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Design and Simulation of Kalman Filter for Estimation of Gas Turbine Inlet Temperature

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Abstract **– The measurement of Gas Turbine (GT) Inlet Temperature remains a significant challenge for engineers, particularly in developing countries, due to the specialized technology required for accurate estimation and covariance noise signal attenuation. This technology is primarily utilized by Gas Turbine manufacturers, who employ closed-source model. To address this limitation, the present study develops an open-source model to estimate the GT Inlet Temperature and mitigate the noise signals in the measurement data. The approach is based on the integration of a Kalman Filter (KF) model and a Plant model within a State-Space framework, utilizing real-time input parameters from two identical ABB Gas Turbines, GT11 and GT12. The primary objective is to ensure that the proposed open-source model delivers optimal performance and solution accuracy comparable to that of the closed-source proprietary models. Initially, the Burner Can Temperature Rise Equation is employed to compute the GT Inlet Temperatures directly for the two turbine models. This equation is subsequently used to derive the system matrices in State-Space representation, which describe the plant model. To complete the modelling, fictitious noise signals are introduced into the plant model and superimposed onto the Kalman Filter model to simulate real-world measurement conditions. The resulting design is implemented in a MATLAB Simulink environment. Simulation results demonstrate that the proposed open-source model achieves accuracies of 98.1% and 97.2% for GT11 and GT12 respectively, when compared to real-time process data from ABB, while the calculated values yield 80% and 65% accuracies respectively.**

Indexed Terms – Kalman Filter, Gas Turbine, Inlet Temperature, State Space, Power Plant.

I. INTRODUCTION

Gas Turbines (GT) have been widely used for power generation and other industrial applications in developing countries like Nigeria, because of massive hydrocarbon deposits, and largely due to high overall efficiencies (Gupta et al., 2007). A Gas Turbine is more robust and adaptive to climatic adversities and load variations. Apart from electricity generation, heavy loads like compressors, drives and various propulsion systems would load a renewable source of energy. It is mainly designed to extract as much as the energy from the fuel (Asgari, 2014), (Harman, 1981), and (Jonathan et al., 2018).

Power generation with Gas Turbine is a complex, nonlinear process. Multiple thermodynamic processes combine to produce the overall complex output power of a Gas Turbine. In this complexity, various process variables or states can be measured directly, while many other variables are not available for direct measurement. In order to achieve effective process control, unknown states must be determined from sensor data (Venkateswarlu and Karri, 2022). This can rather be inferred or estimated based on systems output measured by sensors (Mathworks, 2024). Accurate parameter estimations play major roles in diagnostics, process control and safety considerations.

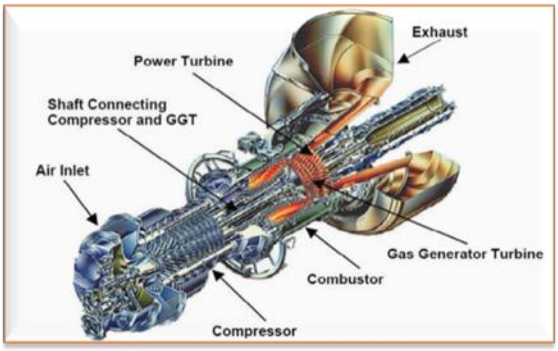

Fig.1: Gas Turbine (Kurz and Ohanian, 2003).

A. Turbine Inlet Temperature

The Turbine Inlet Temperature (TIT) or Firing Temperature is the highest temperature attained in the system (Basu and Debnath, 2019). The Gas Turbine Inlet Temperature measurement is the most difficult process loop to handle because of its indirect measurement. The combustion temperature ranges from 700^0C to 1700^0C depending on some process factors (Salim et al., 2020). Temperature extremes result in material damage, fuel wastage and gaseous emissions. The TIT increases with the fuel gas flow rate. According to (Aminov et al., 2018), increase in GT Inlet Temperature produces a corresponding increase in the thermal and thermodynamic efficiencies of the Brayton Cycle. However, higher TIT significantly increases the thermal stress in the metals, which affects the life spans of the components (Aminov et al., 2018) and (Gupta et al., 2007). The combustion chamber becomes too hostile for smooth measurements. On the other hand, lower TIT may cause low efficiencies and low load conditions (Gupta et al., 2007). To this end, the TIT values are fixed by Turbine Manufacturers. The TIT is not available for measurement, and so requires specialized technologies. Typically, it is achieved by control systems approximation which is only possible with an Advanced Process Control (APC) technology.

