Hybrid Prognostics for Aircraft Fuel System: An Approach to Forecasting the Future

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Abstract

The copious volumes of data collected incessantly from diverse systems present challenges in interpreting the data to predict system failures. The majority of large organizations employ highly trained experts who specialize in using advanced maintenance equipment and have specific certification in predictive maintenance (PdM). Prognostics and health management (PHM) connects research on deterioration models to strategies for PdM. Prognostics refer to the process of estimating the time until failure and the associated risk for one or more current and potential failure modes. Prognostics aim to provide guidance by alerting to imminent failures and predicting the remaining useful life (RUL). This eventually leads to improved availability, dependability, and safety, while also reducing maintenance costs. This research work diverges from existing established prognostic methodologies by emphasising the use of hybrid prognostics to predict the future performance of an aircraft system, especially the point in which the system will cease to operate as intended, often referred to as its time to failure. We have developed a new method that combines a physics-based model with the physics of failure (PoF) and a multiple-layered hyper-tangent-infused data-driven approach. The results are useful. The authors retrieved datasets for analysis using a laboratory aircraft fuel system and simulation model. Consequently, the comparative results demonstrate that the proposed hybrid prognostic approach properly estimates the RUL and demonstrates strong application, availability, and precision.

Keywords: health management; physics of failure; hybrid prognostics; aircraft fuel system; remaining useful life.

1. Introduction

The goal of prognostics is to accurately detect and report impending system failures—that is, to forecast the progression of failure. Prognostic methodologies used in prognostic and health management (PHM) achieve this objective through three distinct classifications: condition-based, usage-based, and traditional. Traditional prognostic approaches can be further classified as model-based, data-driven, or hybrid models (Gu & Pecht, 2008; Liao & Köttig, 2014).

Using failure physics (PoF), likelihood, and reliability models to come up with and use expressions is what model-based prognostic methods do. These models utilise the relationships between materials, manufacturing processes, and the dependability, robustness, and strength of a subsystem. This is typically achieved through controlled, structured experiments and life evaluations. Although modelling offers the potential for high accuracy, its implementation and utilisation in complex operational systems are difficult. The models comprise acceleration factor-incorporated reliability testing models, probability models, distributions, and reliability theory principles. Figure 1 shows the comparison between physics-based and traditional condition-based data (CBD) approaches to PHM.

Data-driven prognostic approaches, such as statistical and machine learning methods, are easier to use than model-based approaches but may result in less precise and accurate prognostic projections (Galar et al., 2021). As shown in Fu et al. (2023), statistical approaches include both parametric and nonparametric models. They also include K-nearest neighbour (KNN), a nonparametric method for classifying or regressing an item based on its nearby data points. Linear discriminant analysis (LDA) sorts many objects into groups, hidden Markov modelling (HMM) deals with systems that have hidden states, and principal component analysis (PCA) changes variables in a straight line. Hybrid approaches combine model-based and data-driven methods to enhance accuracy and gain a deeper understanding of the interactions between parameters and objects. The complexity of computational processing is one of the limitations.

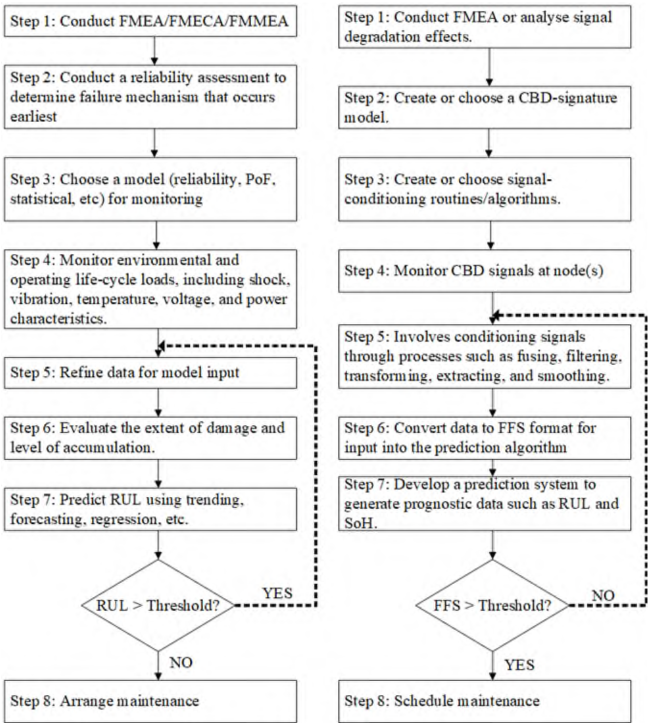

Figure 1. Diagram comparison of model-based and CBD-signature approaches to PHM (Hofmeister et al., 2017).

