

Journal Pre-proof

A time-series turbofan engine successive fault diagnosis under both steady-state and dynamic conditions

Yu-Zhi Chen, Elias Tsoutsanis, Chen Wang, Lin-Feng Gou, Theoklis Nikolaidis



PII: S0360-5442(22)02734-7

DOI: <https://doi.org/10.1016/j.energy.2022.125848>

Reference: EGY 125848

To appear in: *Energy*

Received Date: 28 May 2022

Revised Date: 19 October 2022

Accepted Date: 21 October 2022

Please cite this article as: Chen Y-Z, Tsoutsanis E, Wang C, Gou L-F, Nikolaidis T, A time-series turbofan engine successive fault diagnosis under both steady-state and dynamic conditions, *Energy* (2022), doi: <https://doi.org/10.1016/j.energy.2022.125848>.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2022 Published by Elsevier Ltd.

Yu-Zhi Chen: Conceptualization, Investigation, Methodology, Software, Writing - original draft.

Elias Tsoutsanis *: Conceptualization, Methodology, Visualization, Writing - review & editing.

Chen Wang: Methodology, Writing - review & editing.

Lin-Feng Gou: Methodology, Writing - review & editing.

Theoklis Nikolaidis: Methodology, Writing - review & editing.

Journal Pre-proof

A time-series turbofan engine successive fault diagnosis under both steady-state and dynamic conditions

Yu-Zhi Chen¹, Elias Tsoutsanis^{2,*}, Chen Wang³, Lin-Feng Gou⁴, Theoklis Nikolaidis⁵

* Corresponding author (elias.tsoutsanis@tii.ae)

ABSTRACT

In recent years there has been a growing interest in gas turbine fault diagnosis, especially under dynamic conditions, due to the evolving operating profile of gas turbines and the need to deploy computationally efficient and high-precision diagnostic solutions in real-time. One of the main challenges of fault diagnosis in real-time is the power imbalance between the compressor and turbine that occurs during transient operation. In addition, the heat soakage phenomenon characterizing the transient conditions has a substantial impact on the accuracy of the diagnosis. Finally, any sudden failure that might happen during transient operating conditions creates an additional challenge to fault diagnostics. The present study proposes a gas turbine diagnostic approach based on time-series measurements encapsulating steady-state and transient operating conditions. Specifically, the introduced novel approach is capable of quantifying the surplus/deficit of the power between the compressor and the turbine by utilizing the time-series data representing the observed deviations in the shaft rotational speed in order to determine the power balance in the shaft. The maximum diagnostic errors for constant fault and sudden failure are less than 0.006% during the dynamic maneuver. The results demonstrate and illustrate that the proposed method could effectively and accurately diagnose the severity of aero-engine faults at both steady-state and transient conditions. Therefore, this study has great potential for gas turbine practitioners since the diagnosis under transient conditions in real-

¹ School of Power and Energy, Northwestern Polytechnical University, Xi'an 710129, China

² Propulsion and Space Research Center, Technology Innovation Institute, Masdar City, PO Box: 9639, Abu Dhabi, United Arab Emirates

³ Key Laboratory of Intelligent Control and Optimization for Industrial Equipment (Dalian University of Technology), Ministry of Education, Dalian 116024, China

⁴ School of Power and Energy, Northwestern Polytechnical University, Xi'an 710129, China

⁵ School of Aerospace, Transport and Manufacturing, Cranfield University, Bedford, UK

25 **time can enhance the capability of engine online condition monitoring and improve the**
 26 **condition-based maintenance of gas turbine assets.**

27 **Key Words:** Turbofan Engine Degradation; Time-series Fault Diagnosis; Real-time Engine Fault
 28 Monitoring.

29

30

Nomenclature

31

32 A = Area [m^2]

33 AW = Auxiliary work [W]

34 CP = Characteristic parameter

35 CW = Compressor work [W]

36 HP = High-pressure

37 I = Shaft inertia [$kg \cdot m^2$]

38 LP = Low-pressure

39 n = Number of measurements

40 N = Shaft rotational speed [rpm]

41 P = Pressure [atm]

42 PR = Pressure ratio

43 Q = Heat rate [W]

44 $RMSE$ = Root mean square error

45 SP = Engine shaft surplus power [W]

46 T = Temperature [$Kelvin$]

47 TW = Turbine work [W]

48 U = Heat transfer coefficient [$W/(m^2 \cdot K)$]

49 W = Mass flow rate [kg/s]

50 X = Degradation index

51 Z = Measurements

52

53

Greek Letters

54

55 τ = Time constant [s]

56

57

Subscripts

58

59 a = Actual condition60 c = Clean condition61 E = Efficiency62 F = Flow capacity63 g = Gas flow64 ht = heat transfer65 in = Inlet66 loc = Local component characteristic67 m = Metal68 out = Outlet

69

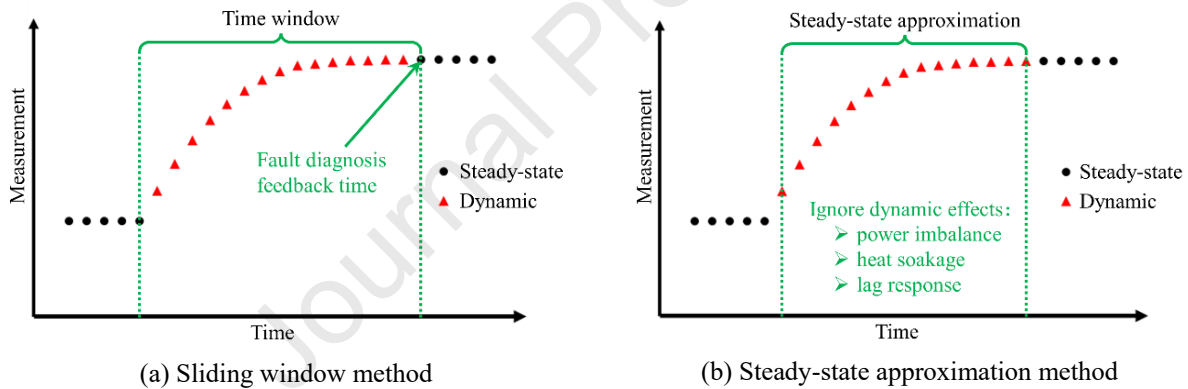
70

1. Introduction

71 The gas turbine engine is among the most important process engines for commercial and military aircraft [1]. Over
72 the past years, there has been a dramatic development in gas turbine technology with more and more complex engine
73 structures [2,3]. Gas path fault diagnosis is crucial to ensure the safety, economy, and reliability of aero-engine
74 operations. Accordingly, a growing interest in gas path analysis (GPA) of gas turbine engines has been witnessed to
75 guarantee effective condition-based maintenance. GPA is a gas path fault diagnosis technique that establishes the
76 relationship between unmeasurable health parameters and measurable operating parameters [4]. GPA, established in
77 1969 by Urban [5], plays an essential role in the condition monitoring of gas turbine engines. As sudden failure has

78 dramatically impacted engine safety, real-time fault diagnosis is becoming a significant area of research in gas turbine
 79 engine condition monitoring.

80 The majority of aero-engine gas path analysis methods are based mainly on gas path measurements available from
 81 steady-state operating conditions [6]. In contrast, the gas path measurements obtained during transient conditions are
 82 mainly analyzed and processed offline, which cannot meet the requirement of online and real-time health monitoring.
 83 If the engine encounters a sudden fault during any transient maneuver, the steady-state gas path fault diagnostic system
 84 will not be able to respond promptly. In addition, engine component performance degradation will affect the
 85 compressor surge margin [7]. Therefore, real-time assessment of the compressor surge margin is crucial for safe
 86 control and operation of the engine transient process. Consequently, there is an urgent need to address the fault
 87 diagnosis in real-time under dynamic maneuvers for gas turbine engines on continuous feedback of gas path fault and
 88 improve the engine's emergency response capability. Until recently, little attention has been paid to the real-time
 89 monitoring of engines under transient conditions.



90 **Fig. 1 Fault diagnosis methods at transient conditions.**

91 In recent years, several attempts have been made to diagnose gas turbine degradation under both steady-state and
 92 transient conditions, where two different approaches have been proposed. The first one, the sliding window method,
 93 is to simulate the gas path measurements during the whole dynamic maneuver with estimated degradation and then
 94 compare them to the actual engine measurements from the monitoring system in order to iterate the predicted fault
 95 (Fig. 1 (a)). Li (2003) [8] developed a fault diagnosis method for turbofan engines under transient conditions based
 96 on the sliding window method. Ogaji et al. (2003) [9] conducted a gas turbine fault diagnosis based on artificial neural
 97 networks during a dynamic maneuver. Tsoutsanis et al. (2015) [10] proposed a fault diagnostic method by map tuning
 98 with selected sliding windows for the targeted gas path measurements, where the average prediction error is 0.15%.
 99 In the following two years, the GPA method has been further developed by Tsoutsanis et al. [11,12] to incorporate the

100 fault prognosis for gas turbines under dynamic conditions. Chen et al. (2022) [13] conducted an aero-engine fault
101 diagnosis based on a sequential method under dynamic conditions. However, the above methods considered only soft
102 degradation during a dynamic maneuver, which is the most common in gas turbines, but attention should be paid to
103 the abrupt degradation scenarios in transient conditions.

104 The second method, the steady-state approximation method, considers time-series measurements independent. A
105 steady-state fault diagnosis model is applied to each set of discrete measurements for both steady-state and dynamic
106 conditions in the timeline (Fig. 1 (b)). Li and Ying (2020) [14] attempted to evaluate the degradation indices of a
107 heavy-duty industrial gas turbine engine based on a steady-state approximation method for both steady-state and
108 dynamic conditions. The diagnostic results were promising for the examined test cases, but the diagnosis accuracy
109 might be compromised for other types of engines. The reason for this lies in the fact that the impact of transient
110 conditions in the fault diagnosis, as expressed by a power imbalance, heat soakage, and lag response under dynamic
111 conditions, has not been considered. Heavy-duty industrial gas turbine engines could ignore the aforementioned
112 transient effects as they have the inertia of slow dynamic response. Still, they should be accounted for faster response
113 gas turbine engines such as aero-derivative and aero-engines. Especially for engines with rapid transient maneuver
114 capabilities and larger temperature and pressure variations in different operation conditions, the above method will be
115 inappropriate, and the integrity of the diagnosis will be severely affected by transient effects. The power imbalance
116 among different components on the same shafts and the heat soakage effect will greatly impact estimating the health
117 parameters during dynamic conditions. Although the method could predict the health state in real-time, the predicted
118 results will not be accurate, In such a situation.

119 The main challenge of fault diagnosis in real-time is the dynamic effect during transient maneuvers. Currently,
120 fault diagnosis methods under transient conditions proceed either with the fault diagnosis after selecting a sliding
121 window [2–5] or the steady-state approximation method without considering the dynamic effects such as heat soakage
122 and power imbalance [14]. Therefore, it is of paramount importance for the condition-based maintenance of gas
123 turbine engines to have a fault diagnosis algorithm that is capable of capturing the actual health state in real-time, even
124 with sudden failure during dynamic operating conditions.

