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Research article

Fault Detection and Diagnosis of Compressor Faults in a Gas Turbine Electric Generator

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ABSTRACT

In modern mechanical and aviation industries, gas turbine engines are essential components. However, due to the intricacy of their nature and functioning, they need to be completely monitored to prevent unanticipated damages and operational faults. The goal of this study is to provide a viable diagnostic approach, estimation of compressor faults in a gas turbine electric generator. An improved frame work for the diagnosis and estimation of fault in a gas turbine was proposed using an extended kalman filter algorithm. The extended kalman filter utilizes data collected over time that contains noise (random variations) and other errors to provide values that are often closer to the actual condition of the system as it pertains to achieving a specific objective. The proposed fault diagnosis framework developed show a 99.85% accurate fault estimation and early detection of compressor faults in a gas turbine electric generator.

Keywords: *Fault Diagnosis; Diagnosis of Compressor Faults; Gas Turbine Electric Generator*

Introduction

The process of finding faults in physical systems while attempting to locate the root of the problem is known as fault detection and diagnostics (FDD). The diagnosis procedure starts by detecting the variations from the normal characteristics of a given system, whose aim is to identify the cause of the failure and find all sources of the unexpected occurrence (Marzat, Piet-Lahanier, Damongeot, and Walter, 2012)

Based on the data that are currently available for the system, the major goal of fault diagnosis is to identify the kind, size, and location of the fault as well as the time at which it was discovered. Figure 1 depicts a generic block description of model-based fault diagnostics.

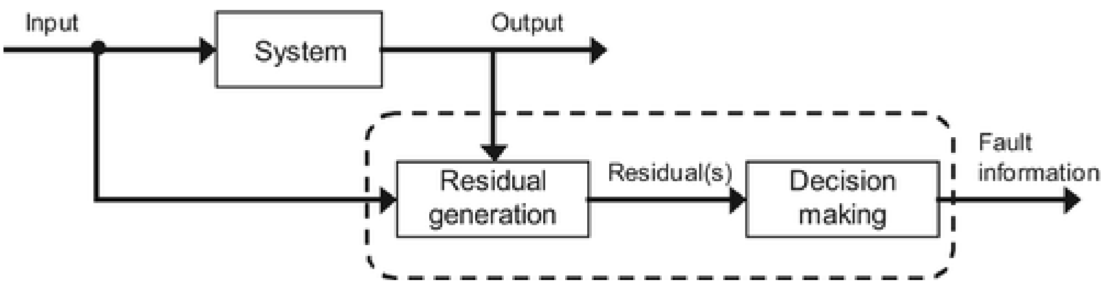

Figure 1: General scheme of model-based fault diagnosis (Alexandros, 2013).

Fault diagnosis is often accomplished in two steps. First, a signal termed residual is generated utilizing relevant input/output metrics from the system under review. If there is no defect in the system, the residual signal should be zero or nearly zero; if there is a failure, the residual signal should be different from zero. Residual can be either vector providing information about several faults or scalar signal carrying information about a single failure. The type of the residual generator might range from a black-box system model to an analytical mathematical model **(**Marzat, Piet-Lahanier, Damongeot, and Walter, 2012).

The decision-making process, which takes place in the second step, involves assessing the possibility of faults in the residuals. The kind of decision-making process might range from a simple threshold to several complex statistical methods. A diagnostic control system often has two goals:

1. Under normal circumstances, it must ensure the best operating point in relation to changes in the load supplied.
2. Under fault conditions, it must locate the fault to isolate the faulty line and reduce possible system failures.

Once the fault is located and identified, the control system can decide all the actions that are required to optimize the subsequent system's operation

Fault diagnosis methods are broadly classified into three main categories (Marzat, Piet-Lahanier, Damongeot, and Walter, 2012).

i. model-based,
ii. hardware-based and
iii. History-based.

Model-Based Fault Diagnosis

Model-based FDD is the process of identifying and diagnosing problems in a system using techniques that extract features from signals that are already accessible (from known measurements and inputs) and the mathematical model of the process (Alexandros, 2013). Model-based FDD is also called analytical redundancy. Model-based fault diagnostic techniques often employ models created using some basic knowledge of the physics of the plant or process **(**Marzat, Piet-Lahanier, Damongeot, and Walter, 2012).

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Faults are identified by applying pre-set or adjustable thresholds on residuals derived from the variation between actual measurements and their estimates obtained by using the process model. A number of residuals can be generated each being sensitive to certain faults occurring in various locations of the system (Shen, Jiang, and Shi 2017). The analysis of each residual, once the threshold is exceeded, leads to fault diagnosis. Figure 2 shows the general block diagram of a model-based FDD. The two main blocks are described as residual generation and residual evaluation blocks.