Figure 2 illustrates an alternative representation of a fault tree for aircraft fuel error-identified systems. Failure Mode and Effects Analysis (FMEA) and Failure Mode, Effects, and Criticality Analysis (FMECA) are used in this study to investigate a fuel-error defect and find the most likely failure mode. This could be air flow, pressure, temperature, or the fuel pump.

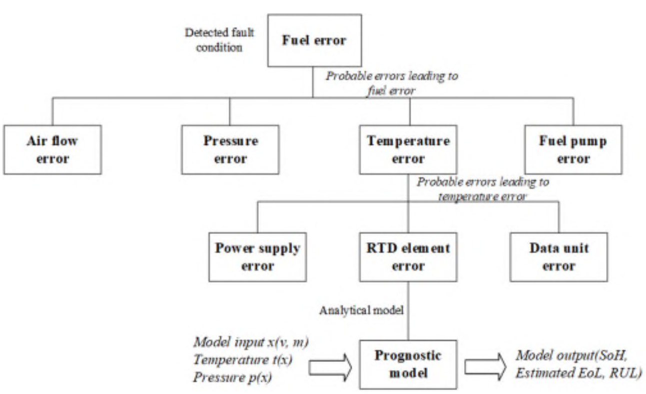

Figure 2. Example of fuel error leading to the application of prognostic model (Douglas Goodman et al., 2019)

In this instance, we conclude that a temperature inaccuracy is the probable factor responsible for the fuel error. The fault tree indicates that three failure modes, namely the power supply, resistive temperature detector (RTD), or an air-data unit, are likely to cause the temperature error. We use an appropriate analytical model to generate prognostic data in the event of an RTD failure.

1.1. Hybrid prognostic mechanisms

A hybrid technique combines physics-based and data-driven prognostics in two phases: offline and online. The initial phase involves creating the nominal and deterioration models, as well as establishing the faults and performance criteria required to predict the remaining useful life (RUL) of the system. The second phase entails using models and thresholds to identify fault initiation, assess the state of system health (SoH), and forecast future SoH and RUL. Data from experiments and synthetic datasets from simulations that replicate real-world settings often validate and optimise the models. We create and utilise sensors to gather data from operational systems, with the aim of monitoring and maintaining the systems' health. The hybrid model offers a higher level of precision compared to employing solely a physics-based or data-driven approach. A physics-based model generates particularly accurate prognostic information when adjusted to sensor data. One drawback is the increased complexity involved in adapting the model to sensor data.

Hybrid models utilise a blend of multiple models to enhance accuracy. Many academics have overlooked hybrid modelling for fault diagnostics and maintenance decision-making. Ahmadzadeh & Lundberg (2014) examined three advanced models for predicting RUL: knowledge-based models, data-driven models, physics-based models, and hybrid prognostic models. Jardine et al. (2006) conducted an examination of machinery diagnostics and prognostics, showcasing the application of statistical, artificial intelligence, and physics-based prognostic methods in condition-based maintenance (CBM) to improve the precision of equipment RUL estimation. A few studies have especially concentrated on hybrid prognostic approaches to capitalise on the benefits of several prognostic models.

Hybrid prognostic methodologies have limitations because they rely on both model-based and data-driven methods. Inaccurate models, noisy data, or both may result in an incorrect RUL forecast. As a result, if not managed correctly, there is a significant likelihood of increased variance in mistakes. A hybrid strategy combines elements of physics-based and data-driven methodologies to leverage their advantages while mitigating their limitations, but it still retains some disadvantages of both. Elattar et al. (2016) developed a flowchart to assist in choosing a prognostic method, as shown in Figure 3.