125 A time-series diagnostic method is proposed for gas turbine engines operating under both steady-state and dynamic
126 conditions to address the gap mentioned above in the literature. The novelty of this study lies in the fact that we
127 proposed a diagnostic method for transient conditions which could quantify the dynamic effects during transient

128 maneuvers at each time instant. The fault diagnosis captures the transient effect in the gas turbine in accordance with
129 time series gas path measurement data. More specifically, the power imbalance between turbine and compressor is
130 addressed by accounting for the shaft acceleration rate in order to determine both the surplus power under dynamic
131 conditions and the power equality constraints for each shaft. The heat soakage effect during transient conditions could
132 also be considered in the diagnosis model when previous measurements in the timeline are utilized to calculate the
133 new metal temperature in the following timeline. In addition, the lag response that characterizes the transient
134 conditions could be addressed by considering the first-order lag. Finally, as the measurements are successive, the
135 sudden failure could also be diagnosed accurately during any time point of a dynamic maneuver. Based on the
136 literature review, no publications have been found so far that could correctly diagnose the fault level in real-time under
137 transient conditions. The main contributions of this study are summarized as follows:

- 138 1) A new real-time successive fault diagnosis method is proposed by considering the engine monitoring system
139 under dynamic conditions.
- 140 2) The proposed algorithm considers transient effects on fault diagnosis based on time-dependence data.
- 141 3) The fault level of five engine components that experience degradation simultaneously could be reflected in
142 real-time when new time-series data is transferred to the diagnostic system while the constant engine
143 degradation is implanted.
- 144 4) In all previous research efforts, the sudden failure during dynamic conditions had a severity level that made
145 it difficult to be monitored in real-time. This study could observe the sudden failure during a transient
146 maneuver with excellent diagnosis accuracy.

147 The remaining part of the paper proceeds as follows: The second section of this paper will describe the
148 methodology for the related methods. The third and fourth section of the paper deals with the application and the
149 analysis, respectively. The final section summarizes the main findings and implications of this study.

150 **2. Methodology**

151 **2.1 Assumptions**

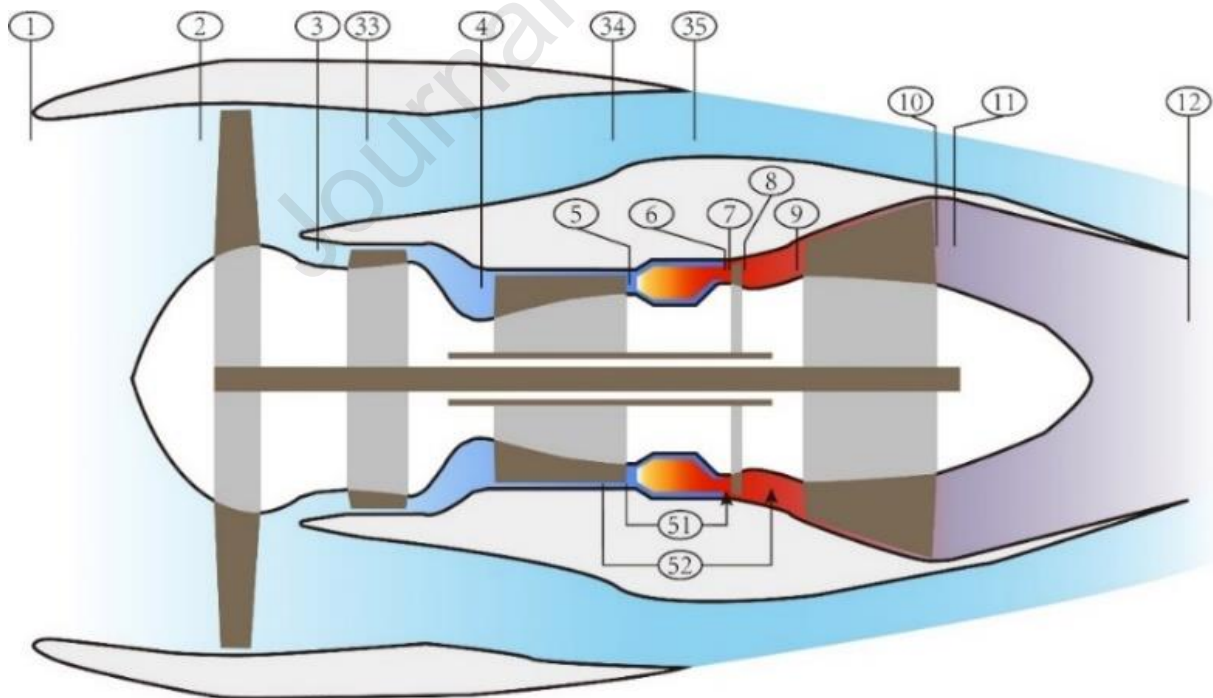
152 The methodology and test cases are based on the following assumptions since these will facilitate the comparison
153 of the proposed method to a recently published benchmark method [14].

- 154 ● Measurement noise/bias is ignored because there are mature methods for noise filtering and sensor
 155 verification [15,16]. Furthermore, rather than sensor-related issues, this research attempts to improve the
 156 performance of the diagnostic algorithm.
- 157 ● The efficiency, flow capacity, and pressure ratio indices are used to quantify the fault level as health
 158 parameters. Furthermore, the pressure ratio index is assumed to be the same as the flow capacity index [17].
- 159 ● All turbofan engine rotating components are experiencing degradation simultaneously. Moreover, any sudden
 160 failure will cause concurrent degradation of all engine components.

161 2.2 Turbofan Engine Performance and Degradation Modelling

162 2.2.1 Performance Modelling

163 Our previous publications have validated the steady-state and transient engine performance models [13,18] in the
 164 C# environment. Fig. 2 [13] presents the turbofan engine configuration with station numbering that includes a fan, a
 165 low-pressure compressor, a high-pressure compressor, a combustor, a high-pressure turbine, and a low-pressure
 166 turbine. The design point specification of the turbofan engine in concern is presented in Table 1. The turbofan engine
 167 measurements on-wing for fault diagnosis are listed in Table 2 [19].



168
 169 **Fig. 2 Configuration of turbofan engine in concern and its station numbering [13].**
 170

171

172

Table 1 Turbofan engine design point specification.

Item	Symbol	Unit	Value
Flight Mach Number	MN	-	0.8
Flight Altitude	ALT	km	11
Intake Airflow Rate	W_{in}	kg/s	222
Burner Fuel Flow	W_{BFF}	kg/s	0.1876
Low Heating Value	LHV	MJ/kg	118.429
Engine Pressure Ratio	EPR	-	33.8
Engine Bypass Ratio	EBR	-	9

173

174

Table 2 Turbofan engine measurements on-wing [19].

No	Measurement	Symbol
1	Ambient pressure	P_1
2	Ambient temperature	T_1
3	Bypass inlet total pressure	P_{33}
4	Low-pressure compressor (LPC) exit total pressure	P_4
5	LPC exit total temperature	T_4
6	High-pressure compressor (HPC) exit total pressure	P_5
7	HPC exit total temperature	T_5
8	Low-pressure turbine (LPT) inlet total pressure	P_9
9	LPT inlet total temperature	T_9
10	LPT exit total pressure	P_{10}
11	LPT exit total temperature	T_{10}
12	Flight Mach Number	MN
13	LP shaft rotational speed	N_{LP}
14	HP shaft rotational speed	N_{HP}
15	Burner fuel flow rate	W_{Fuel}

175

176 2.2.2 Degradation Modelling

177 Normally, the performance of gas turbines is related to the performance of each sub-component [12,20]. Therefore,
 178 Eq. (1) defines the degradation index (X) which is related to the degradation of each component characteristic
 179 parameter[21,22].

$$X = \frac{CP_a}{CP_c} \quad (1)$$

180 where the subscript “ a ” and “ c ” represent the actual and clean conditions, respectively. If X is 1, it means that the
 181 engine is at a nominal clean condition where the denominator is the same as the numerator [23,24].

182 Table 3 [25] summarizes the health parameters relevant to the turbofan engine in concern. The ‘Health State 1’
 183 refers to constant/smooth degradation of the engine in concern, whereas the ‘Health State 2’ refers to a more severe
 184 level of degradation, which is double that in ‘Health State 1’. The magnitude of ‘Health State 2’ refers to a large
 185 bypass turbofan engine that has completed 6000 flight cycles [25]. The ‘Health State 1’ is also applied to the engine
 186 degradation level before sudden failure, whereas ‘Health State 2’ represents the engine degradation level after sudden
 187 failure.

188 **Table 3 Degradation indices of turbofan engine [25].**

Component	Symbol	Health Parameter	Health State 1	Health State 2 [25]
<i>FAN</i>	X_{FAN}	$X_{FAN,E}$ <i>FAN</i> efficiency index	-1.425 %	-2.85 %
		$X_{FAN,F}$ <i>FAN</i> flow capacity index	-1.825 %	-3.65 %
<i>LPC</i>	X_{LPC}	$X_{LPC,E}$ <i>LPC</i> efficiency index	-1.305 %	-2.61 %
		$X_{LPC,F}$ <i>LPC</i> flow capacity index	-2.00 %	-4.00 %
<i>HPC</i>	X_{HPC}	$X_{HPC,E}$ <i>HPC</i> efficiency index	-4.70 %	-9.40 %
		$X_{HPC,F}$ <i>HPC</i> flow capacity index	-7.03 %	-14.06 %
<i>HPT</i>	X_{HPT}	$X_{HPT,E}$ <i>HPT</i> efficiency index	-1.905 %	-3.81 %
		$X_{HPT,F}$ <i>HPT</i> flow capacity index	+1.285 %	+2.57 %
<i>LPT</i>	X_{LPT}	$X_{LPT,E}$ <i>LPT</i> efficiency index	-0.539 %	-1.078 %
		$X_{LPT,F}$ <i>LPT</i> flow capacity index	+0.2113 %	+0.4226 %

189

190 2.3 Benchmark Method

191 Nonlinear gas path analysis is widely used for model-based fault diagnosis, where the engine thermodynamic
 192 performance model may be defined by Eq. (2). The iteration solver is applied to update the degradation index X during
 193 fault diagnosis in order to minimize the difference between the predicted measurements ($Z_{Predict}$) from the engine
 194 model and the actual measurements (Z_{Actual}) available from a service engine. In this study, the Newton-Rapson
 195 method [26] is chosen as the iteration solver for all the cases regarding performance simulation and fault diagnosis.

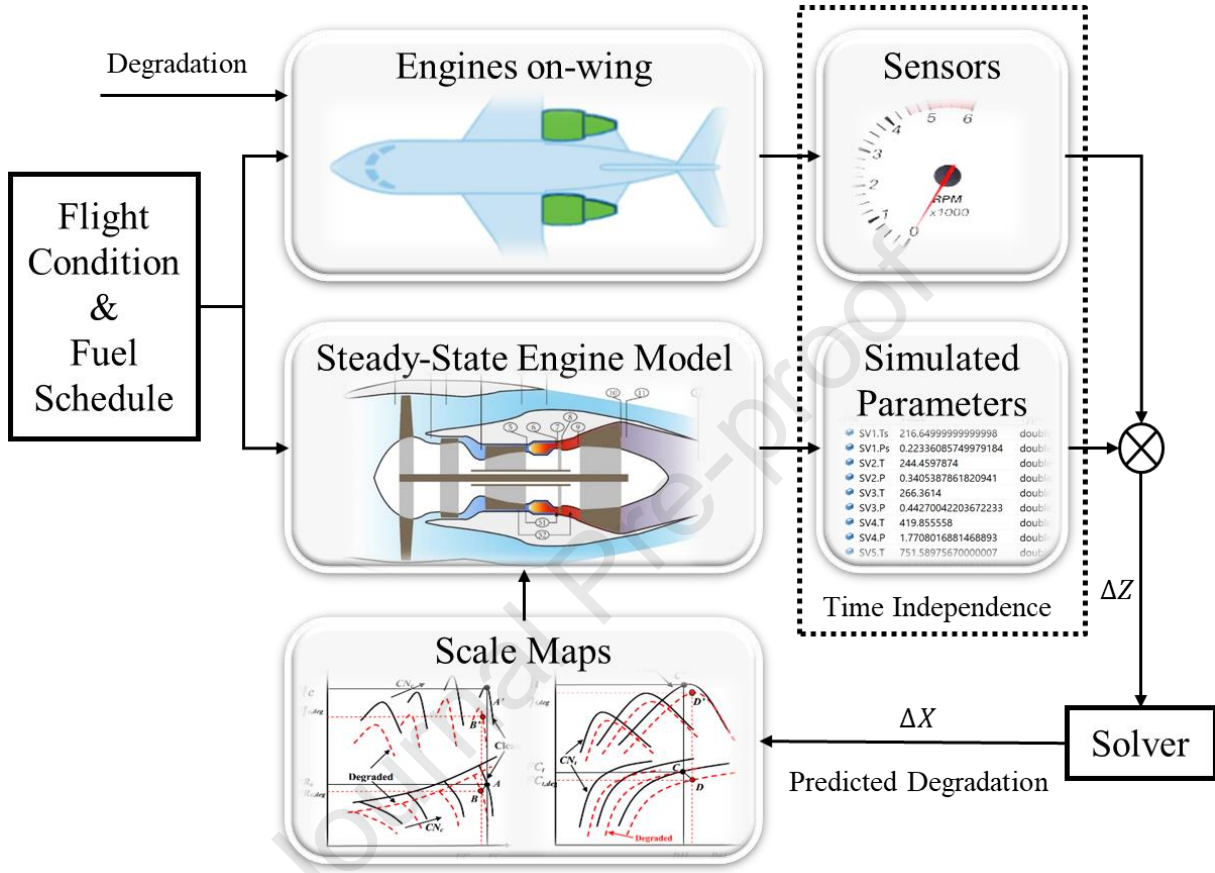
$$Z = f(X) \quad (2)$$

196 where Z denotes measurements of the engine, and X denotes the degradation indices of engine components.