B. Advanced Process Control

Advanced Process Control (APC) is a comprehensive scheme that leverages sophisticated algorithms, mathematical models and advanced control strategies to predict, optimize and improve industrial processes for efficiency, reliability, safety and productivity (ABB, 2024). The APC is a more sophisticated form of process control scheme that goes beyond the limitations of the legacy PID control schemes (Zero Instruments, 2024). With APC, the Kalman Filter Gain (K) is calculated internally by the system using process dynamics and sensor updates (Franklin, 2020). APC can be a rule-based (Fuzzy Logic) or model-based (Kalman Filter, Model Predictive Control) control system.

C. Kalman Filter

Kalman Filter is an algorithm used to estimate the state of a given system using other measurement data. It is used to compute hidden states from observation (Ahmed, 2023). It estimates the State of a system from noisy measurements (Pearson, 2016). In its operation, it combines noisy sensor outputs to estimate the system state with uncertain dynamics. Kalman filters are very fast, making them great tools for embedded systems and real time problems. According to (Biezen, 2015), it is an iterative mathematical process that uses a set of equations and consecutive data inputs to quickly estimate the true value of the object being measured, under unpredicted or random error. In (Ahmed, 2023) explanation, the Kalman filter is an Optimal Estimator for linear systems, and a recursive data processing algorithm that works in a predictor-corrector fashion. The optimal estimate is found by multiplying the prediction and measurement probability functions together, scaling the result and computing the mean of the resulting probability density function (Ulusoy, 2018).

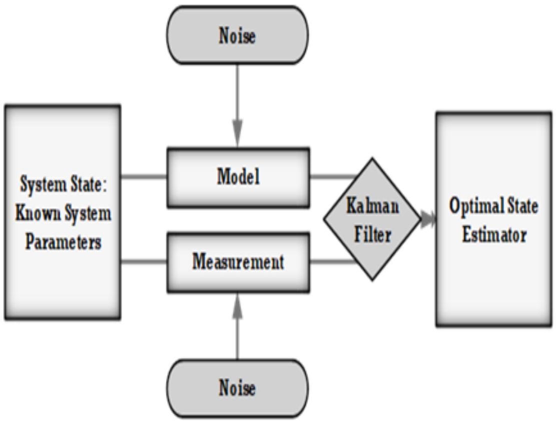

Fig. 2: Kalman Filter Block Diagram

The Kalman Filter combines the system state and the system state error covariance with measurement parameters to establish its model equations:

1. Initialization:
   i. system state estimate $= x_0$
   ii. Error covariance $= P_0$
2. Re-initialization:
   i. System state estimate $= x_{k-1}$
   ii. Error covariance $= P_{k-1}$
3. Prediction (a-priori):
   i. $\hat{x}^-_k = A\hat{x}_{k-1} + Bu_k + w_k$ (1)
   ii. $P_k^- = A\, P_{k-1}\, A^T + Q_k$ (2)
4. Kalman Gain:
   $K_k = P_k^- C^T\, (C\, P_k^- C^T + R)^{-1}$ (3a)
   $K_k = P_k^- C^T \,/\, (C\, P_k^- C^T + R)$ (3b)
5. Updates from Measurements and previous estimates (a-posteriori):
   i. $\hat{x}_k = \hat{x}_k^- + K_k(y_k - C\hat{x}_k^-)$ (4)
   ii. $P_k = P_k^- - K_k\, C\, P_k^-$ (5a)
   $P_k = (1 - K_k C)\, P_k^-.$ (5b)