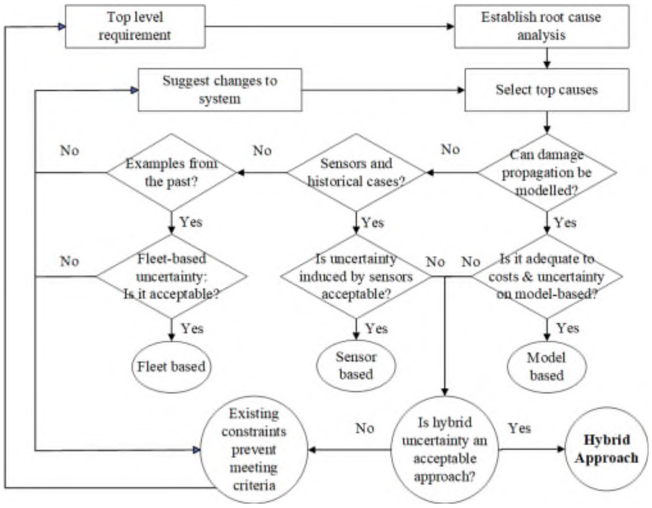

Figure 3. Workflow to select prognostic approaches (Elattar et al., 2016).

A hybrid strategy can effectively integrate data-driven and physics-based methods to optimise their respective strengths when managed appropriately. A physics-based method can address data deficiencies, while a data-driven model can address gaps in understanding the system's mechanics. Performing this fusion before estimating the RUL is known as pre-estimation. Fusion is a process that combines the results of various methods to determine the final RUL after predicting it. Li et al. (2019); Nieto et al. (2016); and Orsagh et al. (2003) used a fusion strategy for aircraft engine bearings to show that this method gives more accurate and long-lasting results than just using data-driven or physics-based approaches alone.

1.2. Prognostic application

In the aircraft sector, there are several instances of prognostic applications that are now in the developmental stage. The current aim of prognostic society is to create a PHM system capable of detecting and isolating problems in both the primary and subsystems of the aircraft. Additionally, this system will offer prognostic information for specific components (Losik, 2012; McCollom & Brown, 2011; Vohnout et al., 2012). PHM, which is critical to improving safety and lowering maintenance costs, has a significant impact on the choice of aircraft. The proposed architecture incorporates an external PHM system that will employ data mining techniques. Figure 4 depicts the forecasting applications.

There has been a notable surge in interest in prognostics due to their ability to improve the health management of intricate engineering systems. Prognostics are important because they allow us to predict future illness progression and treatment outcomes. Daily weather forecasting also employs this technology. Whether they are located on board or off board, prognostic software solutions have the potential to function in real-time or nearly real-time.

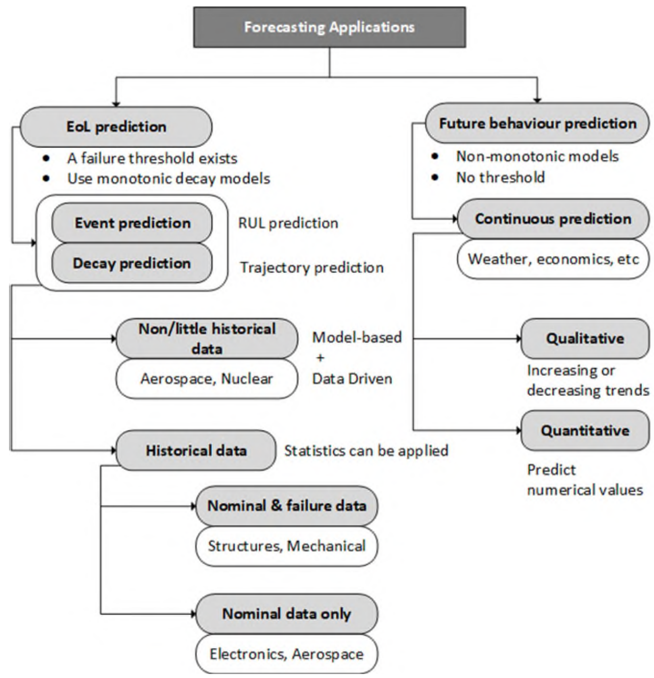

Figure 4. Forecasting applications.

Prognostics can be used offline, regardless of how long the monitored system has been in operation. Real-time prognostics uses the online data collected from the data collection system to accurately estimate the RUL and warn about an imminent breakdown. This allows the system to be reconfigured and the mission re-planned. The offline prognostics system utilises extensive system data from the whole fleet and applies intricate data analysis techniques that are not feasible to conduct in real-time on board due to resource and time constraints. An offline prognostic system in logistical support management can provide useful information for maintenance planning and decision-making.