197 The root mean square error ($RMSE$) defined by Eq. (3) [27,28] is selected to evaluate the convergence with a
 198 threshold of $1E-5$ as the convergence criteria.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(Z_{Predict,i} - Z_{Actual,i})^2}{n}} \quad (3)$$

199 where n is the number of measurements.



200
201 **Fig. 3 Schematic of benchmark fault diagnosis method [13].**

202 The method proposed by Li and Ying in 2020 [14] will be used as the “benchmark method” in this study. The
203 schematic of the benchmark method is shown in Fig. 3 [13]. It is clear that the steady-state fault diagnosis model is
204 characterized by time independence as the steady-state approximation is employed. The method will be applied to a
205 high bypass ratio civil turbofan engine in order to generate some baseline diagnostic results.
206

207 The performance simulation and fault diagnosis processes are invoked in the same iteration loop. The iteration
208 variables of the benchmark method are the ten degradation indices listed in Table 3 and the blocks with a purple color
209 in Fig. 4. The convergence is checked based on compatibility shown in the blocks with blue color in Fig. 4. The
210 detailed process is explained as follows:

211 The flight altitude, Mach Number, and inlet condition are known through on-wing measurements. Then, the fan
 212 inlet condition could be obtained by the intake model. It follows that the fan bypass pressure ratio could be calculated
 213 based on Eq. (4) [29] where P_{33} is a gas path measurement. As the fan inlet condition, shaft speed, and bypass pressure
 214 ratio are known, the fan outlet temperature and pressure at both core and bypass could be determined through the fan
 215 model [13].

$$PR_{FAN,BP} = P_{33}/P_2 \quad (4)$$

216 The *LPC* pressure ratio is obtained by Eq. (5) [30] where P_4 is a gas path measurement and P_3 could be determined
 217 from the fan model. Then, the *LPC* model calculation will follow as the pressure ratio, shaft speed, and inlet condition
 218 are known. It is worth noting that the core mass flow rate obtained in the *LPC* model is used to update the core flow
 219 and bypass flow rates in the fan model, which will also determine the bypass ratio. Moreover, the fan work is also
 220 updated according to the new bypass ratio.

$$PR_{LPC} = P_4/P_3 \quad (5)$$

221 The *HPC* pressure ratio can be obtained by Eq. (6) where P_5 and P_4 are gas path measurements. Then the *HPC*
 222 model could be used to calculate the outlet condition as the pressure ratio, shaft speed, and inlet condition are known.

$$PR_{HPC} = P_5/P_4 \quad (6)$$

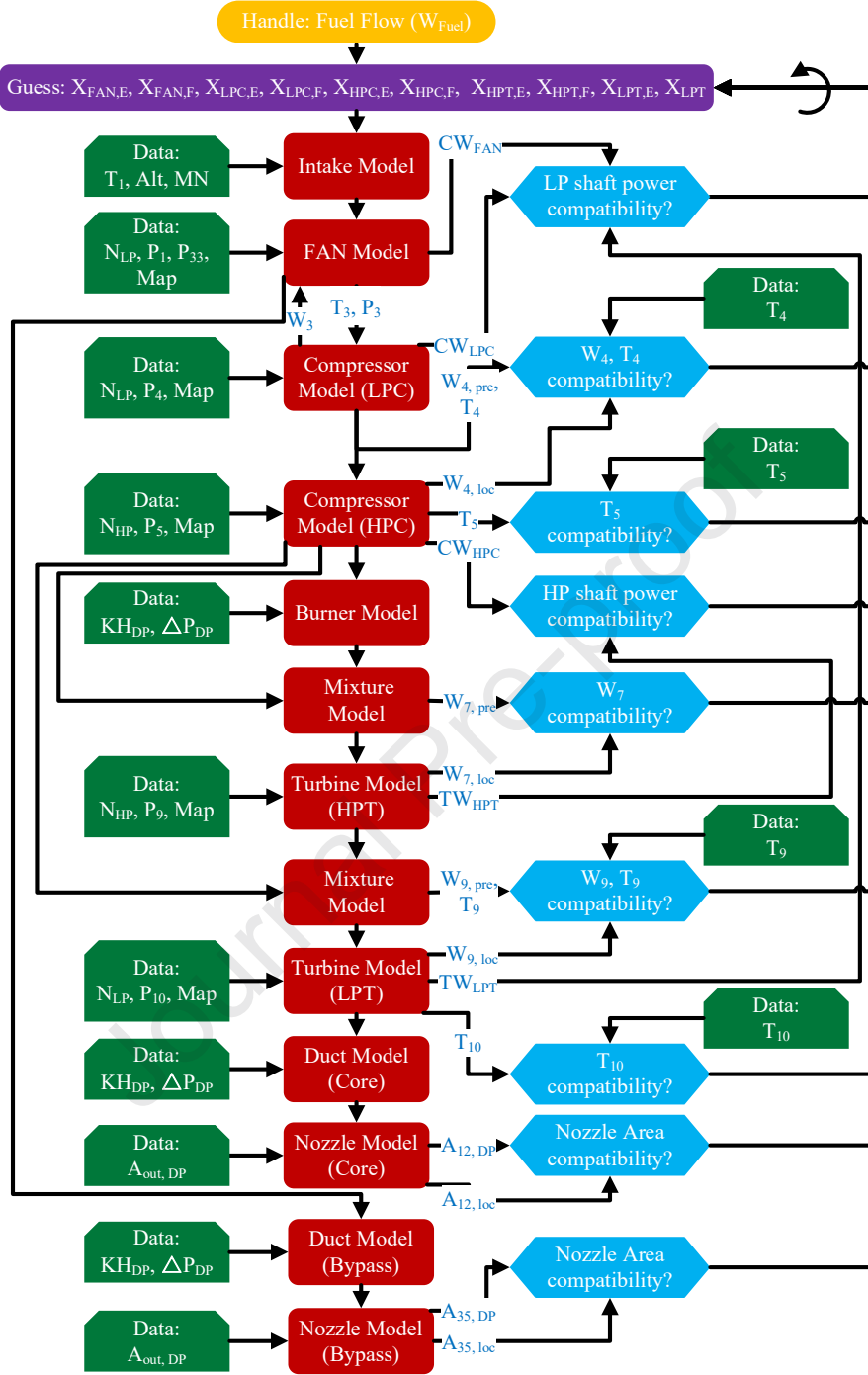
223 As the *HPC* outlet condition is known, the burner outlet condition could be calculated as the fuel flow rate is also
 224 known. The mixture model is applied to calculate the *HPT* inlet condition. The *HPT* pressure ratio could be obtained
 225 by Eq. (7) where P_9 is gas path measurements and P_7 could be known from the mixture model after the combustor.

$$PR_{HPT} = P_7/P_9 \quad (7)$$

226 The *LPT* inlet condition could be obtained by the mixture after *HPT*. The *LPT* pressure ratio could be obtained by
 227 Eq. (8) [31] where P_9 and P_{10} are gas path measurements. Finally, two sets of duct and nozzle are applied to calculate
 228 main flow and bypass flow exhaust condition.

$$PR_{LPT} = P_9/P_{10} \quad (8)$$

229

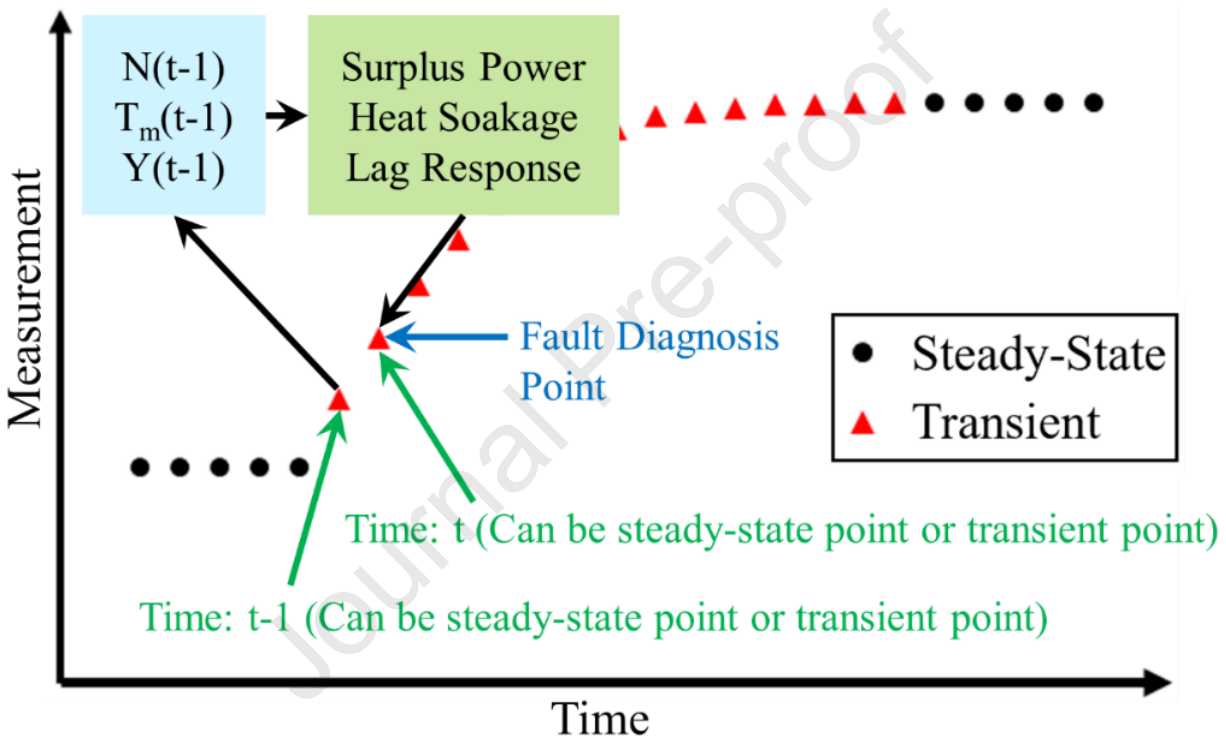


230
231 **Fig. 4 Fault diagnosis based on steady-state model.**

232 There are eleven convergence criteria in the diagnostic algorithm represented in blue blocks in Fig. 4. The
233 convergence criteria could be classified into two categories. One set of convergence criteria is obtained from gas path
234 measurements, including T_4, T_5, T_9 , and T_{10} . The other set of convergence criteria is required to satisfy the mass flow
235 compatibility, shaft power balance, and design nozzle area at the design point. It is worth noting that the LP and HP

236 shaft power compatibility in blue blocks means that the turbine work has to be equal to the compressor work plus any
 237 auxiliary work at all times, as the steady-state approximation fault diagnosis method is employed. This is one of the
 238 main assumptions of the benchmark method that may lead to diagnostic errors since the surplus power during dynamic
 239 conditions is ignored. Another source of uncertainty is the assumption that the typical phenomenon of heat soakage
 240 and lag response during dynamic conditions is ignored when the steady-state model is implemented. In such a
 241 condition, diagnostic accuracy may be compromised.