II. RESEARCH METHODOLOGY

A set of real-time plant data, having process correlations as presented in Table 1, was utilized to derive some unknown parameters required for system modelling. Three parameters namely, fuel to air ratio, thermal efficiency of the GT and compressor air mass flow were derived from theoretical inferences. Additionally, two theoretical constants essential for comprehensive modelling namely, the specific heat capacity of air and the adiabatic index were incorporated. These parameters were initially validated using the thermodynamic burner can temperature equation, which served as the pilot model. The same equation was subsequently employed to compute the A, B, C, D parameters, also known as the system matrices. The system matrices formed the basis for developing the plant model for GT11 and GT12. To characterize a Kalman Filter model, some fictitious noise signals were introduced into the plant model. Both the plant and Kalman Filter models were implemented and simulated within the SIMULINK environment, as illustrated in figure 1.

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Table 1: Real Time Process Data from IPP, Okpai (NAOC, 2024).

S/N	Symbol	GT11	GT12	Unit
1	*T1*	30.16	31.0	^{0}C
2	*T2*	410	369	^{0}C
3	*P1*	1002	1000	mbar
4	*P2*	13.5	9.7	bar
5	*mf*	8.68	4.36	Kg/s
6	*T3*	1100	780	^{0}C
7	*T4*	533	366	^{0}C
8	P_E	145	40	MW
9	*Hv*	39.60	39.60	MJ/Nm^3

Where;

T1 = Compressor Inlet Temperature,

T2 = Compressor Discharge Temperature,

P1 = Compressor Inlet Pressure,

P2 = Compressor Discharge Pressure,

mf = Fuel Gas Flow Rate,

T3 = Turbine Inlet Temperature,

T4 = Temperature After Turbine,

P_E = Output Electrical Power,

Hv = Lower Heating Value of Gas,

Theoretical Parameters:

ϒ = Adiabatic Index = 1.4

cp = Specific Heat Capacity of Air

= 1.005KJ/kg*K

From GT11 Process Data:

mf = 8.68kg/s

ma = (*mf**32)

ma = (8.68*32) kg/s = 277.760kg/s

Hv = 3.9600520MJ/Nm^3

Thermal Efficiency (η_t) for GT11 is computed using real plant data as follows:

$$\eta_t = 1 - \frac{1}{[P2/P1]^\wedge(\gamma - \frac{1}{\gamma})} \quad (\textit{Proctor II, 2003}) \quad (6)$$

$$\eta_t = 1 - \frac{1}{[13.5/1.002]^\wedge(1.4 - \frac{1}{1.4})}$$

$$\eta_t = 1 - \frac{1}{[13.473]^\wedge(0.686)}$$

$$\eta_t = 1 - \frac{1}{5.954}$$

$$\eta_t = 0.83 \approx 83\%$$

From GT12 Process Data:

mf = 4.36kg/s

ma = (*mf**36)

ma = (4.43*36) kg/s = 156.960kg/s

Hv = 3.9600520MJ/Nm^3

Thermal Efficiency (η_t) for GT12 is computed using real plant data as follows:

$$\eta_t = 1 - \frac{1}{[P2/P1]^\wedge(\gamma - \frac{1}{\gamma})} \quad (\textit{Proctor II, 2003})$$

$$\eta_t = 1 - \frac{1}{[9.7/1.000]^\wedge(1.4 - \frac{1}{1.4})}$$

$$\eta_t = 1 - \frac{1}{[9.7]^\wedge(0.686)}$$

$$\eta_t = 1 - \frac{1}{4.753}$$

$$\eta_t = 0.79 \approx 79\%$$

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Burner Can Temperature Rise Equation

The "burner can temperature rise'' equation is given by:

$$f = \frac{\left(\frac{T3}{T2}\right)-1}{\left(\frac{\eta t H v}{c p T2}\right)-\left(\frac{T3}{T2}\right)} \qquad (NASA, 2021) \quad (7a)$$