2. AIRCRAFT FUEL DELIVERY SYSTEM

An aircraft fuel delivery system with three tanks usually consists of a central tank and two wing tanks. The central tank supplies fuel to the engine, and the wing tanks supply fuel to the central tank via pumping stations. Two centrifugal pumps, complete with check valves to prevent backflow, equip each station. Prime movers, operating at a constant angular velocity, power these pumps. Engineers designed the system with varying elevations between the tanks and the engine intake to facilitate fuel flow. This flow is regulated by two-way bidirectional valves that respond to the fuel levels in each tank. Figure 5 illustrates the design of the simulation model, which is based on the MathWorks library.

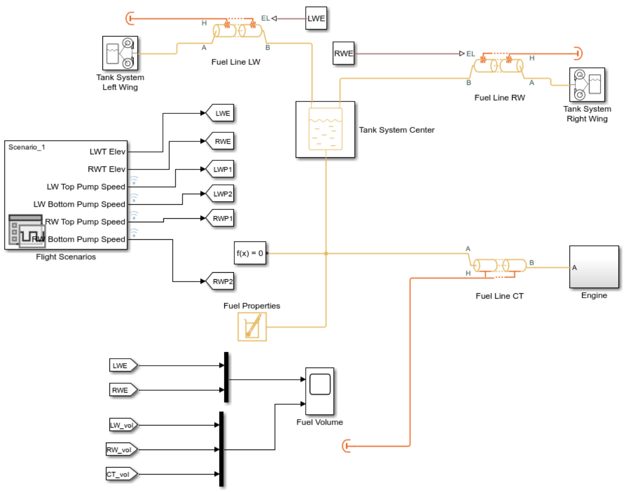

Figure 5. Aircraft fuel delivery simulation system.

The process of simulating this system involves modulating the fluid dynamics associated with the fuel flow, the mechanical design of the pumps and valves, and the control systems responsible for overseeing fuel distribution. The operation will examine the effects of aircraft manoeuvres, specifically changes in bank angle, on the reduction in pressure across the fuel lines. Figure 6 depicts the structure of the central tank in the simulation model.

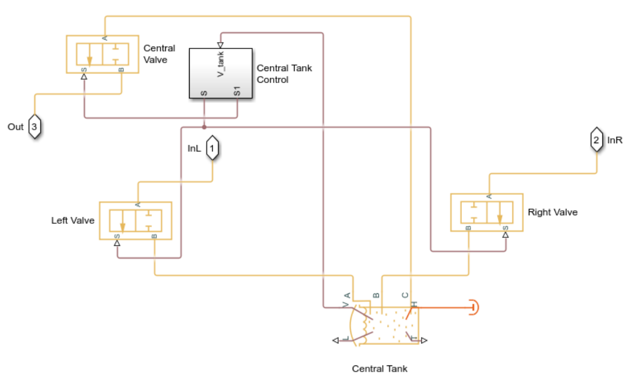

Figure 6. Central tank structure.

There is a storage tank in a thermal liquid network that maintains a constant pressure and allows for a variable number of inlets. The pressure at the liquid surface is considered to be equivalent to the pressurisation. It represents the hydrostatic pressure differential between the fuel surface and the inlets. When the liquid level drops below the inlet height, the port is exposed. It is connected to a partially filled pipe to simulate the ongoing decrease in liquid level within the pipe. In the simulation model, ports A, B, C, D, E, and F are thermal liquid conservation ports connected to the tank inlets. The thermal-conserving port H is associated with the liquid's temperature in the tank. The physical signals V, L, and T represent the liquid volume, liquid level, and liquid temperature, respectively. Bidirectional valves are also depicted within a thermal fuel network. The voltage input S determines the location of the spool. Positive spool displacement facilitates fuel flow by opening the connection between ports A and B. The disconnection is caused by reverse spool movement. We regard the aforementioned component as adiabatic. The system does not transfer thermal energy to its surroundings. Figure 7 illustrates the engine pump and its various subcomponents.