242 2.4 Proposed Method



243

244

Fig. 5 Schematic of proposed fault diagnosis method.

245

246

247

248

249

250

251

252

The benchmark method may be sufficient for slow transient maneuvers which characterize heavy-duty industrial gas turbines as the steady-state approximation is employed in their study. However, the performance of the benchmark method is limited in transient conditions if the power imbalance among shaft, heat soakage, and lag response are not considered. This study intends to diagnose the health of a civil turbofan engine with time-series data during steady-state and transient conditions. The transient effect could not be ignored for the turbofan engine in concern as it exhibits a fast and dynamic response. The schematic of the proposed method is demonstrated in Fig. 5, where shaft speeds derive the surplus power during dynamic processes among adjacent measurement steps in the diagnostic system for the consideration of shaft power compatibility in Fig. 4. Moreover, the heat soakage is also considered in the engine

253 sub-models to represent the heat transfer between gas and engine metal during the transient maneuver for the
 254 temperature compatibility check in Fig. 4. the first order lag is selected in this study to represent the lag response of
 255 sensor property in Fig. 4 under dynamic conditions. It is clear that the measurements are time-dependent in the
 256 proposed method, where the surplus power, transient heat transfer, and lag response are needed to be considered in
 257 consecutive time steps, which are highlighted in the green block in Fig. 5. In addition, the shaft model also takes lag
 258 response into account to capture the dynamic response with increased precision. Although the two red points under
 259 dynamic conditions are selected to illustrate the new method in Fig. 5, the proposed method is also suitable for steady-
 260 state conditions.

261 2.4.1 Rotor Dynamics 262

263 Gas path measurements could not directly monitor the surplus power among each shaft. As the engine shaft speed
 264 is monitored in time-series, the rotor acceleration rate could be derived through the deviation of shaft speed in finite
 265 time steps by Eq. (9) [32,33].

$$\frac{dN}{dt} = \frac{N(t + \Delta t) - N(t)}{\Delta t} \quad (9)$$

266 In such a condition, the surplus power (SP) could be calculated by Eq. (10) [34,35] by rotor acceleration rate, shaft
 267 speed, and shaft inertia (I).

$$SP = \frac{4\pi^2}{3600} \cdot I \cdot N \cdot \frac{dN}{dt} \quad (10)$$

268 Then, the power balance among each shaft could be obtained by (11) [36,37]. The equation is tenable for both
 269 steady-state and dynamic conditions where the SP is zero during the steady-state condition. Hence, the proposed
 270 method could satisfy the shaft power compatibility when surplus power is considered for both steady-state and
 271 dynamic conditions in a more coherent fashion than the benchmark method.

$$TW = SP + CW + AW \quad (11)$$

272 where TW is turbine work, CW is compressor work, and AW is auxiliary work for power offtake.

273 2.4.2 Heat Soakage

274 During transient maneuvering, changing gas temperature in a turbofan engine will affect the engine metal
 275 temperature. This phenomenon is called heat soakage and is not considered in the steady-state fault diagnosis of the
 276 benchmark method.

277 The heat soakage is considered in the dynamic engine model in the proposed method. The heat transfer between
 278 gas flow and engine metal is obtained by Eq. (12) with exponential decay [38].

$$Q = U_{ht} \cdot A_{ht} (T_{g,k+1}^b - T_{m,k}) \cdot (e^{-\Delta t/\tau} - 1) \quad (12)$$

279 where Q is heat rate, U_{ht} is heat transfer coefficient, A_{ht} is the effective contact surface, $T_{g,k+1}^b$ is the gas temperature
 280 in the current step before considering heat soakage, $T_{m,k}$ is the metal temperature in the previous step, Δt is the time
 281 step, and τ is the time constant.

282 The heat transfer coefficient is calculated as follows:

$$U_{ht} = \frac{1}{\frac{1}{FC} + \frac{l_{eff}}{k_m}} \quad (13)$$

283 Additionally, the time constant is determined by Eq. (14).

$$\tau = \frac{c_m \cdot W_m}{U_{ht} \cdot A_{ht}} \quad (14)$$

284 where W_m is the effective mass of engine component, c_m is the specific heat of the engine material.

285 The change of engine metal temperature (dT_m) could be obtained by Eq. (15).

$$\frac{dT_m}{dt} = \frac{Q}{c_m \cdot W_m} \quad (15)$$

286 The metal temperature of the engine component in the current step ($T_{m,k+1}$) could be obtained as follows:

$$T_{m,k+1} = T_{m,k} - dT_m \quad (16)$$

287 The change of gas enthalpy (ΔH_g) when considering the heat transfer could be determined by Eq. (17).

$$\Delta H_g = \frac{Q}{W_g} \quad (17)$$

288 where W_g is the mass flow rate of gas.

289 The gas enthalpy at the current step with the consideration of heat soakage ($H_{g,k+1}$) could be obtained as follows:

$$H_{g,k+1} = H_{g,k+1}^b + \Delta H_g \quad (18)$$

290 where $H_{g,k+1}^b$ is gas enthalpy at current step before considering heat soakage.

291 The gas temperature at the current step with the consideration of heat soakage ($T_{g,k+1}$) could be determined by Eq.
292 (19).

$$T_{g,k+1} = GasProp_{[H,P]}(H_{g,k+1}, P_{g,k+1}, FAR, WAR) \quad (19)$$

293 2.4.3 Lag Response of Engine Shafts

294 The time delay phenomenon of the engine shafts during transient maneuvering is represented using the first-order
295 lag. As $N_{out}(s)$ is measured through an on-wing monitoring system, the $N_{in}(s)$ could be derived by Eq. (20) [39,40]
296 for the engine model.

$$\frac{N_{out}(s)}{N_{in}(s)} = \frac{1}{\tau \cdot s + 1} \quad (20)$$

297 where τ is the characteristic time, $N_{out}(s)$ is the input with delay and $N_{in}(s)$ is the input value without delay.

298 3. Application and Analysis

299 Four case studies are examined in this paper. In order to make a direct comparison between the proposed and the
300 benchmark methods [14], the same computer environment is used. To be more specific, a personal computer with
301 Intel(R) i7 CPU @2.90GHz and 16 GB RAM is used to evaluate the computational time of the diagnostic process for
302 all case studies. The four cases are specified as follows:

303 **Case 1.** This case study aims to evaluate the effectiveness of the benchmark diagnostic method [14] when the
304 engine gas path measurements represent dynamic operating conditions without consideration of heat soakage.

305 **Case 2.** The measurements in this case study represent the dynamic performance with the effect of heat soakage
306 included. This case study aims to investigate the effectiveness of the benchmark diagnostic method [14] for diagnosing
307 the health of the engine from transient measurements by taking into account the heat soakage phenomenon in order to
308 set a baseline diagnostic data set that will be further used for comparing it with the proposed method.

309 **Case 3.** This case study demonstrates and illustrates the proposed method's advantage compared to the baseline
310 diagnostic results from Case 2, which implemented the benchmark method [14].

311 **Case 4.** While the previous three case studies tested the diagnostic results under constant fault levels during a
312 transient maneuver, this case study is designed to demonstrate the capability of the proposed method to deal with
313 sudden failure during transient operation.

314 The first three cases have a constant degradation level called ‘Health State 1’ as shown in Table 3 [25]. In Case
315 study 4, we inject the degradation level denoted as ‘Health State 1’ between [0-3] s and ‘Health State 2’ between [3-
316 15] s with the sudden failure initiated at the time mark of 3.0 s.

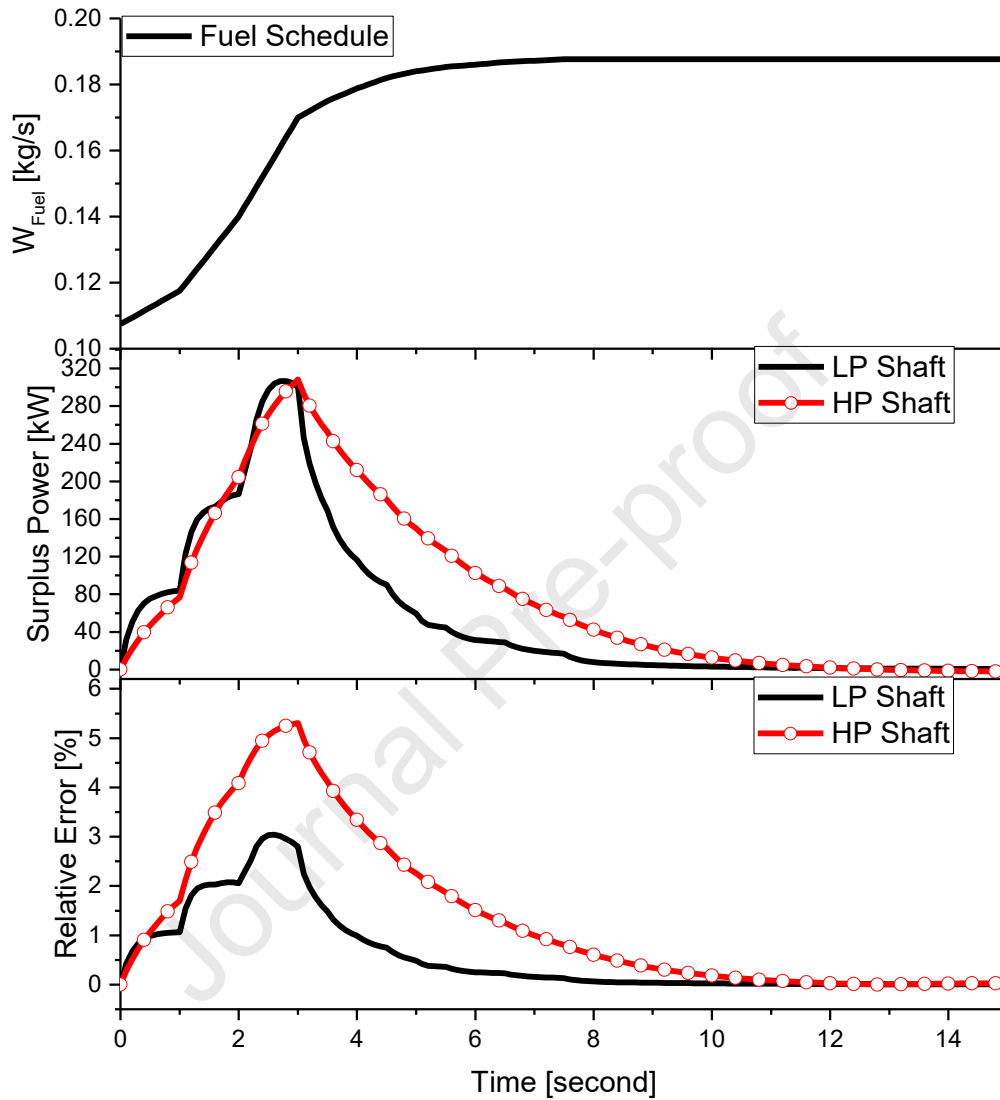
317 **3.1 Case 1: Benchmark Method - Transient Measurements without Considering Heat Soakage**

318 As mentioned in the methodology, the benchmark method [14] did not take into account the surplus power in the
319 fault diagnosis during dynamic conditions. This may be true as the focus of that study was a heavy-duty industrial gas
320 turbine engine. Due to its large shaft inertia, the transient maneuver for heavy-duty gas turbine engines is relatively
321 slower than other gas turbines (i.e., aero-derivative engines and turbofans). However, such an assumption will
322 compromise the diagnostic performance of other gas turbines.