Regularizing (7) above,

$$f = \frac{\left(\frac{T3 - T2}{T2}\right)}{\left(\frac{\eta t H v - c p T3}{c p T2}\right)}$$

$$f = \frac{\left(\frac{T3}{T2}\right) - 1}{\left(\frac{\eta t H v}{c p T2}\right) - \left(\frac{T3}{T2}\right)}$$

$$f = \left(\frac{T3 - T2}{T2}\right) \text{ x } \left(\frac{c p T2}{\eta t H v - c p T3}\right)$$

$$f = \left(\frac{c p T2 (T3 - T2)}{T2 (\eta t H v - c p T3)}\right)$$

$$f = \left(\frac{c p (T3 - T2)}{(\eta t H v - c p T3)}\right) \qquad (7b)$$

Cross-multiplying (7b),

$$\eta t H v f - c p T3 f = c p T3 - c p T2$$

$$-c p T3 f - c p T3 = -c p T2 - \eta t H v f$$

$$-(c p T3 f + c p T3) = -(c p T2 + \eta t H v f)$$

$$T3 = \left(\frac{c p T2 + \eta t H v f}{c p f + c p}\right)$$

$$T3 = \left(\frac{c p T2 + \eta t H v f}{c p (1 + f)}\right) \qquad (8)$$

where;

ma = Air Mass Flow;

f = Fuel - to – Air Ratio (mf/ma)

Computing T3 for GT11 directly from MATLAB COMMAND WINDOW

T3 is calculated from the Burner Can Temperature Equation as follows:

>> cp = [1005];

>> $T2$ = [410];

>> η_t = [0.83];

>> Hv = [39600520]; >> mf = [8680];

>> ma = (mf*32); ma = 277760

>> f = (mf/ma); f = 0.0312

>> den = (cp*(1+ f)); den = 1.0364e+03

>> num = (cp*$T2$) +(η_t*Hv*f)

num = 1.4392e+06

>> $T3$ = (num/den)

$T3$ = 1.3886e+03

$T3 \approx$ 1,388°C

Computing T3 for GT12 directly from MATLAB COMMAND WINDOW

>> cp = [1005];

>> $T2$ = [369];

>> η_t = [0.79];

>> Hv = [39600520];

>> mf = [4360];

>> ma = (mf*36); ma = 156960

>> f = (mf/ma); f = 0.0278

>> den = (cp*(1+ f)); den = 1.0329e+03

>> num = (cp*$T2$) +(ηt*Hv*f)

num = 1.2399e+06

>> $T3$ = (num/den) = 1.2003e+03

$T3 \approx$ 1,200°C

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Characterization of the Kalman Filter Model.
The Systems Matrices required for the Kalman Filter are derived as follows:

System Matrices:
To put equation (8) into state space form, it is first expressed in terms of state variables and inputs.
State Space representation of the system is given as:

$$\dot{x} = Ax + Bu \quad (9)$$

$$y = Cx + Du \quad (10)$$

Assuming two States,

Then let,

$$x1 = T2, \quad (11)$$

$$x2 = T3, \quad (12)$$

Deriving the equations that relate the state variables to the inputs and output of the system using Energy Balance Equation:

$$mfHv = macp\,(x2 - x1) \quad (13)$$

Solving for $x2$ in equation (11),

$$mfHv = maCp\,(x2 - x1)$$

$$mfHv = maCpx2 - maCpx1$$

$$maCpx2 = mfHv + maCpx1$$

$$x2 = \frac{mfHv + macpx1}{macp}$$

Therefore,

$$x2 = \frac{mfHv}{macp} + x1 \quad (14)$$

In the State Space form, the following equations are obtained:

$$x1\_dot = 0 \quad (15)$$

$$x2\_dot = \frac{mfHv}{macp} - \frac{x2(1+f)}{cp(1+f)z} \quad (16)$$

where;

$$z = \frac{maCp}{mfHv} \quad (17)$$

The input and output equations are;

$$u = f \quad (18)$$

$$y = T3 \quad (19)$$

The System Parameters are;

A = [0, 0; 0, -(1+f)/(cp(1+f)z)] (20)

B = [0; 1] (21)

C = [0, 1] (22)

D = [0] (23)

System Matrices for GT11 Plant Model

A = [0, 0;0, -0.00087998844459618209]

B = [0; 1]

C = [0, 1]

D = [0]

System Matrices for GT12 Plant Model

A = [0, 0;0, -0.0012445291122439807]

B = [0; 1]

C = [0, 1]

D = [0]

Process and Measurement Noise Signals

The two covariance noise signals are Process Noise (*PN*) and Measurement Noise (*MN*) signals. Process noise matrix depends on the number of states. For the 2 states, the process noise will have a 2x2 Identity Matrix (*I*) to be multiplied with the Process Noise Variance (*PNV*). The measurement noise matrix on the other hand depends on the number of outputs. In this case, the measurement noise will have a 1x1 Identity Matrix (*I*) to be multiplied with the Measurement Noise Variance (*MNV*).