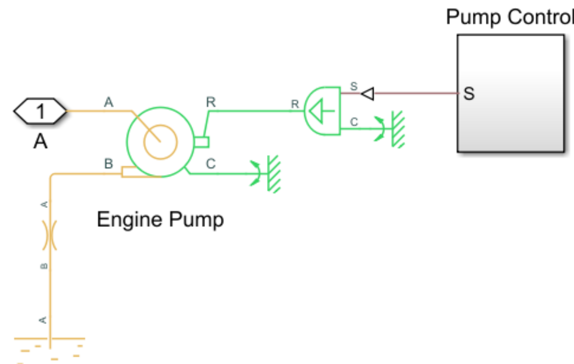

Figure 7. Engine pump and its subcomponents.

The simulation model also includes a centrifugal pump operating within the fuel supply system. We employ affinity laws to establish the relationship between the reference pump characteristics and the actual flow rate and pressure gain. We connect the thermal fuel conservation ports, identified as ports A and B, to the pump's input and outflow, respectively. The drive shaft and casing respectively connect to the mechanical rotational conserving ports, denoted as ports R and C. Mechanical orientation determines the shaft rotation for proper pump functioning, where the flow moves from port A to port B and the pressure increases. The pump's performance in the other direction is indeterminate and perhaps imprecise. Figure 8 shows the engine pump's various characteristics.

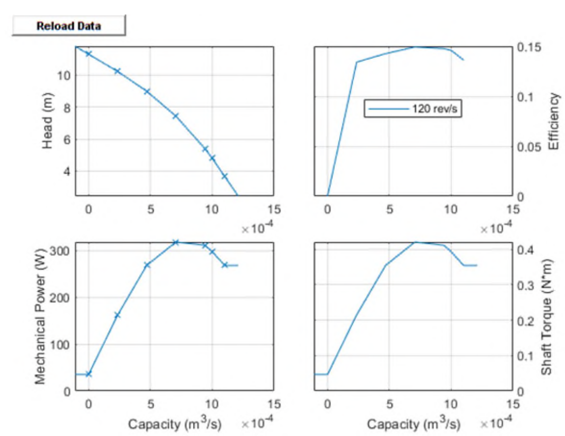

Figure 8. Engine pump characteristics.

It is also possible to get an ideal source of angular velocity from the system, which produces a velocity difference at its ends that is proportional to the physical input signal. The source is considered ideal since it is thought to have sufficient power to sustain a defined velocity regardless of the torque applied to the system. The relative velocity is calculated by subtracting the absolute angular velocity of the terminal $C(W\_C)$ from the absolute angular velocity of the terminal $R(W\_R)$, denoted as $W = W\_R - W\_C$.

3. Hybrid Prognostic Modelling and results

3.1. Physical principles

The simulation model suggests a generic simulation of an aircraft's fuel supply system rather than directly replicating a specific real-world aircraft's fuel system. The model encompasses common components of an aviation fuel system, including:

- Multiple fuel tanks: commercial and military aircraft typically have wing tanks and a centre tank to evenly distribute weight and improve fuel economy. The model provides certain starting pressurisation and volume capacities for the tanks, essential for maintaining fuel flow under different flying conditions.
- The specifications for centrifugal pumps and valves, such as bidirectional valves and check valves, demonstrate the intricate systems used to control fuel supply from the tanks to the engines.
- It contains essential information regarding the fuel line's length, diameter, and resistance properties, crucial for accurately modelling fuel flow within the system.

The simulation provides a valuable resource that can be customised or expanded to accurately replicate the fuel system of a particular aircraft. Factors such as tank sizes, pump capacity, and system layout may be able to be adjusted in accordance with the aircraft's technical requirements. Table 1 presents the initial circumstances and parameters of the model.

The physics-based model often involves the monitoring of many parameters, including pressures, temperatures, fuel levels, flow rates, and valve functioning. These parameters are determined by the components involved, as well as their established failure modes. While conducting an analysis of a simulated aircraft fuel system, researchers strive to identify consistent patterns in:

- Fuel consumption rates during comparable operating conditions. Substantial variances could indicate inefficiencies or deterioration, such as pressure or temperature fluctuations in tanks or fuel lines that differ from the usual values, signalling possible problems.
- Valves and pumps have operational behaviour, including unforeseen operations or alterations in performance measurements.

