., Koç, M. A., & Ermiş, K. (2024). Hybrid ANFIS-PSO algorithm for estimation of the characteristics of porous vacuum preloaded air bearings and comparison performance of the intelligent algorithm with the ANN. *Engineering Applications of Artificial Intelligence*, *128*, 107460. https://doi.org/10.1016/j.engappai.2023.107460

Shalahuddin, L., Fajar, R., & Bismantoko, S. (2023). Review of artificial neural network applications for prediction of internal combustion engine performance. In *AIP Conference Proceedings*. https://doi.org/10.1063/5.0117389

Shi, B., Liu, Y., Lu, S., & Gao, Z.-W. (2024). A new adaptive feature fusion and selection network for intelligent transportation systems. *Control Engineering Practice*, *146*, 105885. https://doi.org/10.1016/j.conengprac.2024.105885

Singh, V., Osen, O., & Bye, R. (2023). *Explainable Artificial Intelligence for Autonomous Surface Vessels by Fuzzy-Based Collision Avoidance System*.

Song, X., Peng, Z., Song, S., & Stojanovic, V. (2024). Anti-disturbance state estimation for PDT-switched RDNNs utilizing time-sampling and space-splitting measurements. *Communications in Nonlinear Science and Numerical Simulation*, *132*, 107945. https://doi.org/10.1016/j.cnsns.2024.107945

Stephen, D. S., & Sethuramalingam, P. (2024). ANFIS prediction modeling of surface roughness and cutting force of titanium alloy ground with carbon nanotube grinding wheel. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, *7*(4), 3285-3300. https://doi.org/10.1007/s41939-024-00411-9

Sun, P., Song, X., Song, S., & Stojanovic, V. (2023). Composite adaptive finite-time fuzzy control for switched nonlinear systems with preassigned performance. *International Journal of Adaptive Control and Signal Processing*, *37*(3), 771-789. https://doi.org/10.1002/acs.3546

Tancredi, G. P., & Vignali, G. (2024). Machine Learning tool to prevent and control Bag Filter clogging. *5th International Conference on Industry 4.0 and Smart Manufacturing (ISM 2023)*, *232*, 2358-2365. https://doi.org/10.1016/j.procs.2024.02.054

TJAHE, A., Fotso, B., FOGUE, M., & Zerhouni, N. (2021a). Integration of future maintenance actions in the prediction parameters of the ATLAS COPCO ZR 200 compressor. *International Journal of Prognostics and Health Management*, *12*. https://doi.org/10.36001/ijphm.2021.v12i2.2916

TJAHE, A., Fotso, B., FOGUE, M., & Zerhouni, N. (2021b). Integration of future maintenance actions in the prediction parameters of the ATLAS COPCO ZR 200 compressor. *International Journal of Prognostics and Health Management*, *12*. https://doi.org/10.36001/ijphm.2021.v12i2.2916

Ude, C. N., Igwilo, C. N., Nwosu-Obieogu, K., Nnaji, P. C., Oguanobi, C. N., Amulu, N. F., Eze, C. N., & Omenihu, U. C. (2023). Optimization of dual transesterification of jatropha seed oil to biolubricant using hybridized response surface methodology (RSM) and adaptive neuro fuzzy inference system (ANFIS)-genetic algorithm (GA). *Sustainable Chemistry for the Environment*, *4*, 100050. https://doi.org/10.1016/j.scenv.2023.100050

Vasavi, S., Aswarth, K., Sai Durga Pavan, T., & Anu Gokhale, A. (2021). Predictive analytics as a service for vehicle health monitoring using edge computing and AK-NN algorithm. *3rd International Conference on Materials, Manufacturing and Modelling*, *46*, 8645-8654. https://doi.org/10.1016/j.matpr.2021.03.658