Process Noise for GT11 Plant Model

$$PNstd = 0.002$$

$$PNV = PNstd\hat{}2 = 0.0004$$

$$I = \begin{matrix} 1 & 0 \\ 0 & 1 \end{matrix}$$

$$Q = I * PNV \quad (24)$$

$$= \begin{matrix} 0.0004 & 0.0000 \\ 0.0000 & 0.0004 \end{matrix}$$

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Measurement Noise for GT11 Plant Model

$MNstd \quad = \quad 0.05$

$MNV \quad = \quad MNstd\text{^}2 = 0.0025$

$I \quad = \quad [1]$

$R \quad = \quad I * MNV \qquad (25)$

$\quad = \quad$ 2.5e-03

Process Noise for GT12 Plant Model

$PNstd \quad = \quad 0.06$

$PNV \quad = \quad PNstd\text{^}2 = 0.0036$

$$I = \begin{matrix} 1 & 0 \\ 0 & 1 \end{matrix}$$

$Q \quad = \quad I*PNV$

$$= \begin{matrix} 0.0036 & 0.0000 \\ 0.0000 & 0.0036 \end{matrix}$$

Measurement Noise for GT12 Plant Model

$MNstd \quad = \quad 0.05$

$MNV \quad = \quad MNstd\text{^}2 = 0.0025$

$I \quad = \quad [1]$

$R \quad = \quad I * MNV$

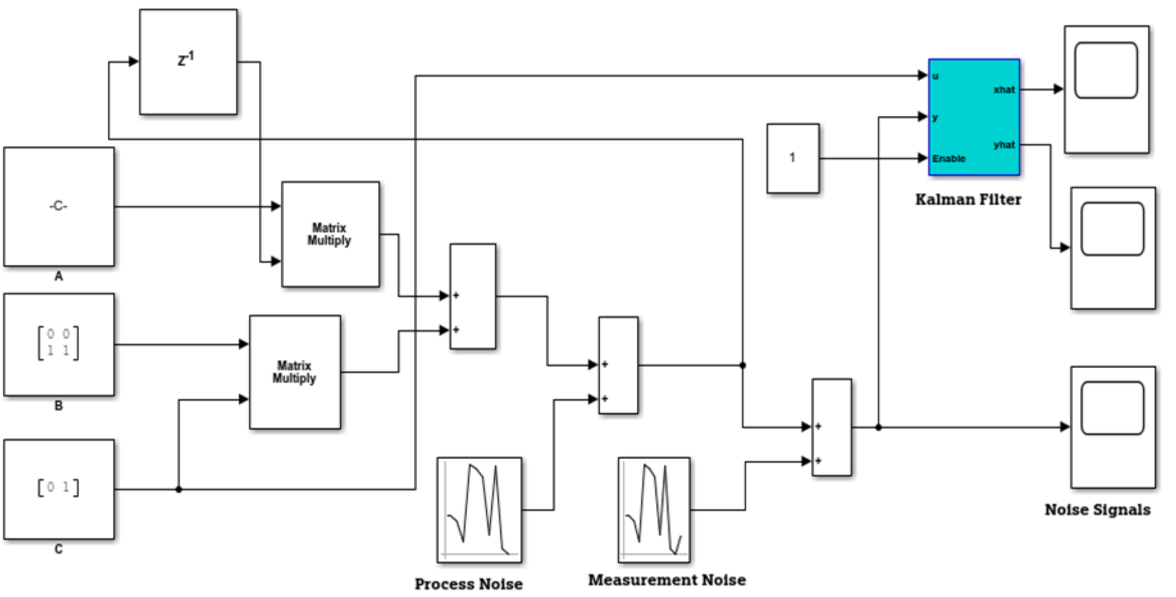
$\quad = \quad$ 2.5e-03

where;

std = Standard deviation

R = Measurement Noise Covariance Matrix

Q = Process Noise Covariance Matrix



'TITSim'