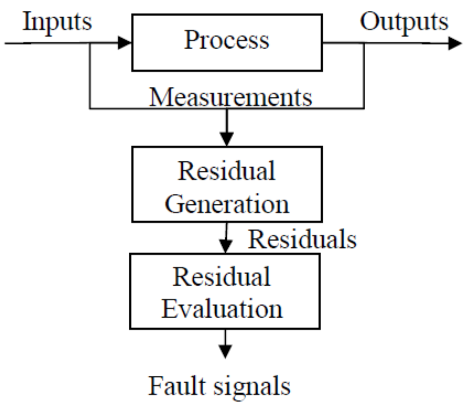

Figure 2: Structure of a model-based FDD system (Marzat, Piet-Lahanier, Damongeot, and Walter2012).

Hardware-Based Fault Diagnosis

Hardware-based fault diagnosis methods do not deploy a mathematical model of the physics of the plant or process. In general, hardware-based fault diagnosis methods are generally categorized into voting techniques, hardware redundancy, special hardware, frequency analysis, and limit checking (Alexandros, 2013).

History-Based Fault Diagnosis

In history-based fault diagnostic methods, a model developed from known and observed input and output process data is used instead of a mathematical model of the physics of the plant or process (Shen, Jiang and Shi, 2017). Creating a model of the process that mathematically connects measured inputs to measured outputs is the primary ideal of history-based fault diagnostics. Since these strategies are data-driven, the significant impact of these strategies is highly dependent on the quantity and quality of the process data (Andrea, Alessandro, and Sauro, 2020).

Operations of Gas Turbine

One of the most versatile components of turbo engines available today is the gas turbine. It is employed in a variety of ways in vital sectors including aviation, oil and gas, power generation, and smaller related industries. The performance of the gas turbines is a complicated phenomenon and there are some parameters that cannot be measured directly and can only be estimated due to excessive heat generated in the system (Bijay, 2018). Mathematical models are prepared to represents the actual gas turbine systems and to estimate certain parameters which cannot be measured directly due to various constraints. Figure 3 represents a schematic of an open turbine gas cycle.

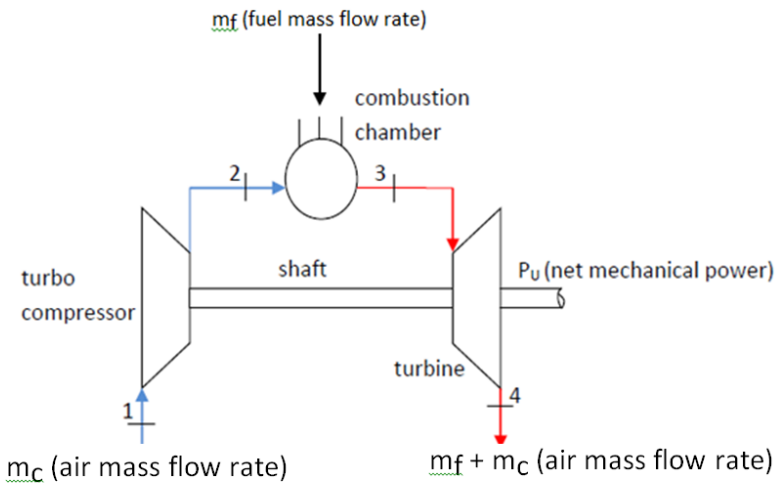

Figure 3: Open Turbine Gas Cycle

The open turbine gas cycle operates as follows:

1. Air at room pressure and temperature is compressed to a high pressure in the turbo compressor.
2. Fuel is added in the combustion chamber where combustion takes place resulting in high-temperature combusted gases.
3. The hot gases expand in the turbine back to the atmospheric pressure producing mechanical power.

The cycle is considered to be open because fresh air is continually pumped into the compressor and exhaust gas is released, but thermodynamically it appears as though the operating fluid returns to its starting condition. Part of the mechanical power produced by the turbine is utilized to drive the compressor (Bijay, 2018).

When diagnosing a failure in a gas turbine engine, the first step is to determine the precise state of the sensor and actuator system components (Alexandros, 2013). An early and precise diagnosis directly influences the availability of machines for operation and maintenance. The need of early detection of faults cannot be overlooked, as the presence of faults in the plants may result in significant losses in terms of equipment and human resources (Benyounes, Hafaifa, and Guemana. 2016).

Mathematical Model of a Gas Turbine Electric Generator

Figure 4 represents the block components of an industrial gas turbine engine and their thermodynamic interactions.