323 Fig. 6 (top) demonstrates an acceleration fuel schedule with a 0.1 s time step during a dynamic maneuver for the
324 turbofan engine in concern. It is well known that the power balance between compressor work and turbine work will
325 not be satisfied during the transient maneuver. As shown in Fig. 6 (middle), the maximum surplus power obtained
326 from the power imbalance between the compressor and turbine is close to 320 kW during the maneuver for both *LP*
327 and *HP* shafts. The maximum difference between compressor work and turbine work is 5.3% and 3.0% for *LP* and
328 *HP* shaft in Fig. 6 (bottom), respectively. Therefore, if the surplus power is ignored, the relative error will propagate
329 to the diagnostic results. It follows that the larger the surplus power, the less accurate the diagnostic results will worsen
330 in steady-state approximation.

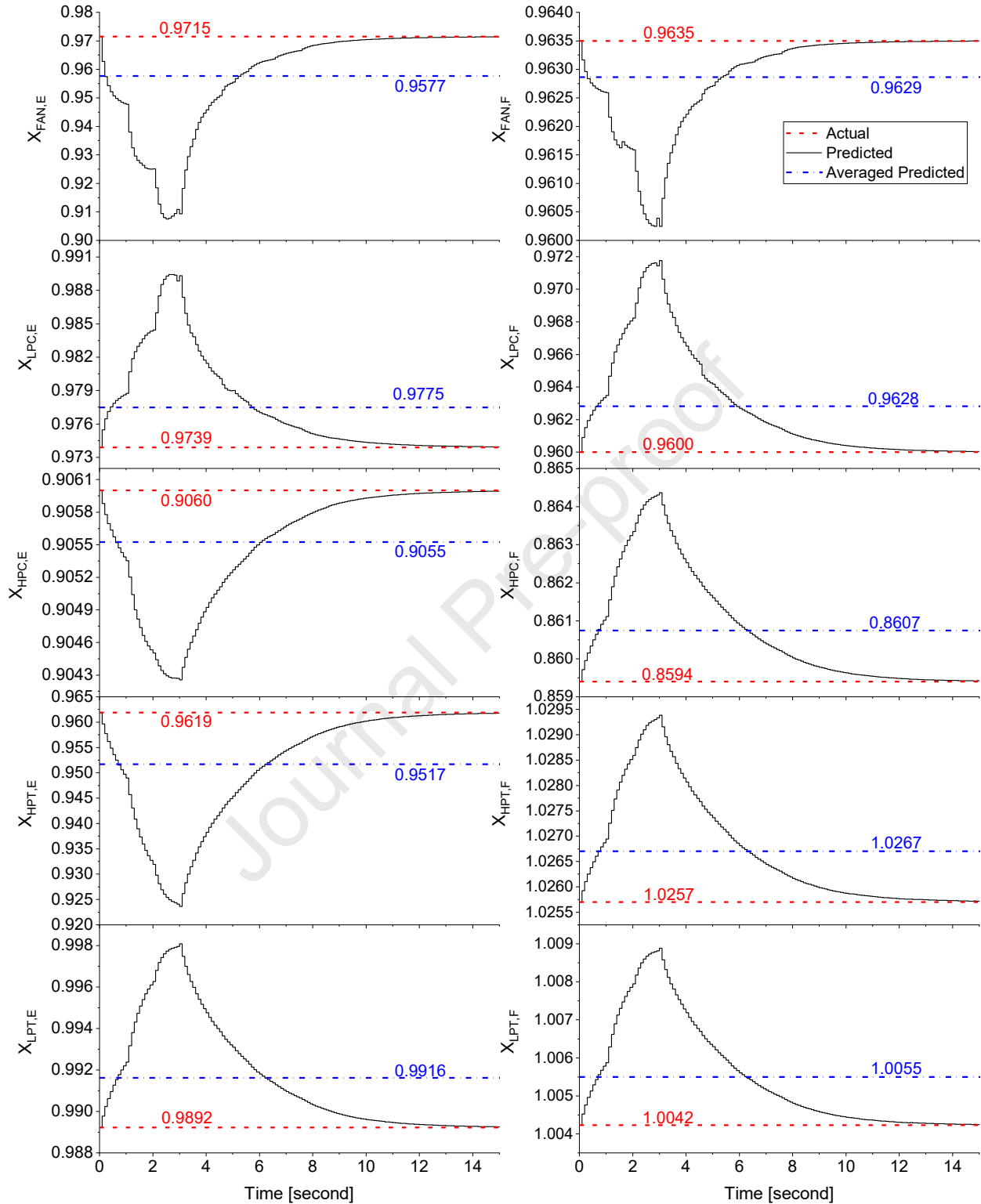
331 The average computation time for diagnosis with the benchmark method is 0.2024 s. Fig. 7 presents the diagnostic
332 results based on the benchmark method. It is apparent from this figure that the surplus power impacts the accuracy of
333 the diagnosis. The error of the diagnosis keeps increasing until approximately the 3 s mark, where the maximum
334 prediction error is observed. Then, the prediction error of health parameters decreases as the surplus power falls off.
335 In such a condition, the benchmark method will lead to fluctuation of the diagnostic results and may set a false alarm
336 of sudden engine degradation. Moreover, the faster the variation of the fuel schedule is, the larger the surplus power
337 and the bigger the prediction errors are going to be. The average prediction error of all ten health parameters during
338 the transient maneuver is shown in Fig. 8. Although the average maximum prediction error of ten health parameters

339 hovers at 1.4265% in Fig. 8, the maximum prediction error during the dynamic maneuver is 6.3396 % at 2.6 s for
 340 $X_{FAN,E}$. Such a prediction error may lead to inaccurate diagnosis.



341
 342 **Fig. 6 Fuel schedule and power imbalance between CW and TW during a transient maneuver.**

343 In summary, the benchmark method could be beneficial if the surplus power is negligible. This typically happens
 344 when there is a slow variation of fuel flow rate with respect to time during a transient maneuver. In other cases, the
 345 benchmark method will significantly fluctuate its diagnostic results. Consequentially, the benchmark method cannot
 346 monitor the engine health state in real-time when each set of measurements is recorded. Thus, such a method is not
 347 capable of monitoring the sudden engine failure that a bird strike may cause.



348

349

Fig. 7 Predicted health parameters during a transient maneuver.

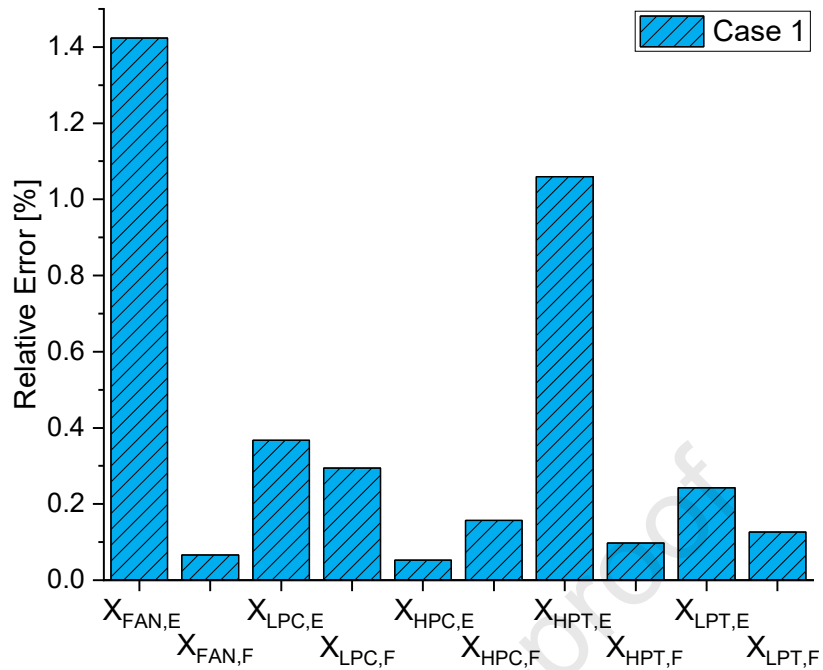


Fig. 8 Average relative error of health parameters during a transient maneuver.

3.2 Case 2: Benchmark Method - Transient Measurements by Considering Heat Soakage

During dynamic operating conditions, the gas turbine is not only facing power imbalance among shafts but also experiences heat transfer between gas and engine components. Fig. 9 presents the effect of heat soakage on exhaust gas temperature with time during a transient maneuver with and without considering heat soakage. It is evident that heat soakage impacts the gas path measurement of the exhaust temperature by delaying its increase in comparison with the case where heat soakage is ignored, as seen in Fig. 9. If the engine is faced with a slam transient maneuver, the predicted engine health parameters are likely to be affected.

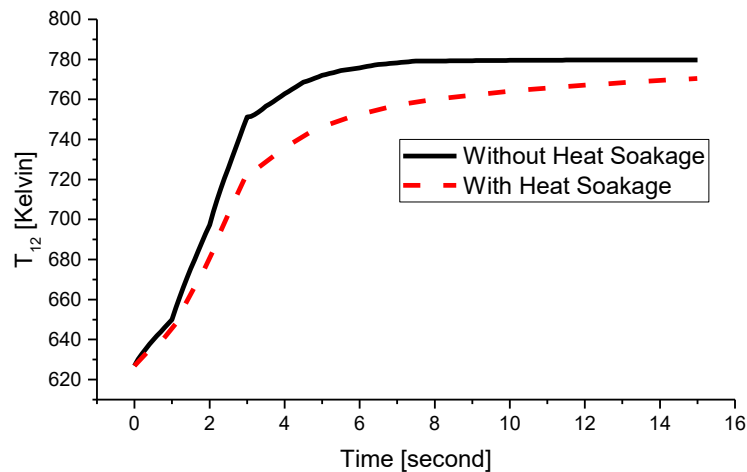
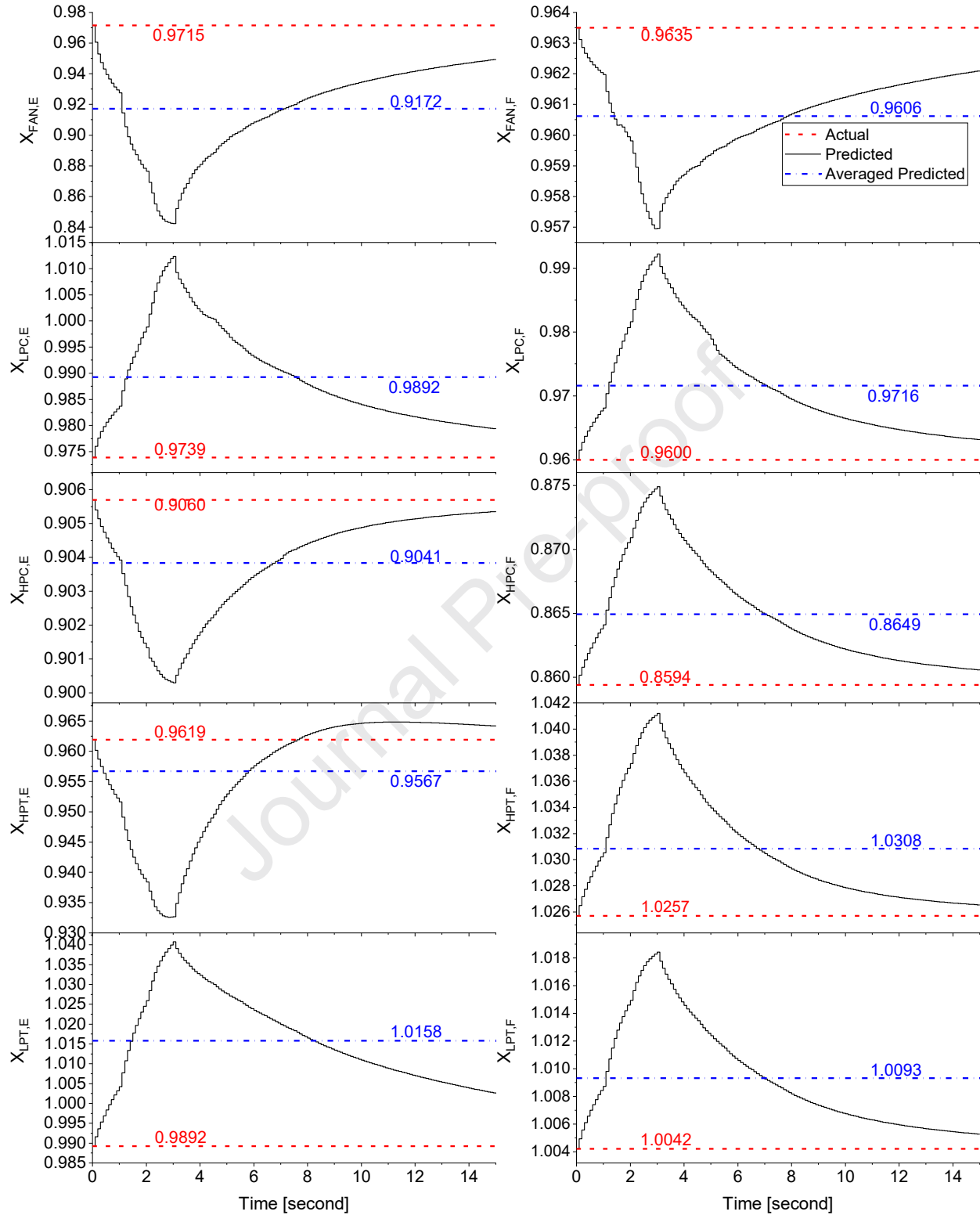


