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A Prognostic Approach to Improve System Reliability for Aircraft System

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***Abstract*— The primary aims of prognostics encompass the timely detection of potential failures, mitigation or elimination of unscheduled maintenance, prediction of the most suitable timing for preventive maintenance replacement, optimization of maintenance cycles and operational readiness, and enhancement of system reliability by improving design and logistical support for existing systems. In order to facilitate the progress of these approaches, currently available datasets provide a unique and reliable compilation of flight-to-failure trajectories linked to small aircraft engines that have been observed in actual flight conditions. Furthermore, the paper offered an improved neural network that utilized the TanH hyperbolic tangent function. This neural network was enhanced later by integrating it with the TanH, linear, and Gaussian functions. Additionally, a random holdback validation approach was employed in the paper. The results suggest that the NN TanH technique, when implemented, has the potential to significantly enhance the reliability of an aircraft component. This is achieved through accurate estimates of the remaining useful life (RUL) and a proactive understanding of the failure system.**

Keywords—prognostics, health management, remaining useful life, aircraft engine, neural network.

I. INTRODUCTION

Prognostics offer insights into the deteriorated condition of a system and enable precise forecasts on the probable timing of a future system breakdown. The purpose of prognostication is to identify deterioration and offer predicted insights, such as evaluations of system health and estimations of remaining useful life (RUL). This presents several advantages. The objectives of prognostics include: (i) providing advanced notice of potential failure; (ii) reducing the occurrence of unscheduled maintenance; (iii) forecasting the optimal timing for preventive maintenance replacement; (iv) enhancing maintenance cycles and operational readiness; (v) decreasing costs associated with inspections, inventory, and time; and (vi) improving system reliability through the enhancement of design and logistical support for current systems [1], [2]. Prognostic data typically encompasses the processes of data acquisition (DA), data processing (DP), and data manipulation (DM) performed by sensors and processing within sensor frameworks [3]. These processes involve the collection, analysis, and manipulation of data to generate feature data (FD), which includes condition indicators that serve as primary indicators of failure. Additionally, state detection (SD) is achieved through the utilization of processing and calculation routines within feature vector frameworks. Furthermore, health assessment (HA) and prediction assessment (PA) are conducted within prediction frameworks or information frameworks to evaluate the overall health status and make predictions based on the available data. The prediction subsystem of the prognostic and health management/monitoring system (PHM) consists of many frameworks, namely the sensor framework, characteristic vector framework, forecast framework, and control and data flow framework [4], as seen in Fig. 1.

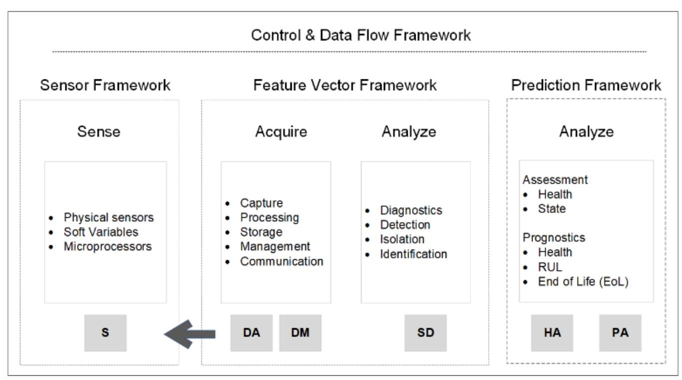

Fig. 1. Operational diagram of the PHM system capability (adopted from [4])

II. PROGNOSTICS AND CONDITION BASED MAINTENANCE

The PHM system is characterized by its intricate nature, comprising several interconnected subsystems. The conventional techniques for this intricate system rely on probabilistic considerations and exhibit several limitations when contrasted to the novel ideas put forward and examined. The