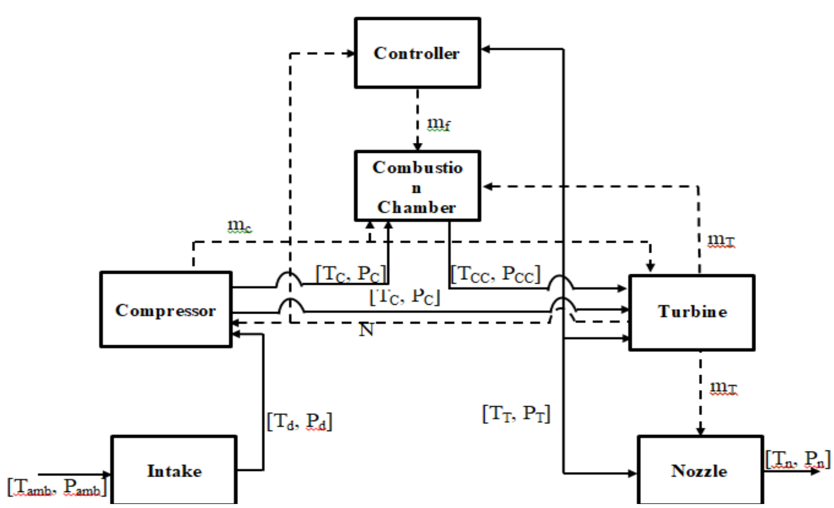

Figure 4: Block description of an Industrial Gas Turbine Engine

From figure 4, the complete mathematical model of a gas turbine electric generator can be obtained as shown in equation 1.

$$\left\{\begin{array}{c} T_C = T_d\left[1+\frac{1}{\eta_C}\left(\pi_C^{\frac{\gamma-1}{\gamma}}-1\right)\right] \\ \dot{m_C} = \frac{\dot{m}\sqrt{\theta}}{\delta} \\ \dot{T_{CC}} = \frac{1}{C_v m_c}\left[\left(C_P T_c \dot{m}_c + \eta_{cc} H_u \dot{m}_f - C_P T_{cc} \dot{m_T}\right) - C_v T_{cc}\left(\dot{m_c} + \dot{m_f} - \dot{m}_T\right)\right] \\ \dot{P_{CC}} = \frac{P_{cc}}{T_{cc}} T_{cc} + \frac{\gamma R T_{cc}}{V_{cc}}\left(\dot{m_c} + \dot{m_f} - \dot{m}_T\right) \\ \dot{P}_t = \frac{R T_M}{V_M}\left(\dot{m}_t + \frac{\beta}{1+\beta} m_c - m_f\right) \\ Where, T_M = \frac{m_t T_t + \beta m_c T_c}{m_t + \beta m_c} \\ T_t = T_{CC} - T_{CC}\left[1 + \eta_T\left(1 + \pi_T^{\frac{\gamma-1}{\gamma}}\right)\right] \\ N = \frac{\eta_{mech} m_t C_p(\dot{T_{CC}} - T_t) - m_c C_p (T_C - T_d)}{J N \frac{\pi^2}{30}} \\ \text{The expansion ratio } (\beta) \text{is given as: } \beta = \frac{P_T}{P_n} \end{array}\right\} \quad (1)$$

Applying equation 1 the complete Matlab/Simulink model for the healthy state of a gas turbine electric generator is developed as a shown in figure 5.