Table 1. The initial circumstances and parameters of the simulated aircraft fuel delivery model

Components	Parameters	Specs
Initial Conditions	Temperature	333.15 K
	Pressure	0.1 MPa
Fuel Tanks	Pressurisation	0.1 MPa
	Minimum fuel volume	0.09463525 m^3
Wing Tanks	Initial volume	10 m^3
	Maximum capacity	12 m^3
Centre Tank	Pressurisation	0.1 MPa
	Initial volume	5 m^3
	Maximum capacity	284 m^3
Pumps	Reference density	920.027 kg/m^3
	Reference angular velocity	120 rev/s
	Angular velocity threshold	10 rad/s
	Operational ranges for angular velocity	0 to 200 rev/s
	Mover time constant	0.2 s
Valves	Maximum opening area	$\pi/4\times(0.03048)^2$ m^2
	Leakage area	1e – 10 m^2
	Cutoff time constant	0.1 s
	Maximum valve opening (2-Way directional valves)	5.1e-3 m
Fuel line piping	Length	5m
	Hydraulic diameter	3.05e-2 m
	Aggregate equivalent length for local resistances	2.56 m

To develop a physics-based model for an aviation fuel system, one needs to understand the basic concepts of fluid dynamics and the mechanical operations of these systems. Common mathematical formulas and concepts are summarised to reflect the physics of aviation fuel systems, establishing a solid foundation for developing a physics-based model.

The principle of mass conservation is applicable to the process of fuel transfer between tanks and its subsequent use by an airplane's engines. The generic equation provided can be used to analyse each tank:

$$\frac{dV}{dt} = Q_{in} - Q_{out} \tag{1}$$

Where:

- V is the volume of fuel in the tank.
- t is time.
- Q_{in} is the inflow of fuel into the tank, and
- Q_{out} is the outflow rate of fuel from the tank to the engines or to other tanks.

The application of Bernoulli's equation, which establishes a relationship between the pressure, velocity, and height head of the fluid, can aid in the analysis of fluid flow between tanks. This is especially beneficial when the tanks are located at varying heights or when calculating the necessary pressure for fuel transfer between them.

$$P + \frac{1}{2}\rho\nu^2 + \rho gh = constant \quad (2)$$

Where:

- P is the pressure within the fluids.
- ρ is the density of the fluid (fuel).
- ν is the velocity of the fluid.
- g is the acceleration due to gravity, and
- h is the height of the fluid column (which could represent the fuel level in the tank).

PID (proportional-integral-derivative) control effectively manages pump speeds or valve positions to maintain predetermined fuel levels in individual tanks. Fuel level sensors provide the input for this control mechanism. The conventional arrangement of a PID controller is as follows:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + Kd \frac{de(t)}{dt} \quad (3)$$

Where $u(t)$ denotes the control signal (e.g., pump speed), $e(t)$ denotes the error signal (difference between desired and actual fuel level), and K_p, K_i, and K_d denote the proportional, integral, and derivative gains, respectively.

In aircraft fuel systems, where turbulent flow is common, we can use the Darcy-Weisbach equation to calculate the pressure drops (ΔP) along a pipe length:

$$\Delta P = f \frac{L}{D} \frac{\rho \upsilon^2}{2} \quad (4)$$

The variables are defined as follows: f is the friction factor, L is the length of the pipe, D is the diameter of the pipe, ρ is the density of the fuel, and υ is the velocity of the fuel.

3.2. Hybrid prognostic integration methodology

According to Chao et al. (2021), provided $X_{s_i} = \left[x_{s_i}^{(1)}, \ldots, x_{s_i}^{(m_i)}\right]^T$ are multivariate time-series data from condition monitoring sensors and their accompanying RUL $Y_i = \left[y_i^{1}, \ldots, y_i^{m_i}\right]^T$ for a fleet of N units ($i = 1, \ldots, N$). Each observation $x_{s_i}^{(t)} \in R^p$ consists of a vector of ρ raw measurements taken at operating conditions $\omega_i^{(t)} \in R^s$. The length of the sensory signal for the i^{th} unit is determined by m_i, and may vary between units.