Fig 1: SIMULINK Model for Kalman Filter Implementation (I Love MATLAB, 2020)

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III. RESULTS

A. GT11 Plant Model Results:

Figure 2 is a State Space model showing the Gas Turbine Inlet Temperature (TIT) Estimation for GT11. The estimated temperature value is 1130^0C (brown), while the noise (N) signal is negligible along the X-axis (blue).

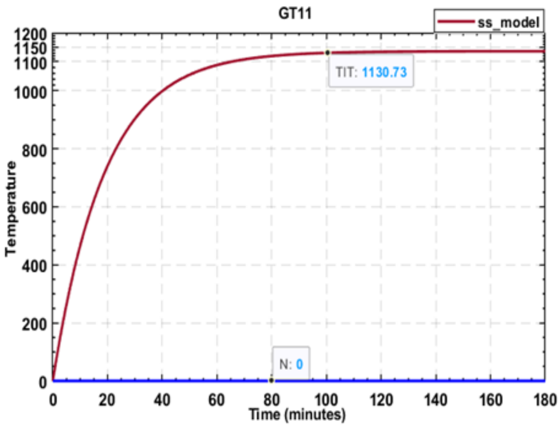

Fig. 2: Estimated Temperature for GT11

Figure 3 below is a plot showing the fictitious noise signals superimposed into the plant model before the filter action. The Measurement and Process Noise signals are represented as blue and yellow colours respectively.

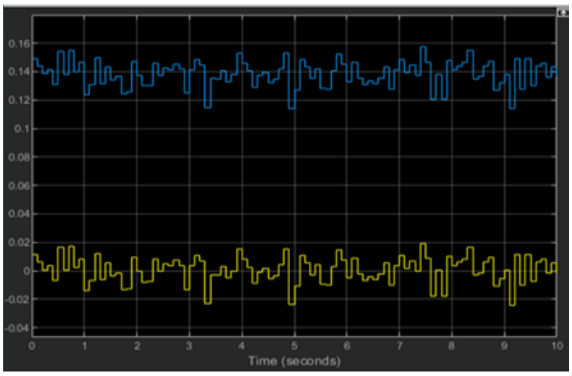

Fig. 3: Unfiltered Noise Signals for GT11.

Figure 4 below is a plot of the two noise signals for GT11 being properly filtered and decoupled from the estimated temperature. The Measurement Noise (brown) is always higher than the Process Noise (blue).

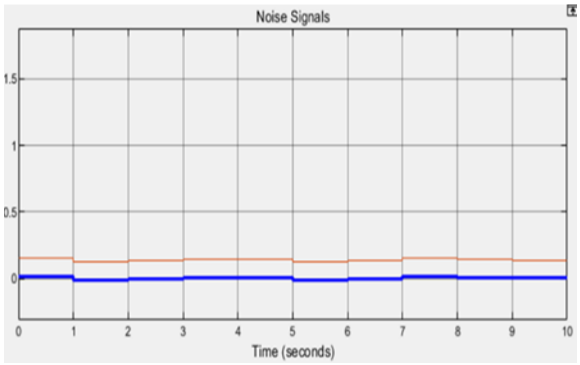

Fig. 4: Filtered Noise Signal for GT11

Kalman Filter Gain (K) and Positive Definite Matrix (P) for GT11 Plant Model.

K = (2x2)

$$\begin{matrix} 0.5370 & -0.4630 \\ -0.4630 & 0.5370 \end{matrix}$$

P = (2x2)

$$\begin{matrix} 0.0001852 & 0.0001852 \\ 0.0001852 & 0.0001852 \end{matrix}$$

B. GT12 Plant Model Results:

Figure 5 is the State Space model plot for GT12 Estimated Temperature. The Turbine Inlet Temperature estimate is 801.49^0C as indicated on the figure. Here again the Noise signals (N) have been filtered from the measurement and relegated to the background along the X-axis.