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probability distribution characterises the collective behaviour of several identical entities rather than the behaviour of an individual entity. Additionally, it should be noted that the accuracy of the parameters associated with the distribution functions utilised in the procedure is questionable, as previously demonstrated. A more pragmatic strategy involves the utilization of condition-based maintenance (CBM), wherein function data are derived from failure-critical indicators. Subsequently, signal conditioning, data transformations, and domain transformations are conducted, as required, to generate data that constitute a failure-to-failure progression (FFP) signature. Prediction algorithms effectively analyse FFP signatures, yielding precise estimations of system health and usable lifespan. Enhanced precision is attained by converting FFP signature data into deterioration progression signature (DPS) data and subsequently converting DPS data into functional failure signature (FFS) data. The data obtained from FFS are subjected to processing through various prediction algorithms, such as extended Kalman filtering (EKF), random walking, and other trend analysis algorithms. These algorithms have demonstrated the ability to generate predictions with a high level of accuracy and achieve rapid convergence. For example, one approach involves employing a heuristic argument to decrease the number of signature models utilised in EKF, thereby enhancing the adaptive prediction estimates. The rapid and precise convergence of this phenomenon proves to be highly advantageous in the context of CBM for PHM systems [5].

The PHM system in the CBM architecture engages in the monitoring, capturing, and processing of CBM signals in order to extract information on the state of health (SoH) of various system elements, including devices, components, assemblies, and subsystems. Additionally, extraneous signals are subjected to processing to provide predictive information, such as SoH and RUL. These processed signals are then utilized to effectively manage system maintenance and logistics [6]. The framework has six components: (i) a sensor framework, (ii) a feature vector framework, (iii) a prediction framework, (iv) a health management framework, (v) a performance validation framework, and (vi) a control and data flow framework.

III. Relationship of PHM to System Reliability

The relationship between PHM and system reliability is inherently interconnected. For instance, consider a scenario where the PHM system is specifically engineered to effectively prognosticate the precise moment when each target is likely to experience functional impairment. Additionally, assume that the fault and health management framework of this system facilitates timely replacement or repair of each target prior to the occurrence of functional failure. It is further assumed that maintenance activities are performed subsequent to the detection of degradation in each target. Lastly, it is assumed that the PHM system's ability to replace or repair a target is quicker than the time it takes for an unexpected outage to transpire. In systems that are equipped with PHM-enabled systems, the effective mean time before failure (MTBF) of the system is enhanced [7], resulting in an increase in the reliability of the system. In addition to enhancing system reliability, PHM has the potential to decrease system maintenance expenses through the extension of the operational lifespan of predictive targets. Furthermore, it has the advantage of decreasing the overall cost associated with the management of planned events in comparison to unforeseen occurrences, including both temporal and material aspects.

The foundational framework for PHM-enabling systems is often established by employing one of many conventional modelling methodologies. These methods may be categorized as model-based predictions or physics-based models, data-driven forecasts, or hybrid-based predictions [6], [8], [9]. Model-based predictions are frequently characterised by enhanced accuracy in estimating forecasts, although their use in intricate systems might pose challenges. Data-driven methodologies are often more straightforward to implement, yet they may provide lower levels of accuracy and precision in predictive projections. Hybrid methodologies exhibit a notable degree of precision and accuracy, rendering them valuable in the context of intricate systems that include both on- and off-vehicle domains. This characteristic allows optimization of both data-driven models and model-based models [10]. Fig. 2 shows the categorization of prognostic approaches.

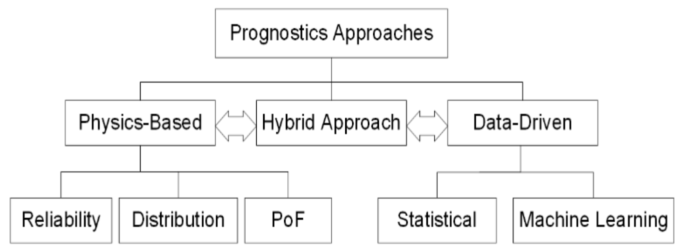


Fig. 2. Categorisation of Prognotics (adopted from Pecht (2008))

The precise prediction of RUL is a crucial component of prognostics and holds considerable significance in improving the reliability of aviation systems through many methods. The effective implementation of optimal maintenance planning is supported by the capability to provide accurate RUL predictions. This empowers maintenance teams to schedule maintenance activities with improved accuracy. Instead than relying on pre-established schedules or arbitrary intervals for the replacement of components, maintenance may be carried out with precision at the necessary moment. This strategy successfully reduces unnecessary maintenance interventions and decreases the probability of component problems caused by excessive usage or neglect.