The overall cumulative length of the available data collection is $m = \sum_{i=1}^{N} m_i$. We designate the provided dataset more compactly as $D = \left\{W_i, X_{s_i}, Y_i\right\}_{i=1}^{N}$. The objective is to develop a predictive model $\mathcal{G}$ that can accurately estimate the RUL ($\widehat{Y}$) on a test dataset $D_{T*} = \{X_{sj*}\}_{j=1}^{M}$ consisting of M units, which $X_{sj*} = \left[x_{sj*}^{1}, \ldots, x_{sj*}^{k_j}\right]$ are multivariate time series of sensor measurements. The overall cumulative length of the test data set is $m_* = \sum_{j=1}^{M} k_j$.

The subsequent subsections provide a comprehensive analysis of each of these phases. Eker et al. (2019) proposed the following input and output processes for physical-based approaches, as depicted in Figure 9.

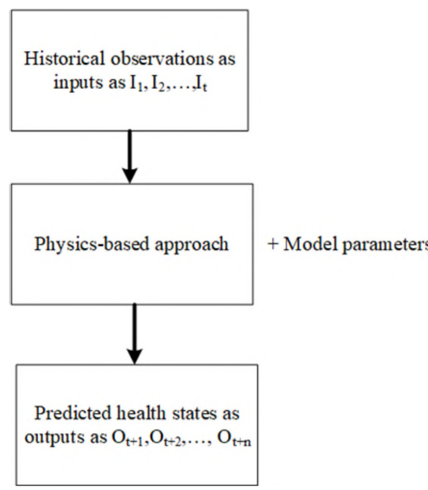

Figure 9. Input and output of the physics-based model.

The flowchart depicted in Figure 10 illustrates the operational mechanism of a hybrid predictive strategy employed in aeroplane fuel distribution systems. This approach combines physics-based and data-driven models. The commencement of the process occurs subsequent to the identification of the components and modes of aircraft failure, the process commences. The aviation fuel system is analysed using physics-based techniques and domain expert knowledge to estimate the short-term RUL. We conduct the analysis using either a real-world or synthetic dataset.

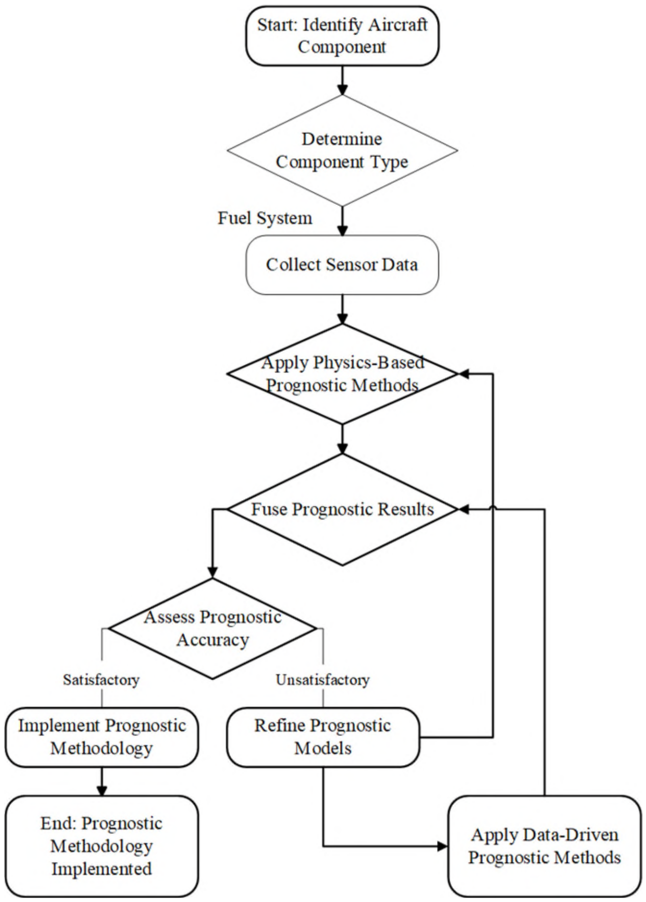

Figure 10. Illustration of fusion mechanism of a hybrid prognostic methodology for an aircraft fuel system

The prediction results will be assessed using several prognostic metrics, as demonstrated in the studies conducted by Chao et al. (2021) and Fu & Avdelidis (2023). The optimisation process will be carried out by comparing the accuracy results with the actual RUL. Once the desired outcome is attained, a hybrid prognostic technique will be included. As long as the engineering systems adhere to specific physical deterioration, the methodology flowchart can be used for other complicated systems.