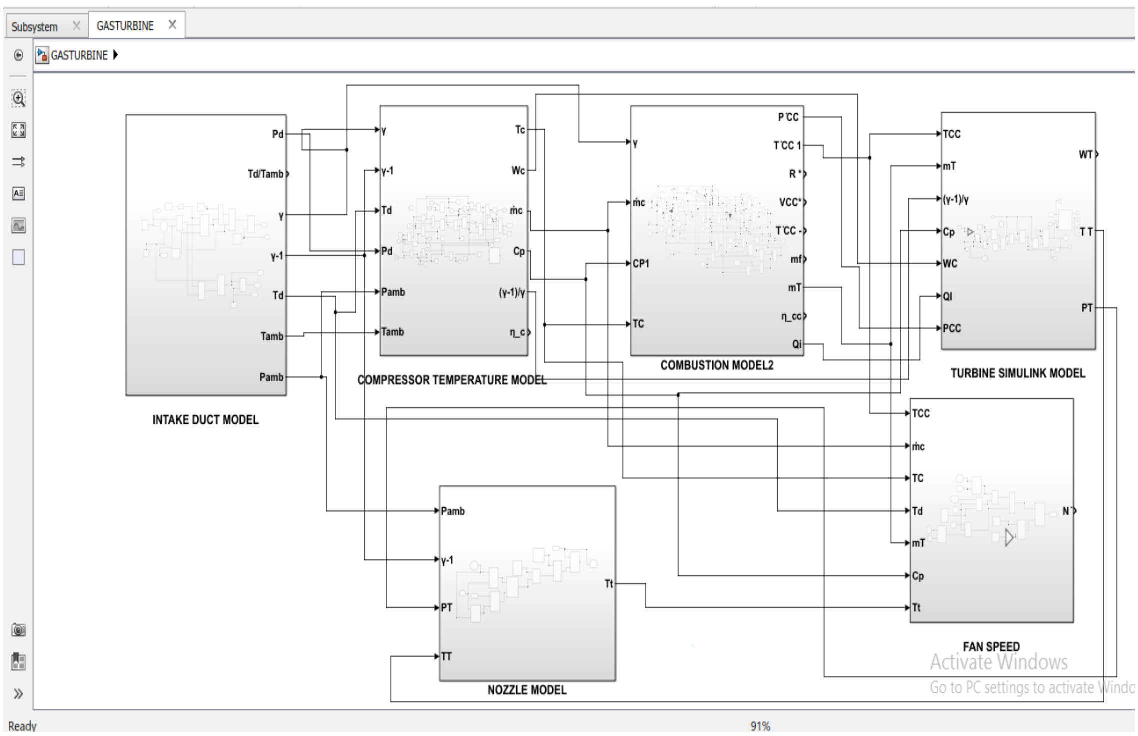

Figure 5: Simulink Model of an industrial Gas Turbine

Fault Detection Algorithm

The propose fault detection and diagnosis framework involve the use of an extended kalman filter for fault estimation and reference signal tracking. The kalman filter is a set of mathematical equations that provides an efficient computational means to estimate the state of a process, in a way that minimizes the mean of the squared error. Kalman filter is also used for predicting the likely future courses of dynamic systems that people are not likely to control. It has become a universal tool for integrating different sensor and data collection systems into an overall optimal solution (Armando, Malek, Francisco, and Nonnarit, 2021). Figure 6, illustrates a typical application of Kalman Filter.

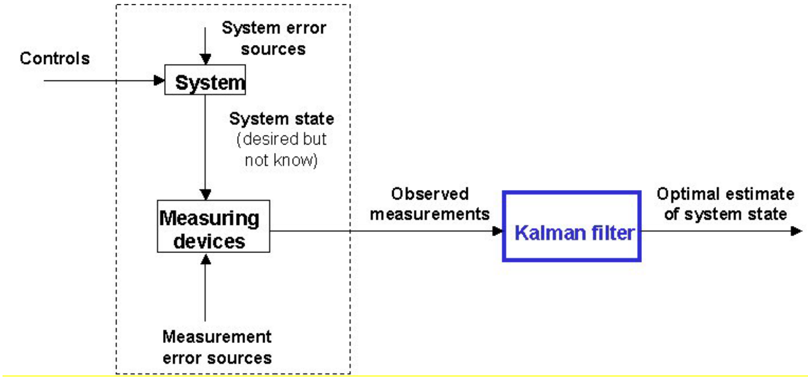

Figure 6: Typical application of the Kalman Filter

Figure 6 represents a physical system that is driven by a set of external inputs or controls and its outputs are evaluated by measuring devices or sensors. In this physical system, the knowledge on the system's behaviour is solely given by the inputs and the observed outputs.

The observations convey the errors and uncertainties in the process, namely the sensor noise and the system errors. Based on the available information (control inputs and observations) it is required to obtain an estimate of the system's state that optimizes a given criteria. This same principle will be applied to the gas turbine electric generator. The general form of an extended kalman filter for nonlinear systems is given in equation 4. The general filter problem for a complex nonlinear dynamic system may be formulated below (Armando, Malek, Francisco, and Nonnarit, 2021).

$$x(k+1) = f(x(k), u(k), w(k)) \quad (2)$$
$$y(k) = h(x(k), v(k)) \quad (3)$$

Equation 2 and equation 3 represent the state dynamics of a general non-linear time-varying system, where;

$x(k+1) = \text{The } (k+1)\text{th component of the vector } x$
$x \in R^n$ is the system state vector,
$f(.,.,.)$ defines the system's dynamics,
$u \in R^m$ is the control vector,
w is the vector that conveys the system error sources (Process noise vector),
$y \in R^r$ is the observation vector,
y *is the* measurement vector
$h(.,.,.)$ is the measurement function or the measurement sensitivity,
u is the control input vector
v is the vector that represents the measurement error sources (measurement noise vector)The EKF for the fault estimation of compressor temperature (Tc) and compressor mass flow rate (mc) is given as;

$$T_{C(k+1)} = f(T_{C(K)}, u(k), w(k)) \quad (4)$$
$$m_{C(k+1)} = f(m_{C(K)}, u(k), w(k)) \quad (5)$$

The proposed algorithm for the fault estimation and diagnosis of compressor fault is given as follows:

1. Initialize state transition Matrix (, B, C, D, Q)
2. Initialize Process noise (w(k)) and Observation noise(v(k))
3. Initialize $Control\ input\ (u(0))$
4. Initialize $System\ state\ (X_k)$
5. Compute Previous Estimate of $X_k(X_{K-1})$
6. Compute the primary estimation at the current time step of $X_k(X_{k-pre})$

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7. Calculate kalman Gain (K_g) (X_{k-pre}*C'*(C*X_{k-pre}*C'+ w(k)))^(-1))
8. Compute current observable system output UL_{-obs}
9. Calculate the predicted system output value of X_k (UL_{-Pre})
10. Compute ($UL_{-obs} - UL_{-Pre}$)
11. Computer the update (X_upd = X_pre + K_g*(UL_obs-UL_pre))
12. Obtain (X_k) Estimate
13. Output ($X_{k,}$) predicted

To estimate the fault in the compressor of the gas turbine model using the developed algorithm, the compressor model is further decomposed into various blocks as shown in figure 7.