The application of RUL estimations can significantly enhance the extension of aircraft component lifespan by enabling timely replacement of these components when judged necessary. This method not only reduces the frequency of component replacements but also enhances the overall lifespan use of each component, leading to cost savings. The utilization of intelligent decision-making, which involves data analysis and predictive modeling, is employed in the prediction of RUL. Maintenance teams has the capacity to effectively allocate resources by taking into account the estimated RUL of various components. This enables them to prioritize their work and focus their efforts on areas that demand the utmost attention. Through the use of this technique, it ensures that critical systems are swiftly attended to, thus enhancing their reliability. Through the use of proactive maintenance procedures, companies may successfully reduce possible faults before they exert a detrimental impact on reliability.

IV. An Approach for enhancing system reliability through the implementation of PHM – A Case Study

A. *Data Exploration*

The data set utilised and analysed in this paper was sourced from NASA's prognostic data repository. This repository has eight distinct data sets comprising flight-to-fault paths for a total of 128 aircraft engines, each subjected to varying flight circumstances. Failures in the flow (F) and efficiency (E) of several subsystems, including the fan, low pressure compressor (LPC), high pressure compressor (HPC), high pressure turbine (HPT), and low pressure turbine (LPT), might potentially manifest, as seen in the following table I.

TABLE I. Failure data set

Dataset	Failure Modes	Units	Flight Classes	Size
DS01	HPT	10	1,2,3	7.6M
DS02	HPT+LPT	9	1,2,3	6.5M
DS03	HPT+LPT	15	1,2,3	9.8M
DS04	Fan	10	2,3	10.0M
DS05	HPC	10	1,2,3	6.9M
DS06	LPC+HPC	10	1,2,3	6.8M
DS07	LPT	10	1,2,3	7.2M
DS08	All	54	1,2,3	35.6M

In order to develop prediction models based on data, it is important to use a dataset that includes trajectories leading up to system failure. To enhance the advancement of these methodologies, the provided data sets offer a novel and authentic collection of flight-to-failure trajectories pertaining to small aircraft engines, observed under realistic flying conditions. The synthetic dataset included in this paper was generated using a damage propagation model based on established modelling methodologies. The dataset encompasses a power management system that enables the engine to function throughout a broad spectrum of thrust levels across all flight conditions, which are categorized into three distinct flight classes based on the duration of the flight. It is assumed that each flight of the fleet only operates in a particular flight class [11]. The dataset was produced using a simulation of a new commercial modulated air propulsion system (N-CMAPSS) dynamic model. The dataset was collaboratively contributed by the prognostics centre of excellence (PCoE) at NASA in conjunction with the University of Zurich and PARC [12].

Each dataset comprises a comprehensive collection of flight data pertaining to an aircraft engine simulation, encompassing second-by-second records from a total of 100 flights or instances of engine failure. Each individual unit undergoes a specific flight time, as denoted by the flight class, and then enters an anomalous deterioration condition based on the assigned file number and the designated failure type. The dataset comprises several components. Firstly, it includes generic air flow cycles along the engine length, encompassing total temperature, total pressure, and flow. Secondly, it incorporates two rotating speeds, compressor stall margins, and various operational parameters, such as Mach number, altitude, throttle resolver angle (TRA), current cycle number, and flight class. Lastly, it consists of a binary health state indicator. In addition to the thermodynamic model of the engine, this data set encompasses an atmospheric model that is capable of operating within a range from sea level up to 40,000 feet. The atmospheric model is designed to accommodate Mach values ranging from 0 to 0.90 as well as sea temperatures spanning from -60 to 103 degrees Fahrenheit.

B. *Methods*

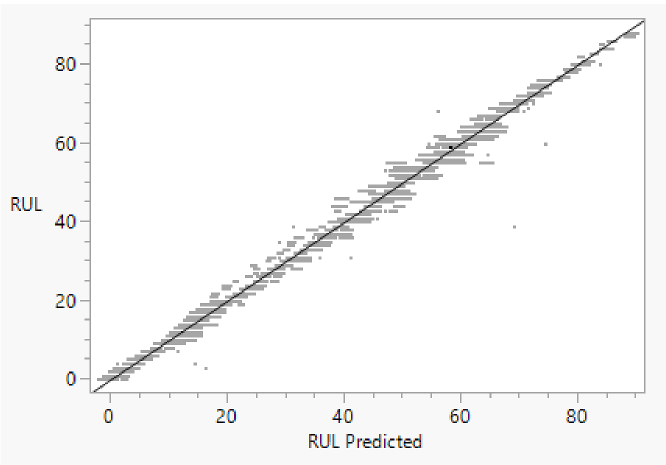
The approach employed for the creation of the N-CMAPSS dataset adheres to the methods outlined in reference [13] and illustrated as follows. In summary, the technique aligns with the subsequent procedure according to [12]:

- Flight conditions refer to the specific set of circumstances and environmental factors that an aircraft encounters throughout its operation in the atmosphere. These conditions encompass several variables such as altitude, airspeed, temperature, humidity, and wind speed, and the engine simulator utilizes real flight circumstances that are captured on board a commercial jet.
- Implement degradation. The degradation of engine components occurs with each flight.
- A simulation of impaired flying. The N-CMAPSS dynamical model [14] is used to simulate a comprehensive flight that encompasses the climbing, cruise, and descent circumstances.
- The concept of flight until failure refers to the phenomenon of an aircraft continuing to operate until it reaches a point of mechanical or structural failure. The health condition of the engine deteriorates as a result of the depreciation of its components. The process of simulating complete flights with progressively worsening conditions persists until the engine's health index reaches zero, indicating the end-of-life stage.

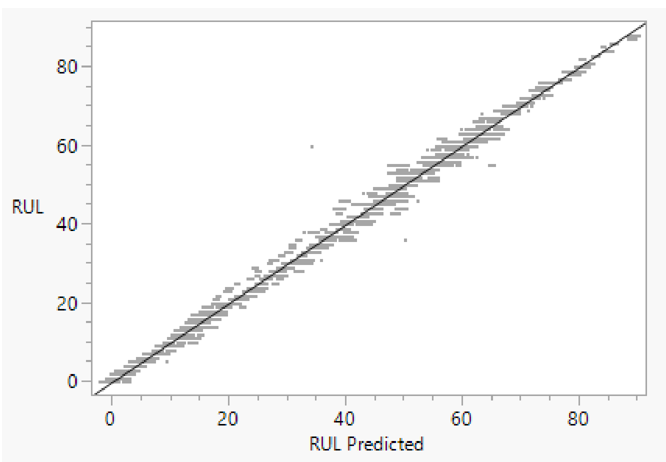
C. *Model and Results*

The authors employed two training techniques, including an improved neural network NtanH and another complex neural network (NN) model, and implemented a random holdback validation approach using the N-CMAPSS DS02-006 dataset. NNs are renowned for their user-friendly nature, versatility, and adaptability, as they are founded on models inspired by the structural organisation of the human brain. During the training process, the neural network is capable of deducing the connections between the input and output, thereby establishing the relative potency of inter-neuronal connections. Each individual neuron within the network computes a weighted sum of its inputs and generates a binary signal when the cumulative input surpasses a predetermined activation threshold. This intricate mechanism enables the network to successfully execute highly intricate tasks.

The procedure for generating the dataset implies that the failure modes of the main rotating engine sub-components, namely the fan, LPC, HPC, HPT, and LPT, demonstrate a continual decline. The deterioration effects are simulated by modifying the flow capacity and efficiency of the engine sub-components, which are represented by the engine health parameters θ. The prediction results and the corresponding measurements, including the training and validation, are shown separately in Fig. 3, as depicted below.



(a) NNs training results



(b) NNs validation results

Fig. 3. Outcomes of the predictions conducted under various scenarios. (a) The outcomes of the training process; (b) The outcomes of the validation process

For validation, a holdback portion is used. The random seed is set to 1234 for reproducibility, and the default holdback portion is fixed at 0.333 with the learning rate preset at 0.1. That is, one third of the data will be held out of model building for validation. This model has 41 variables as input variables, one hidden layer with 41 nodes, and an output layer. Statistics for the training and the holdout validation data are provided. For each node in the hidden layer, there is an intercept and parameter estimate for each of the input variables. As aforementioned, the first layer opts to use 41 nodes using the TanH hyperbolic tangent function. The penalty method is executed using the squared value and setting the number of tours to 1 due to computation complexity. The NN-NtanH R-square value of 0.9943 on the training set is equivalent to the validation set.