Fig. 9 Effect of heat soakage on exhaust gas temperature.



361

362

Fig. 10 Predicted health parameters during a transient maneuver.

363

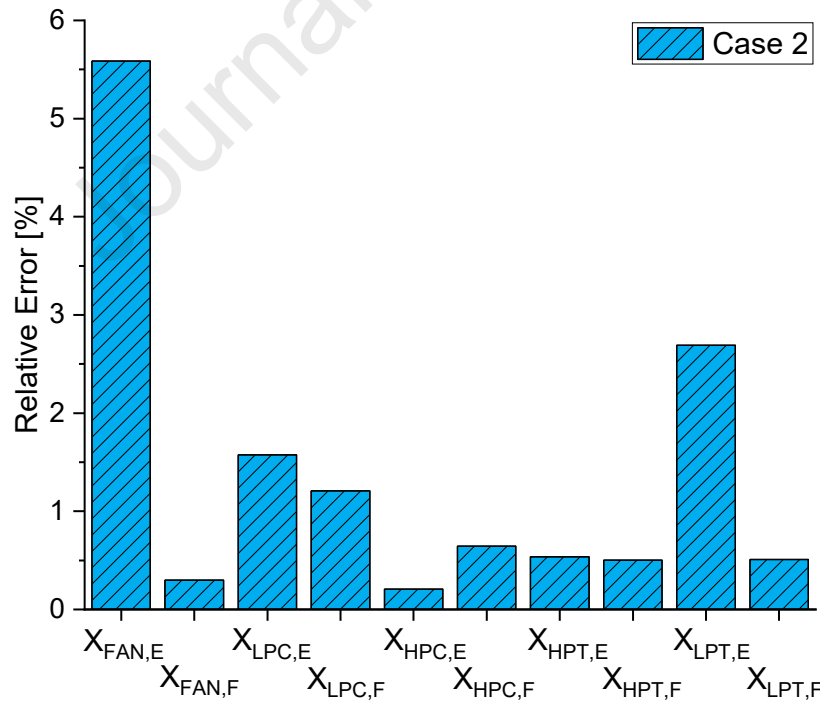
The average computation time for diagnosis is 0.1997 during the 15 s maneuver, where the benchmark method has

364

been implemented. It can be seen from the plot in Fig. 10 that the estimated degradation indices have a relatively

365 higher deviation from the actual health state when compared with Case 1. Apart from the *HPT* efficiency degradation
 366 index, the heat soakage phenomenon will increase the prediction error when considering the heat soakage in transient
 367 measurements. The surplus power will lead to over-prediction of the *HPT* efficiency degradation, while the heat
 368 soakage will under-predict the *HPT* efficiency degradation. Fig. 11 provides the summary of the average prediction
 369 error for ten health parameters. The maximum average error of the benchmark method has increased from 1.4265 %
 370 in Case 1 to 5.8738 % in Case 2 when the transient measurements consider heat soakage. Moreover, the maximum
 371 error during the entire transient maneuver is 13.3647 in Case 2 at 3.0 s for $X_{FAN,E}$. The consideration of heat soakage
 372 in the engine measurements will delay the prediction of the maximum degradation for all ten degradation indices.
 373 Ignoring the heat soakage during transient diagnosis will impact the prediction accuracy during transient conditions.

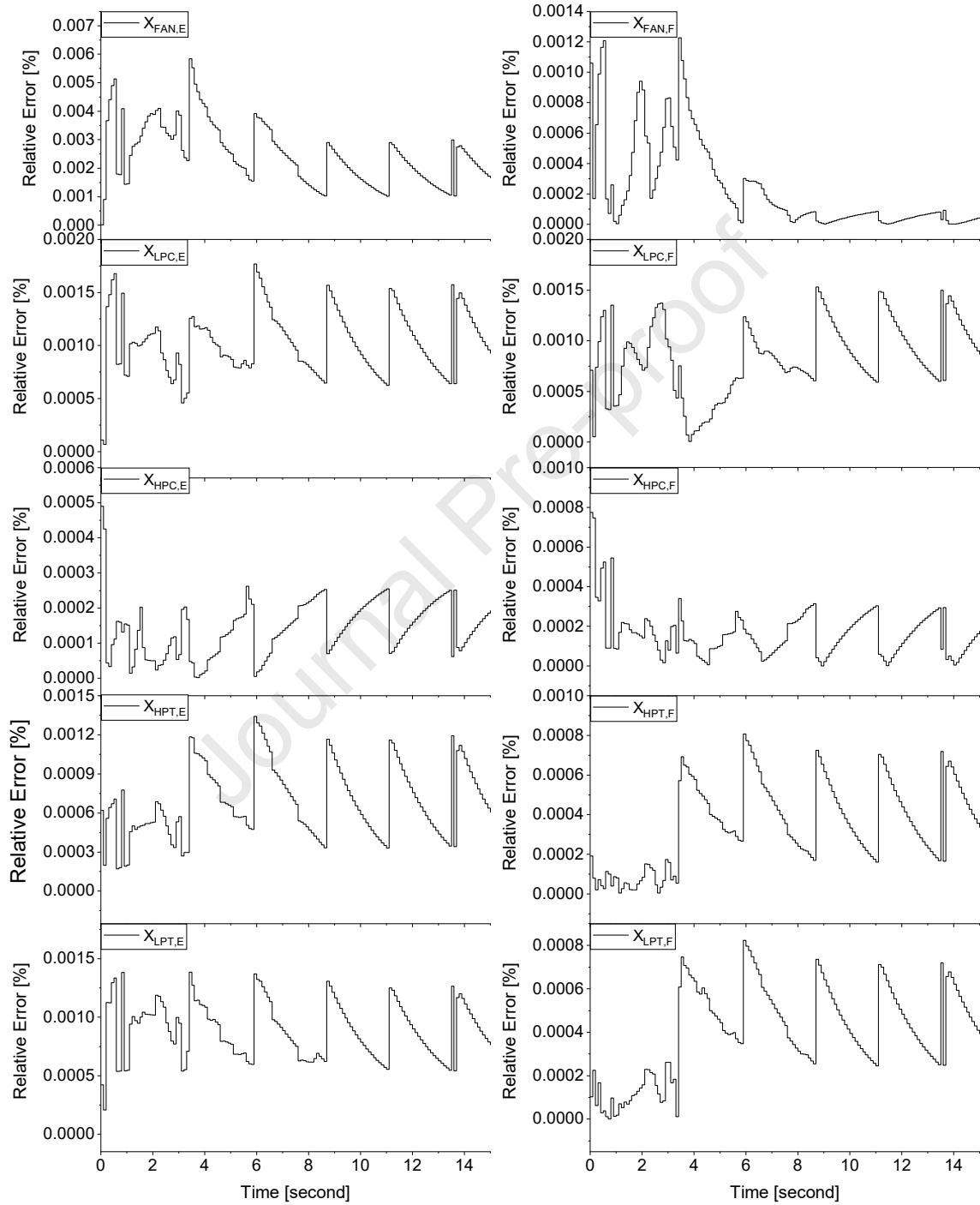
374 The results of this case study provide important insights into the applicability of the benchmark method for engine
 375 transient maneuvers. It becomes clear that using transient measurements in a steady-state approximation fault
 376 diagnostic system will have noticeable prediction errors during dynamic operating conditions. Moreover, the shift of
 377 diagnostic results is possible to raise a false alarm. If the diagnostic system dispatches frequent false alarms, the fault
 378 diagnostic program's confidence will be significantly compromised from an operation and maintenance perspective.



379
380 **Fig. 11 Average relative error of health parameters during a transient maneuver.**

381 3.3 Case 3: Proposed Method - Constant Health State during Transient Manoeuvre

382 This case study employs the proposed method for fault diagnosis during a transient maneuver while considering
 383 heat soakage in the transient engine measurements. Fig. 12 illustrates the relative error of the ten degradation indices
 384 during a dynamic maneuver.

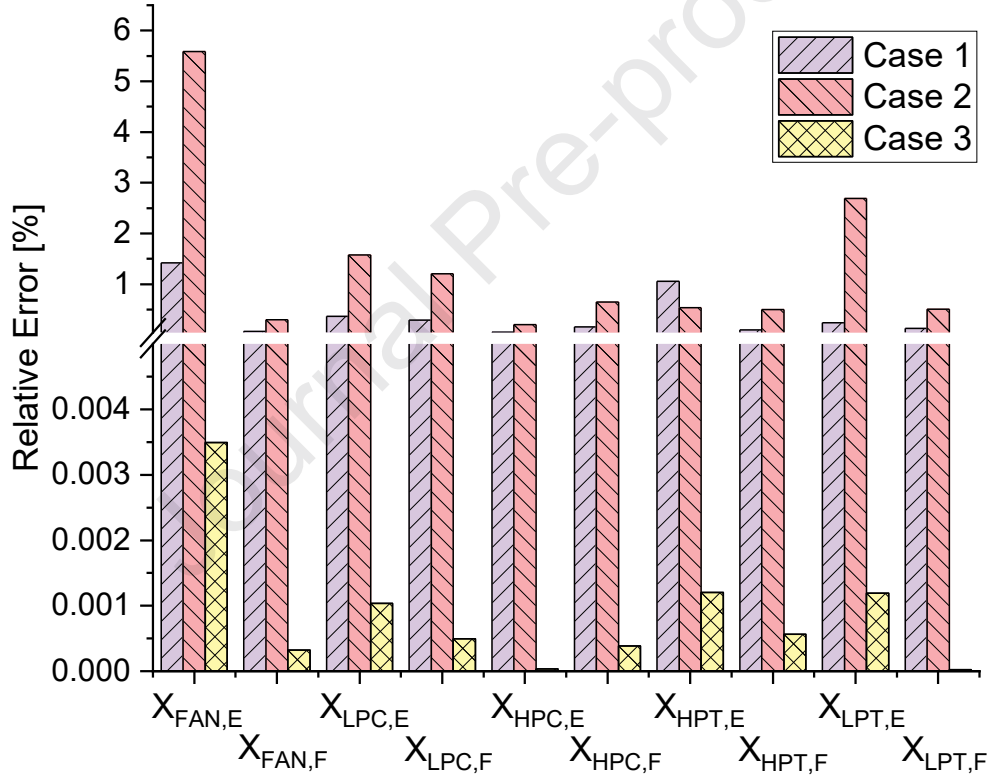


385

386

Fig. 12 Relative error of degradation indices during a dynamic maneuver.