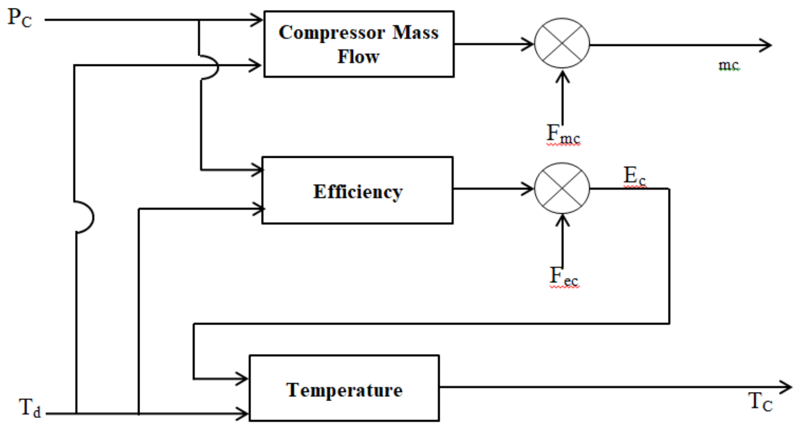

Figure 7: Compressor Block Decomposition

In figure 7 the input to the compressor model are the compressor pressure (Pc) and the inlet temperature (Td). Changes in both parameters affect the compressor mass flow rate and the compressor temperature. Also, when fault is introduced to the system it results in decrease in the compressor mass flow rate capacity (F_{mc}), decrease in the compressor efficiency (Fec) resulting in abnormal rise in temperature. Using kalman filter in the system enables quick detection and estimation of fault conditions before they occur.

Figure 8 represents the compressor model of the gas turbine with the operation of the proposes algorithm. The script for the algorithm was done in MATLAB.

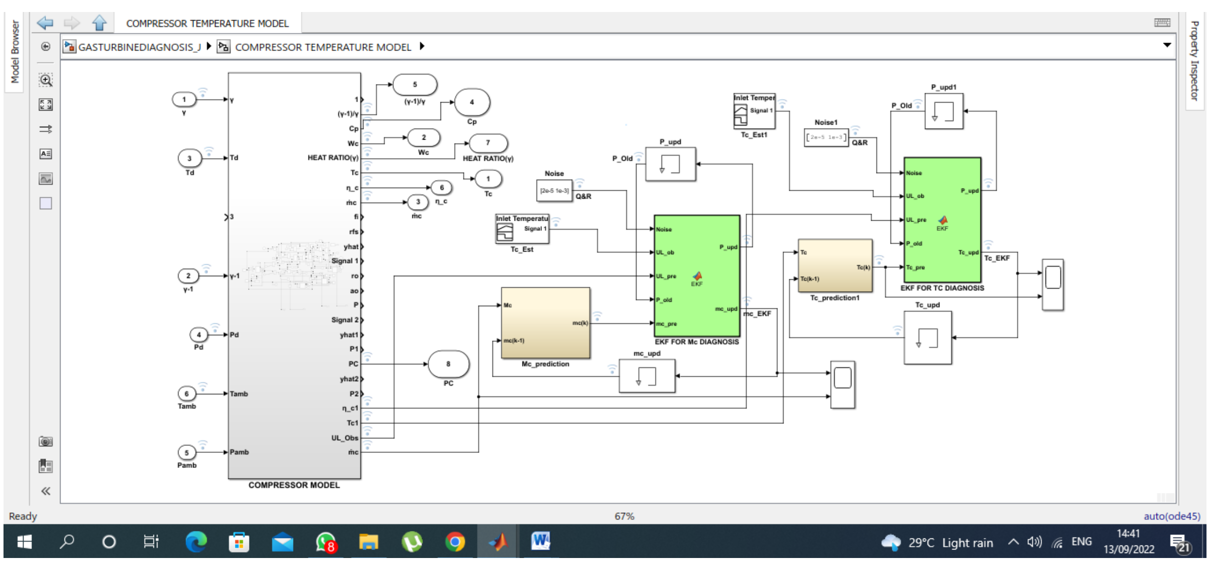

Figure 8: Simulink model of compressor fault estimation and diagnosis in using Extended kalman filter