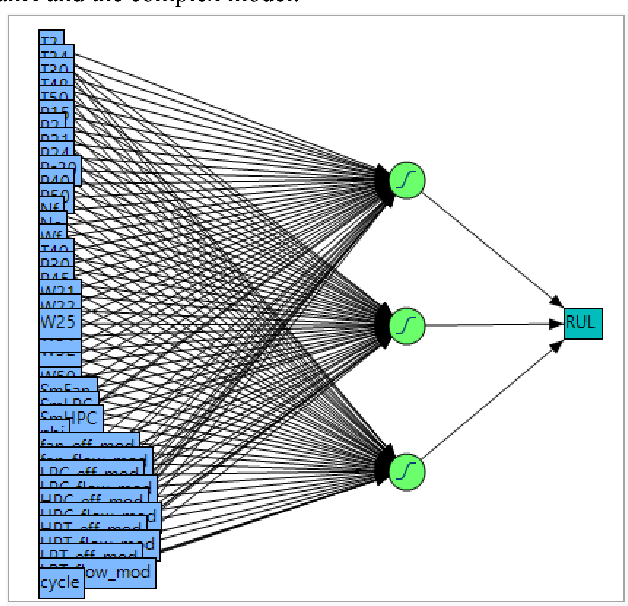
The simplified NtanH training algorithm is illustrated as follows:

New Column("H1_1_1",
        "Numeric",
Formula(
                TanH
                (weights(ω_1) * variables),
        Set Property("Intermediate", 1));
…

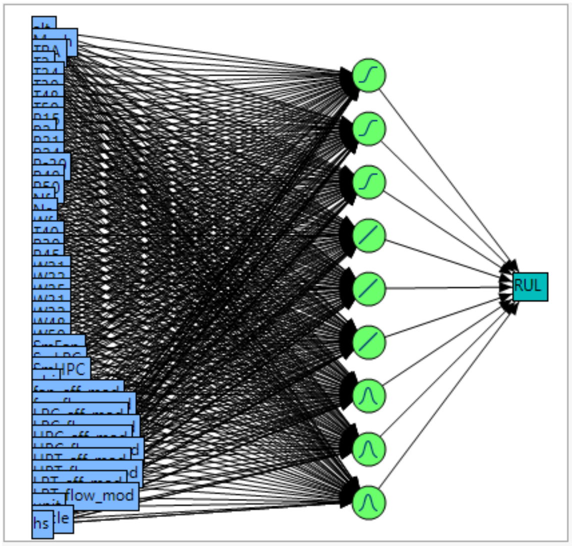
New Column("H1_n_1",
        "Numeric",
Formula(
                TanH
                (Weights (ω_n) * variables),
        Set Property("Intermediate", 1));

New Column("Predicted RUL_1",
        "Numeric",
Formula(
                ω_1 * :H1_1_1, +…, + ω_n* :H1_3_1),
        Set Property(
                "Predicting",
                {:RUL,
            Creator("Neural"), Std Dev( )}));;

A more complex model is later built, opting to use equal 41 nodes for the TanH, linear, and Gaussian functions on the hidden layer, ultimately resulting in 41 nodes in the hidden layer of the proposed model. As a presumption, the complex model runs the risk of creating a model that relies on too much randomness. Fig. 4 below compares the difference in complexity between the NtanH and the complex model.



(a) Training diagram of NN NtanH



(b) Training diagram of NN complex model

Fig. 4. Training graphs of the neural network models NN NtanH and the complicated model. (a) This figure illustrates the training process of a neural network utilizing the hyperbolic tangent activation function (NtanH); (b) This diagram depicts the training process of a neural network employing a complicated model

Several measurement and evaluation metrics are proposed to compare the prognostic results. The following measures of fit are included:

- Generalized RSquare: A metric that may be utilized for broad regression models. The value of the function is determined by the probability function L and normalized to attain a maximum value of 1. The value assigned to a perfect model is 1, whereas a model that performs no better than a constant model is assigned a value of 0. The generalised RSquare metric may be reduced to the conventional RSquare metric when dealing with continuous normal responses inside the typical least squares framework. The generalised RSquare, sometimes referred to as the Nagelkerke or Craig and Uhler R^2, is a normalised adaptation of Cox and Snell's pseudo R^2.
- RASE: Gives the RSquare for the model as in the square root of the mean squared prediction error. This is computed as follows: square and sum the prediction errors (differences between the actual responses and the predicted responses) to obtain the SSE. Denote the number of observations by n. RASE is denoted as (1):

$$RASE = \sqrt{\frac{SSE}{n}} \tag{1}$$

- Mean Abs Dev: The mean of the absolute discrepancies between the observed reaction and the projected response. In cases where the answer is nominal or ordinal, the observed differences are within the range of 1 and p, which represents the estimated probability for the specific level of response that was seen.
- -LogLikelihood: Gives the negative of the log-likelihood.
- SSE: Provides the sum of squares for the inaccuracy. This feature is accessible exclusively in cases where the response is uninterrupted.
- Sum Freq: Provides the total count of observations utilised in the study. When a Freq variable is supplied in the neural launch window, the Sum Freq function calculates the sum of the values in the frequency column.

The complex model exhibits a decline in model accuracy, as indicated by the RSquare value and other metrics in Tables II and III. Additionally, the evaluated value of the complex model increases with the square root of the mean squared prediction error and other relevant metrics. Despite variations in outcomes across different models, neural network models provide the advantage of accommodating a number of input variables, regardless of the presence of multicollinearity among these parameters or their limited influence on the dependent variable. Therefore, it can be confirmed that the optimized neural NtanH model demonstrates superior performance compared to the complex model when applied to the used dataset.

TABLE II. NN-TANH MEASUREMERNT RESULTS

(A) TRAINING RESULTS

Measures	Value
RSquare	0.9943186
RASE	1.6864235
Mean Abs Dev	1.2315266
Loglikelihood	6813165.7
SSE	9980079.4

(B) VALIDATION RESULTS

Measures	Value
RSquare	0.9943197
RASE	1.6860187
Mean Abs Dev	1.2314788
Loglikelihood	3405651.1
SSE	4986896.9

TABLE III. COMPLEX NN MEASUREMERNT RESULTS

(A) TRAINING RESULTS

Measures	Value
RSquare	0.9923164
RASE	1.9609583
Mean Abs Dev	1.3880437
Loglikelihood	7342425.6
SSE	13493897

(B) VALIDATION RESULTS

Measures	Value
RSquare	0.9923078
RASE	1.9624767
Mean Abs Dev	1.3879187
Loglikelihood	3672020.3
SSE	6756388.2

V. CONCLUSION AND FUTURE WORK

Prognostics are generally methods or algorithms that are deployed to attempt to model an expected future event (i.e., component failure). The primary objective of this initiative is to provide timely alerts about probable failures, minimise instances of unplanned maintenance, predict the most opportune times for maintenance activities, optimise maintenance cycles, promote operational readiness, save costs, and improve the overall reliability of a system. The present study conducted an analysis on a dataset sourced from NASA's forecast data repository, employing the methodologies previously delineated. The authors utilized two training methodologies, including an enhanced neural network architecture known as NtanH and a complex model accommodated with linear and Gaussian activation functions. In addition, a random holdback validation strategy was applied utilising the provided dataset. The training procedure encompassed the adjustment of the flow capacity and efficiency of the primary rotating engine sub-components, denoted as engine health parameters θ. A number of measurement and assessment metrics have been established in order to facilitate the comparison of prognostic outcomes. The findings demonstrate that the suggested NN-NTanH methodology has a strong capacity to enhance the overall dependability of the aircraft subsystem through accurate prediction of RUL and effective health management in comparison to the other model. In conclusion, the accurate forecast of RUL is a crucial component of prognostic, since it greatly enhances the dependability of aviation systems. This technology facilitates the ability of airlines and operators to optimize their maintenance planning, minimize periods of inactivity, improve safety measures, achieve cost savings, prolong the lifespan of components, and make choices based on data analysis. The cumulative advantages mentioned above enhance the reliability and efficiency of aircraft systems, thereby guaranteeing a higher level of safety and dependability in air transportation. The authors will further emphasise the integration of various data-driven and physics-based models into a hybrid prognostic method to achieve enhanced results in the future.

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