387 Comparing the results in three cases (Fig. 13) reveals that the proposed method could estimate the health
 388 parameters with greater precision than the benchmark method. Table 4 summarises the diagnostic results for all three
 389 case studies. The computation time of Case 3 is 0.1567 s which is slightly better than that of Case 2. This is because
 390 the maximum allowed iteration steps terminate the diagnostic process; rather than the convergence threshold when
 391 affected by surplus power, heat soakage, and lag response during a transient maneuver. The average diagnostic error
 392 by the proposed method is 0.0007 % which is superior to the benchmark method (1.5239 % in Case 2). Moreover, the
 393 maximum error during the entire transient maneuver is 13.3647 % and 0.0058 % in Cases 2 and 3, respectively. It
 394 follows that the proposed time-series fault diagnosis method is superior to the benchmark method in both
 395 computational time and prediction accuracy aspects.



396
397 **Fig. 13 Comparison of diagnosis effectively of three cases.**

398
399 **Table 4 Summary of three diagnosis cases.**

Parameter	Symbol	Unit	Case 1	Case 2	Case 3
Average Run Time	RT	Second	0.2024	0.1997	0.1567
Average Error	AE	%	0.4224	1.5239	0.0007
Maximum Error	ME	%	6.3396	13.3647	0.0058

400

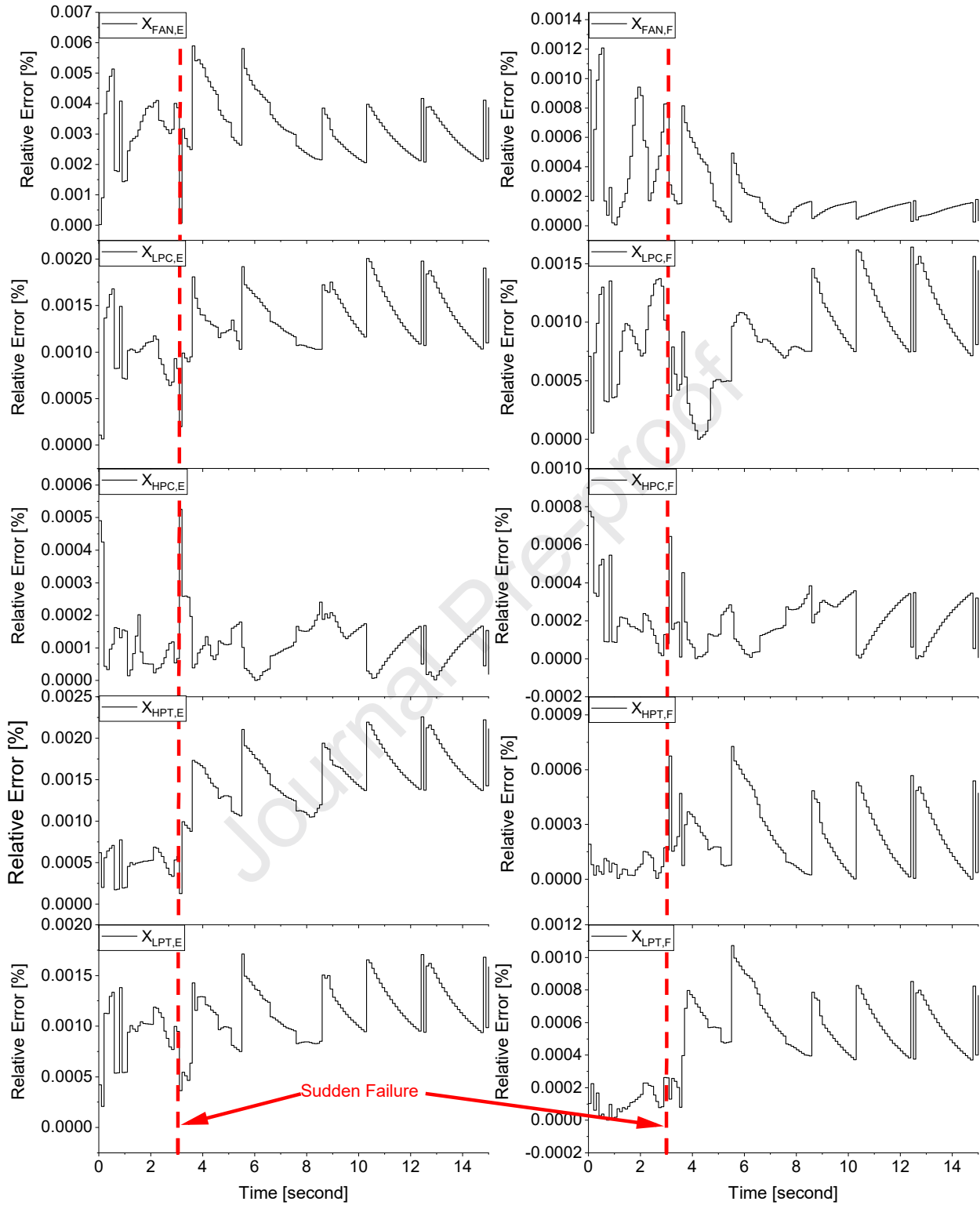
401 3.4 Case 4: Proposed Method - Sudden Failure during Transient Manoeuvre

402 The aero-engine may be faced with foreign object damage like bird strikes during flight. In such a condition,
403 sudden degradation may happen during the flight. Moreover, the bird strike is more likely to occur during the take-off
404 and landing processes when the engine runs under a transient or quasi-steady-state condition. Hence, it is necessary
405 to verify the capability of the proposed method under sudden failure during dynamic conditions in real-time.

406 The sudden failure is assumed to happen at the 3.0 s mark during the transient maneuver in Fig. 6 (top). The health
407 state is suddenly changed from 'Health State 1' to 'Health State 2' represented in Table 3. Fig. 14 presents the relative
408 error of diagnostic results obtained from the proposed method during dynamic conditions with sudden failure. It can
409 be seen from Fig. 14 that the proposed method could capture the sudden failure with high prediction accuracy. Fig. 15
410 compares the results of ten health parameters among all four Cases. The maximum relative error of all ten degradation
411 indices is less than 0.0059 % in Case 4. It is evident that the relative error of all health parameters with sudden failure
412 in Case 4 is similar to that of Case 3.

413 Table 5 presents the diagnostic results of all four Cases. The average computation time of Case 4 is only 0.1582 s
414 which amplifies the suitability of the proposed method for real-time implementation. It is worth noting that the
415 computation time of Case 4 is similar to Case 3. The sudden failure does not affect the computational efficiency of
416 the proposed method. From the perspective of diagnostic accuracy, the average and maximum errors for all ten health
417 parameters during the dynamic maneuver are 0.0009 % and 0.0059 %, respectively. The maximum error is observed
418 at 3.6 s for $X_{FAN,E}$ and the sudden failure is taking place at 3.0 s, which means that the proposed algorithm is not
419 compromised when dealing with sudden failures. The average and maximum errors of Case 4 are similar to those of
420 Case 3. The sudden failure during the dynamic condition also does not affect diagnostic accuracy.

421 In summary, the results demonstrate and illustrate that the proposed method is capable of diagnosing the engine
422 health state with time-series data at both steady-state and dynamic conditions in real-time, even when there are sudden
423 faults during transient conditions.



424

425

Fig. 14 Relative error of degradation indices during dynamic maneuver.

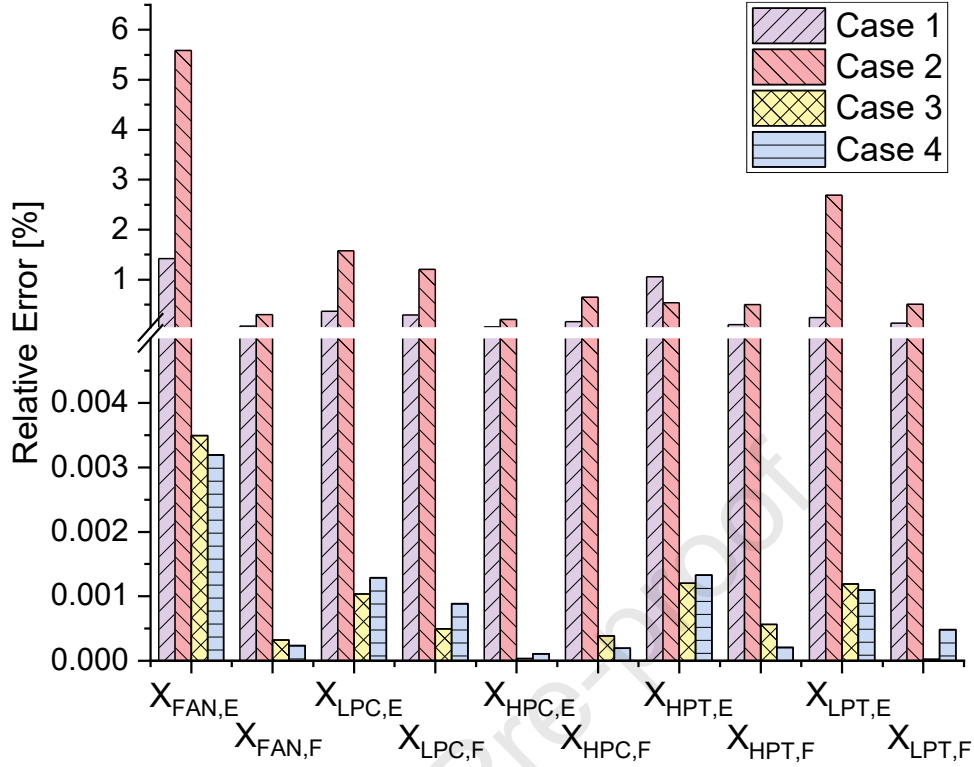


Fig. 15 Comparison of diagnosis effectively of four cases.

Table 5 Summary of four diagnostics cases.

Parameter	Symbol	Unit	Case 1	Case 2	Case 3	Case 4
Average Run Time	RT	Second	0.2024	0.1997	0.1567	0.1582
Average Error	AE	%	0.4224	1.5239	0.0007	0.0009
Maximum Error	ME	%	6.3396	13.3647	0.0058	0.0059

426
427
428

429

430 Despite the dynamic effect of rotor inertia, heat soakage and lag response during transient maneuver, the volume
 431 dynamic does not engage with the proposed method which may affect the diagnostic precision when very small-time
 432 step is selected. The volume dynamic is suggested to be considered in future work. However, it is worth noting that
 433 the effect of volume dynamics is less important when compared with the three dynamic effects mentioned in this study
 434 unless a limited time step is employed in the diagnostic system. Moreover, Further studies are suggested to integrate
 435 the proposed method with the aircraft and gas turbine starting models to track the engine health state from engine start
 436 until engine shut down during the whole aircraft mission. The health monitoring system could provide a real fault
 437 diagnosis in real-time on-wing, improving aircraft engine reliability, availability, and safety in such a condition.