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Simulation Results

Fault modelling parameters, which represent the faulty behaviour in the gas turbine, was introduced in the simulation in other to ascertain the performance of the fault estimation and diagnosis model. Comparison and results of fault diagnosis and estimation were conducted during the simulation, the following fault scenarios were observed:

i. Fault Estimation and diagnosis in mass flow rate of the compressor (m_c).
ii. Fault Estimation and diagnosis in Changes in Compressor Pressure (Pc)

Fault Estimation and Diagnosis in Mass Flow Rate of the Compressor (M_c)

The fault observed, during simulation shows an increase in compressor pressure (Pc) and compressor temperature (Tc) as shown in figure 9 and figure 10

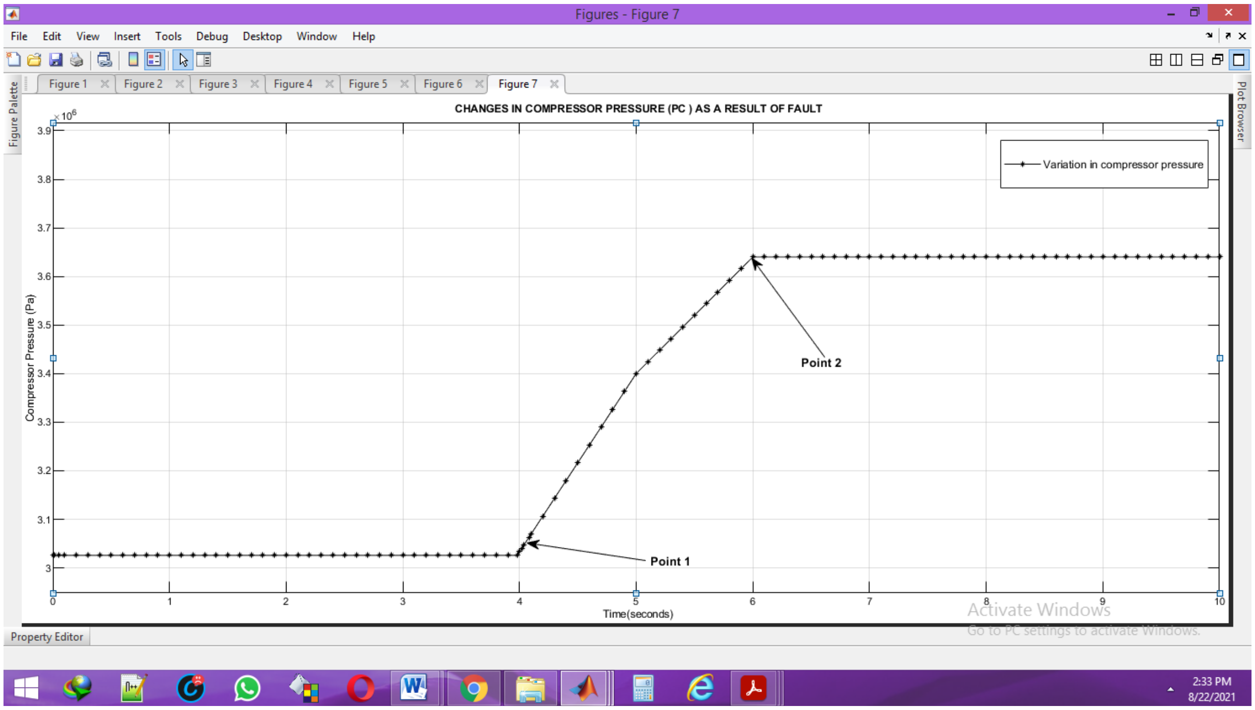

Figure 9: Changes in Compressor Pressure as a result of Component Fault

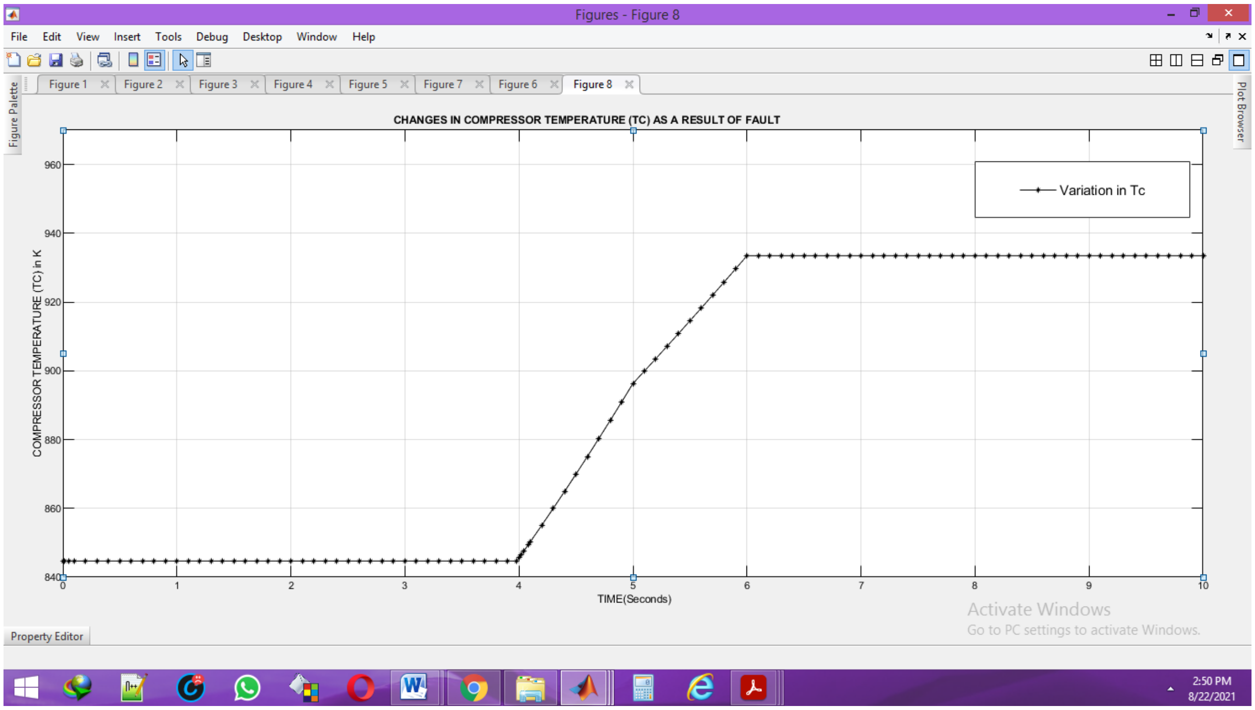

Figure 10: Changes in Compressor inlet Temperature (T_C) as a result of Sensor Fault

The fault observed in the compressor section of the gas turbine, could present itself as a component fault, for example a leakage in a valve, reduction in tip clearance as a result of dust or eroded or broken compressor blades which may lead to abnormal decrease or rise in compressor pressure or inlet temperature and decrease in compressor mass flow.

Figure 11 represent comparison of a fault estimation and diagnosis in the compressor model.

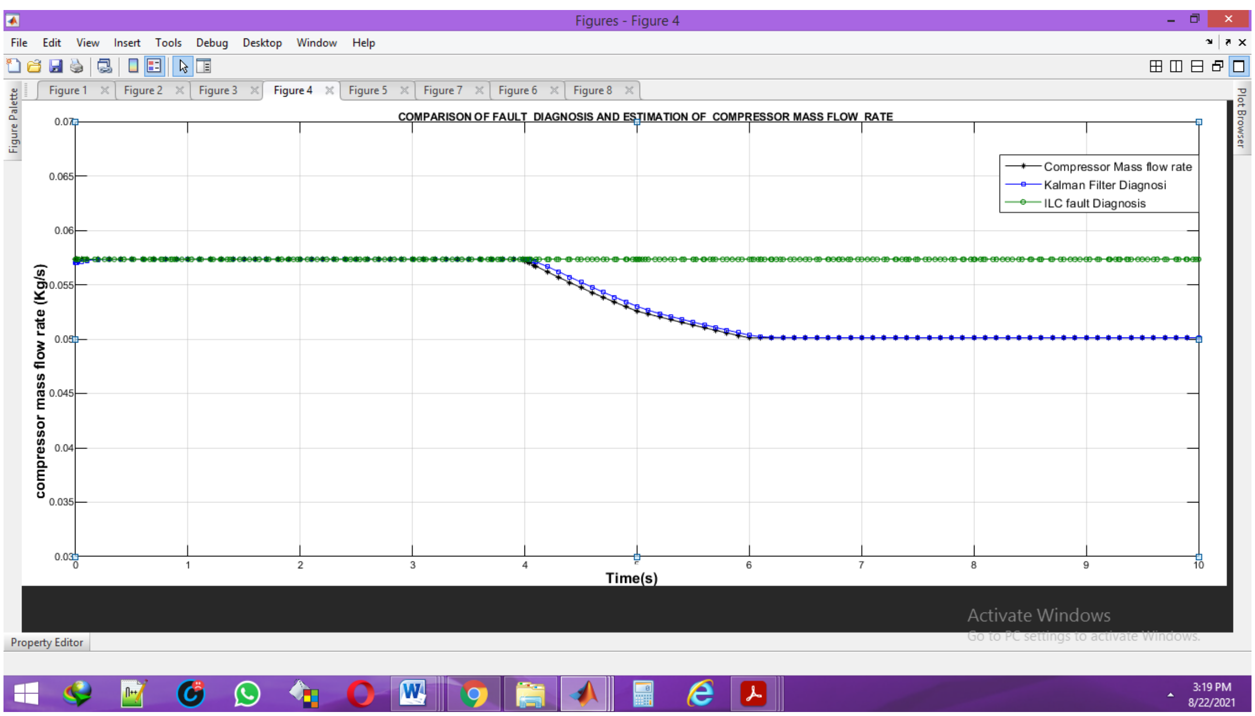

Figure 11: Comparison of kalman filter fault Estimation with that of the ILC algorithm.