Wang, H., Ji, C., Yang, J., Ge, Y., & Wang, S. (2023). Implementation of a novel dual-layer machine learning structure for predicting the intake characteristics of a side-ported Wankel rotary engine. *Aerospace Science and Technology*, *132*, 108042. https://doi.org/10.1016/j.ast.2022.108042

Wang, Y., Wang, G., Yao, G., Shen, Q., Yu, X., & He, S. (2023). Combining GA-SVM and NSGA-III multi-objective optimization to reduce the emission and fuel consumption of high-pressure common-rail diesel engine. *Energy*, *278*, 127965. https://doi.org/10.1016/j.energy.2023.127965

Wang, Y., Wu, X., Wang, Y., & Zhou, X. (2020). Fuzzy logic based feedback control system for the frequency stabilization of external-cavity semiconductor lasers. *International Journal of Optomechatronics*, *14*(1), 44-52. https://doi.org/10.1080/15599612.2020.1828516

Wang, Z., Yang, S., Xiang, X., Vasilijević, A., Mišković, N., & Nađ, Đ. (2021). Cloud-based mission control of USV fleet : Architecture, implementation and experiments. *Control Engineering Practice*, *106*, 104657. https://doi.org/10.1016/j.conengprac.2020.104657

Y. Zhou, L. Zhu, J. Yi, T. H. Luan, & C. Li. (2020). On Vehicle Fault Diagnosis : A Low Complexity Onboard Method. *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, 1-6. https://doi.org/10.1109/GLOBECOM42002.2020.9322534

Yang, Z., Wu, B., Shao, J., Lu, X., Zhang, L., Xu, Y., & Chen, G. (2024). Fault detection of high-speed train axle bearings based on a hybridized physical and data-driven temperature model. *Mechanical Systems and Signal Processing*, *208*, 111037. https://doi.org/10.1016/j.ymssp.2023.111037

Yang, Z.-X., Rong, H.-J., Wong, P. K., Angelov, P., Vong, C. M., Chiu, C. W., & Yang, Z.-X. (2022). A Novel Multiple Feature-Based Engine Knock Detection System using Sparse Bayesian Extreme Learning Machine. *Cognitive Computation*, *14*(2), 828-851. https://doi.org/10.1007/s12559-021-09945-3

Zandie, M., Ng, H. K., Gan, S., Muhamad Said, M. F., & Cheng, X. (2023). Multi-input multi-output machine learning predictive model for engine performance and stability, emissions, combustion and ignition characteristics of diesel-biodiesel-gasoline blends. *Energy*, *262*, 125425. https://doi.org/10.1016/j.energy.2022.125425

Zhang, X., Gao, Y., Guo, Z., Zhang, W., Yin, J., & Zhao, W. (2023). Physical model-based tool wear and breakage monitoring in milling process. *Mechanical Systems and Signal Processing*, *184*, 109641. https://doi.org/10.1016/j.ymssp.2022.109641

Zhang, Y., Li, J., Fei, L., Feng, Z., Gao, J., Yan, W., & Zhao, S. (2023). Operational performance estimation of vehicle electric coolant pump based on the ISSA-BP neural network. *Energy*, *268*, 126701. https://doi.org/10.1016/j.energy.2023.126701

Zhang, Z., Al-Bahrani, M., Ruhani, B., Heybatian Ghalehsalimi, H., Zandy Ilghani, N., Maleki, H., Ahmad, N., Nasajpour-Esfahani, N., & Toghraie, D. (2023). Optimized ANFIS models based on grid partitioning, subtractive clustering, and fuzzy C-means to precise prediction of thermophysical properties of hybrid nanofluids. *Chemical Engineering Journal*, *471*, 144362. https://doi.org/10.1016/j.cej.2023.144362

Zhuo, Y., Zhang, T., Du, F., & Liu, R. (2023). A parallel particle swarm optimization algorithm based on GPU/CUDA. *Applied Soft Computing*, *144*, 110499. https://doi.org/10.1016/j.asoc.2023.110499