Random holdback is the chosen approach for validation. The neural network consists of two layers in total. In the initial layer, three radial Gaussian activations are employed, whereas the subsequent layer utilises two times Sigmoid TanH and a linear activation function, which bears a striking resemblance to the activations used in two-layer models. We set the learning rate at 0.1, allowing for robust fitting. A single round of a tour is subject to a penalty approach. The authors of this paper used a variety of neural networks with different activation functions, including Sigmoid TanH, identity linear, and radial Gaussian. There are variations in the outcomes observed among the different models. Various characteristics were obtained, and the highest-ranked attributes that have the most impact on achieving the best result were selected. Figure 11 depicts the simplified neural network that yields the best results.

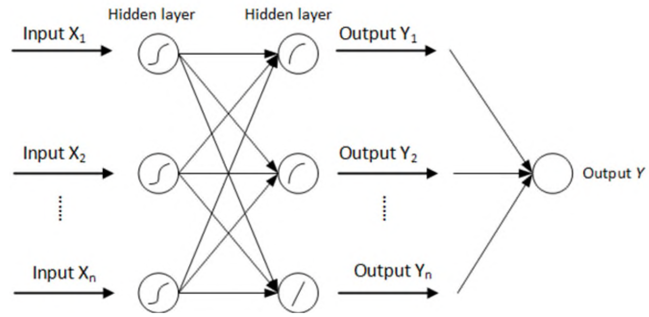

Figure 11. Simplified boosted neural network model NGaussian(3) NTanH(2)NLinear(1)

In its fitting routine, the boosted neural network employs a validation mechanism. Validation methods include holdback, K-fold, or the use of a validation column that performs the following actions to fit the model:

- The model parameters are subject to a penalty.
- The validation set adjusts the penalties applied to the parameters.

The actual-by-predicted plot calculates the comparison between the training's actual and expected values. The suggested methodology reveals the correlation between the observed value and the projected value on the training dataset. The ideal situation involves aligning all data points along a straight path where the anticipated values accurately match the observed values. The data points in this graph display a mostly linear trend that is primarily located close to the actual RUL value. This observation suggests that the projected values exhibit a degree of resemblance to the observed values. As a result, the model exhibits higher levels of predicted accuracy for positive values in comparison to negative values. Table 2 presents the results for both training and validation methods.

Table 2 suggests multiple measuring and evaluation measures to compare prognostic outcomes. Fu et al. (2023) provide comprehensive explanations for each rating metric. Table 2 demonstrates that the R^2 value is 0.9998 for both the training and validation stages, indicating a substantially identical outcome in both phases. The training procedure yielded a higher RASE value of 14.56 compared to the validation process value of 21.26, indicating that the prognostic algorithm exhibits superior performance during the training phase as opposed to the validation phase. We may attribute the tiny difference to the inadequate amount of training data, which led to less accurate predictions. Future optimisation and updates have significant potential to improve accuracy. MathWorks extracts the simulation data from the simulated fuel distribution systems, which you can view at https://zenodo.org/doi/10.5281/zenodo.10888497.

Table 2. Optimal variation in terms of evaluation performance.

	Measures	Value
Training	RSquare	0.9997863103
	RASE	14.563087252
	Mean Abs Dev	8.6751876436
	-LogLikelihood	2308.3148678
	SSE	127038.02268
	Sum Freq	599
Validation	RSquare	0.9997561214
	RASE	21.260680304
	Mean Abs Dev	9.1951405963
	-LogLikelihood	1173.5466987
	SSE	135604.9581
	Sum Freq	300

4. Conclusion

Prognostics are essential in PHM, comprising several elements like system monitoring, fault detection and diagnostics, failure prognostics, and operating management. Prognostic models in both industry and research commonly utilise physics-based and data-driven methodologies. Every strategy has unique benefits and drawbacks. The current work presents a hybrid prognostic model that efficiently incorporates the benefits of both approaches while reducing their limits whenever possible.

Hybrid prognostics were modified in order to incorporate the short-term forecast from physics-based prognostics. This concept has been used in aviation fuel distribution systems. The present research compares the RUL estimations achieved by the hybrid method with those acquired through several physics-based and data-driven methodologies. In real-world scenarios with insufficient data on long-term failures, the hybrid strategy significantly outperforms any of its component techniques.

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