438

4. Conclusions

439 This study is designed to provide the first systematic account of aero-engine transient characteristics during fault
440 diagnosis in time-series data to fill the research gap in engine fault diagnosis under dynamic conditions. The findings
441 clearly indicate that the proposed method could accurately diagnose the engine fault level under dynamic conditions.
442 The most prominent finding to emerge from this study is that the sudden failure during transient conditions could be
443 quantified correctly in real-time. In general, this study strengthens the idea that the proposed method could address
444 the fault diagnosis of aero-engine in real-time under both stable and dynamic conditions.

445 The conclusions extracted from this study are below:

- 446 • When the heat soakage phenomenon during a dynamic condition is not considered, the diagnosis results
447 predicted by the benchmark method come with a maximum error of 6.3396 %. Moreover, the predicted
448 degradation indices fluctuate during a transient maneuver.
- 449 • The maximum diagnostic error has increased to 13.3647 during the entire transient maneuver when
450 considering the heat soakage phenomenon in engine gas path measurements. It is clear to see that the
451 benchmark method cannot provide correct results for the test cases.
- 452 • The proposed method could take both surplus power, heat soakage, and lag response into consideration. The
453 maximum error of the health parameter is only 0.0058 % under a constant health state during transient
454 conditions with a computation time of 0.1567 s.
- 455 • More importantly, the proposed method could also diagnose the sudden failure during transient maneuvers
456 with a maximum error of 0.0059 % in 0.1582 s.

457 Before this study, the challenging real-time determination of the aero-engine fault level in dynamic conditions had
458 not been investigated in detail. The present study extends our knowledge of turbofan engine fault diagnosis under
459 dynamic conditions. A key strength of the present study is the fault diagnosis of sudden failure under transient
460 maneuvers.

461 Overall, the findings of this investigation complement those of earlier studies of engine fault diagnosis under
462 dynamic maneuvers in real-time. These findings contribute in several ways to our understanding of aero-engine fault
463 diagnosis and benefit engine safety, availability, and reliability.

464

Acknowledgments

465 This work is supported by “the Fundamental Research Funds for the Central Universities” under Grant No.
 466 D5000220161. The authors acknowledge the support of the Propulsion and Space Research Center (PSRC) of the
 467 Technology Innovation Institute (TII) in Abu Dhabi, United Arab Emirates.

468

References

- 469 [1] Balli O, Caliskan H. Turbofan engine performances from aviation, thermodynamic and environmental perspectives. *Energy* 2021;232:121031.
 470
 471 [2] Sun R, Shi L, Yang X, Wang Y, Zhao Q. A coupling diagnosis method of sensors faults in gas turbine control system. *Energy* 2020;205:117999.
 472
 473 [3] Ibrahem IMA, Akhrif O, Moustapha H, Staniszewski M. Nonlinear generalized predictive controller based on ensemble of
 474 NARX models for industrial gas turbine engine. *Energy* 2021;230:120700.
 475 [4] Kiaee M, Tousi AM. Vector-based deterioration index for gas turbine gas-path prognostics modeling framework. *Energy*
 476 2021;216:119198.
 477 [5] Urban Louis A. Gas Turbine Engine Parameter Interrelationships. 2nd ed. Hamilton Standard Division of United Aircraft
 478 Corporation; 1969.
 479 [6] Volponi AJ, Tang L. Improved Engine Health Monitoring Using Full Flight Data and Companion Engine Information. *SAE*
 480 *Int J Aerosp* 2016;9:91–102.
 481 [7] Tahan M, Tsoutsanis E, Muhammad M, Abdul Karim ZA. Performance-based health monitoring, diagnostics and
 482 prognostics for condition-based maintenance of gas turbines: A review. *Applied Energy* 2017;198:122–44.
 483 [8] Li YG. A gas turbine diagnostic approach with transient measurements. *Proceedings of the Institution of Mechanical*
 484 *Engineers, Part A: Journal of Power and Energy* 2003;217:169–77.
 485 [9] Ogaji SOT, Li YG, Sampath S, Singh R. Gas Path Fault Diagnosis of a Turbofan Engine From Transient Data Using
 486 Artificial Neural Networks. Volume 1: Turbo Expo 2003, Atlanta, Georgia, USA: ASME/EDC; 2003, p. 405–14.
 487 [10] Tsoutsanis E, Meskin N, Benammar M, Khorasani K. Transient gas turbine performance diagnostics through nonlinear
 488 adaptation of compressor and turbine maps. *Journal of Engineering for Gas Turbines and Power* 2015;137:1–12.
 489 [11] Tsoutsanis E, Meskin N, Benammar M, Khorasani K. A dynamic prognosis scheme for flexible operation of gas turbines.
 490 *Applied Energy* 2016;164:686–701.
 491 [12] Tsoutsanis E, Meskin N. Derivative-driven window-based regression method for gas turbine performance prognostics.
 492 *Energy* 2017;128:302–11.
 493 [13] Chen Y-Z, Tsoutsanis E, Xiang H-C, Li Y-G, Zhao J-J. A dynamic performance diagnostic method applied to hydrogen
 494 powered aero engines operating under transient conditions. *Applied Energy* 2022;317:119148.
 495 [14] Li J, Ying Y. Gas turbine gas path diagnosis under transient operating conditions: A steady state performance model based
 496 local optimization approach. *Applied Thermal Engineering* 2020;170.
 497 [15] Hu RL, Granderson J, Auslander DM, Agogino A. Design of machine learning models with domain experts for automated
 498 sensor selection for energy fault detection. *Applied Energy* 2019;235:117–28.
 499 [16] Palmé T, Fast M, Thern M. Gas turbine sensor validation through classification with artificial neural networks. *Applied*
 500 *Energy* 2011;88:3898–904.
 501 [17] Li YG. Gas turbine performance and health status estimation using adaptive gas path analysis. *Journal of Engineering for*
 502 *Gas Turbines and Power* 2010;132:1–9.
 503 [18] Chen Y, Zhao X, Xiang H, Tsoutsanis E. A sequential model-based approach for gas turbine performance diagnostics.
 504 *Energy* 2021;220:119657.
 505 [19] Verbist M. Gas path analysis for enhanced aero-engine condition monitoring and maintenance. PhD thesis, Delft University
 506 of Technology, 2017.
 507 [20] Park Y, Choi M, Kim K, Li X, Jung C, Na S, et al. Prediction of operating characteristics for industrial gas turbine combustor
 508 using an optimized artificial neural network. *Energy* 2020;213:118769.
 509 [21] Chen Y-Z, Li Y-G, Tsoutsanis E, Newby M, Zhao X-D. Techno-economic evaluation and optimization of CCGT power
 510 Plant: A multi-criteria decision support system. *Energy Conversion and Management* 2021;237:114107.
 511 [22] Wei Z, Zhang S, Jafari S, Nikolaidis T. Self-enhancing model-based control for active transient protection and thrust
 512 response improvement of gas turbine aero-engines. *Energy* 2022;242:123030.
 513 [23] Pang S, Li Q, Feng H. A hybrid onboard adaptive model for aero-engine parameter prediction. *Aerospace Science and*
 514 *Technology* 2020;105:105951.
 515 [24] Tsoutsanis E, Hamadache M, Dixon R. Real-Time Diagnostic Method of Gas Turbines Operating Under Transient
 516 Conditions in Hybrid Power Plants. *Journal of Engineering for Gas Turbines and Power* 2020;142:101002.

- 517 [25] Chatterjee S, Litt JS. Online model parameter estimation of jet engine degradation for autonomous propulsion control. AIAA
518 Guidance, Navigation, and Control Conference and Exhibit, Austin, Texas, USA: 2003, p. 1–17.
- 519 [26] Chen YZ, Li YG, Newby MA. Performance simulation of a parallel dual-pressure once-through steam generator. *Energy*
520 2019;173:16–27.
- 521 [27] Park Y, Choi M, Choi G. Fault detection of industrial large-scale gas turbine for fuel distribution characteristics in start-up
522 procedure using artificial neural network method. *Energy* 2022;251:123877.
- 523 [28] Hu Y, Sun Z, Cao L, Zhang Y, Pan P. Optimization configuration of gas path sensors using a hybrid method based on tabu
524 search artificial bee colony and improved genetic algorithm in turbofan engine. *Aerospace Science and Technology*
525 2021;112:106642.
- 526 [29] Zheng J, Chang J, Ma J, Yu D. Modeling and analysis of windmilling operation during mode transition of a turbine-based-
527 combined cycle engine. *Aerospace Science and Technology* 2021;109:106423.
- 528 [30] Mohammadian PK, Saidi MH. Simulation of startup operation of an industrial twin-shaft gas turbine based on geometry and
529 control logic. *Energy* 2019;183:1295–313.
- 530 [31] Seyam S, Dincer I, Agelin-Chaab M. Investigation of two hybrid aircraft propulsion and powering systems using alternative
531 fuels. *Energy* 2021;232:121037.
- 532 [32] Sheng H, Chen Q, Li J, Jiang W, Wang Z, Liu Z, et al. Research on dynamic modeling and performance analysis of helicopter
533 turboshaft engine's start-up process. *Aerospace Science and Technology* 2020;106:106097.
- 534 [33] Wang C, Li YG, Yang BY. Transient performance simulation of aircraft engine integrated with fuel and control systems.
535 *Applied Thermal Engineering* 2017;114:1029–37.
- 536 [34] Singh R, Maity A, Nataraj PSV. Dynamic modeling and robust nonlinear control of a laboratory gas turbine engine.
537 *Aerospace Science and Technology* 2022:107586.
- 538 [35] Kim S. A new performance adaptation method for aero gas turbine engines based on large amounts of measured data. *Energy*
539 2021;221:119863.
- 540 [36] Collins JM, McLarty D. All-electric commercial aviation with solid oxide fuel cell-gas turbine-battery hybrids. *Applied*
541 *Energy* 2020;265:114787.
- 542 [37] Kim MJ, Kim TS, Flores RJ, Brouwer J. Neural-network-based optimization for economic dispatch of combined heat and
543 power systems. *Applied Energy* 2020;265:114785.
- 544 [38] Li Z, Li Y-G, Sampath S. Aeroengine transient performance simulation integrated with generic heat soakage and tip
545 clearance model. *Aeronaut j* 2022:1–23.
- 546 [39] Tsoutsanis E, Meskin N. Dynamic performance simulation and control of gas turbines used for hybrid gas/wind energy
547 applications. *Applied Thermal Engineering* 2019;147:122–42.
- 548 [40] Wei Z, Jafari S, Zhang S, Nikolaidis T. Hybrid Wiener model: An on-board approach using post-flight data for gas turbine
549 aero-engines modelling. *Applied Thermal Engineering* 2021;184:116350.
- 550

Highlights

- A novel real-time successive fault diagnosis method is proposed.
- Time-series data consider the transient effect in gas path measurements.
- Constant engine degradation could be monitored with high accuracy in real-time.
- Sudden failure during dynamic conditions could be captured with great precision.
- The proposed method is far better than the benchmark method.

(maximum 85 characters, including spaces, per bullet point, 3-5 bullet points)

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Journal Pre-proof

A time-series turbofan engine successive fault diagnosis under both steady-state and dynamic conditions

Chen, Yu-Zhi

2022-10-29

Attribution-NonCommercial-NoDerivatives 4.0 International

Chen Y-Z, Tsoutsanis E, Wang C, et al., (2023) A time-series turbofan engine successive fault diagnosis under both steady-state and dynamic conditions. *Energy*, Volume 263, Part D, January 2023, Article number 125848

<https://doi.org/10.1016/j.energy.2022.125848>

Downloaded from CERES Research Repository, Cranfield University