The air mass flow rate in the compressor chamber is required to be constant for efficient combustion process and adequate turbine mechanical power generated. In figure 11, a constant air mass flow rate of 0.057Kg/s was observed from 0second to 4 seconds until fault was observed in the system at 4 seconds of the simulation le ding to decrease in air mass flow rate in the compressor. A decrease to about 0.005Kg/s was recorded during the fault conditions. The extended kalman filter developed was able to estimate and diagnose the fault at 4 seconds till the end of the simulation. The ILC algorithm shows a large deviation from the fault signal recorded. A negligible 0.15% percent was obtained as the Percentage deviation, showing an accuracy of reference tracking of 99.85% (100-0.15) using the kalman filter model.

Fault Estimation and diagnosis in Compressor Pressure (Pc)

Figure 12 represents the changes in compressor pressure as a result of fault.

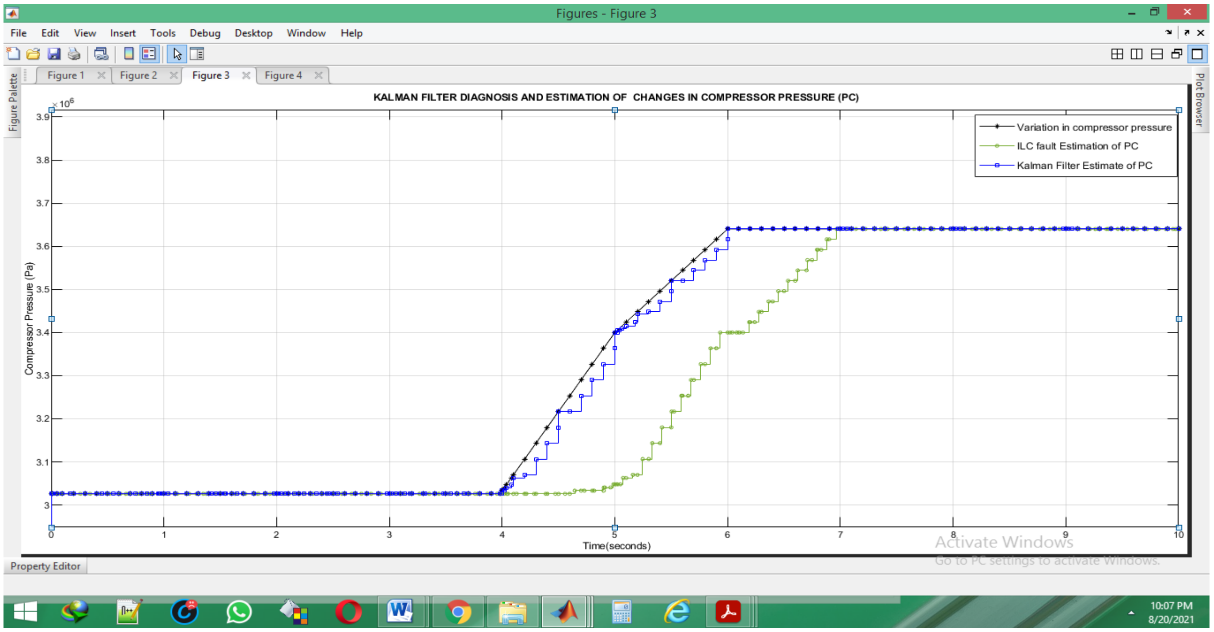

Figure 12: Changes in compressor pressure during component fault condition

The proposed kalman filter algorithm was able to provide early estimate and diagnose the fault and provided a close-range reference tracking by monitoring the actual signal with that of the predicted signal. Compensation is provided by the kalman gain to ensure that the reference signal is closely track and fault is diagnosed on time and accurately. Also, the ILC algorithm also provided reference tracking for the compressor pressure and fault estimation. The ILC had a large deviation from the reference signal during the period when fault occur in the system.

Conclusion

An improved frame work for the diagnosis and estimation of fault in a gas turbine was developed using an extended kalman filter. The algorithm for the extended kalman filter was developed using Matlab script. Also, the proposed kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error.

Various fault scenarios were investigated and the results obtained showed the effectiveness of the proposed method in terms of both rapid fault detection and fault diagnosis. The extended kalman filter framework provided the following improvement: On the increase in accuracy of fault estimation and diagnosis of compressor mass flow rate to 99.85%.

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