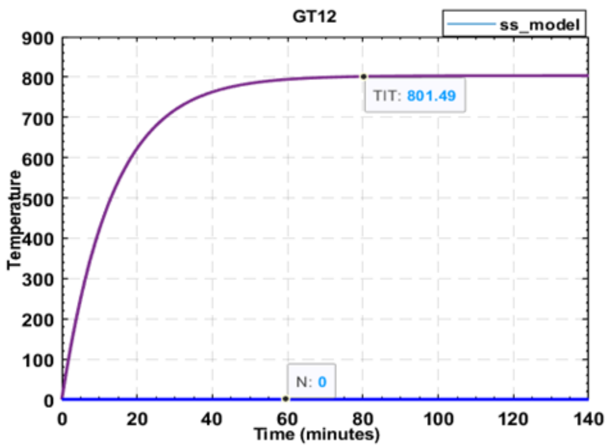

Fig. 5: Estimated Temperature for GT12

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Figure 6 is a plot showing Process Noise (blue) and Measurement Noise (yellow).

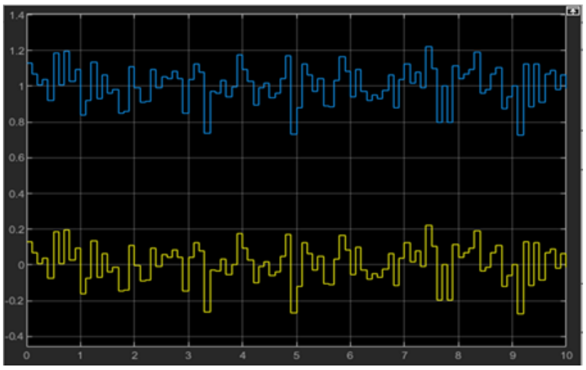

Fig. 6: Unfiltered Noise Signals for GT12

Figure 7 is a plot of the Process and Measurement Noise signals for GT12 after the Kalman Filter action.

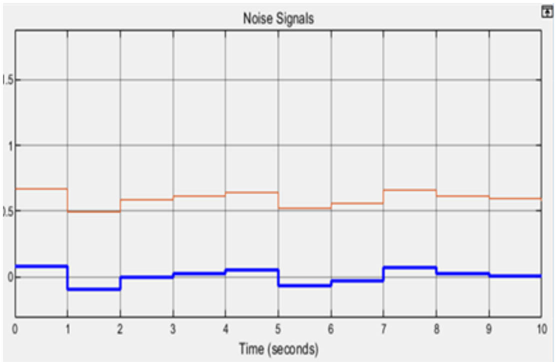

Fig. 7: Filtered Noise Signal for GT12

Kalman Filter Gain (K) and Positive Definite Matrix (P) for GT12 Plant Model

K = (2x2)

0.7093 -0.2907

-0.2907 0.7093

P = (2x2)

0.0010 0.0010

0.0010 0.0010

C. Validation of the Kalman Filter Model

Table 2 presents the numeric values obtaind both from the simulations and theoretical calculations in a comparative approach.

Table 2: Validation Table.

Plant Model	GT11 (^{0}C)	Acc. (%)	GT12 (^{0}C)	Acc. (%)
Calc.	1388	80	1200	65
Sim.	1130.73	98.1	801.49	97.2

where;

Acc. = Accuracy

Calc. = Calculated

Sim = Simulated

IV. DISCUSSIONS

Theoretical computations of the GT Inlet Temperature produced 80% and 65% accuracies for GT11 and GT12 respectively. Ordinary calculations alone cannot sufficiently estimate the unknown States of the turbulent Gas Turbine system. The noise factors cannot be addressed with the ordinary Temperature equation. Simulation results from the Kalman Filter model have shown great improvements. As obtained on the Table 2, the model achieved 98% and 97% accuracies for GT11 and GT12 respectively. Achieving this great feat was made possible by manipulating the Fuel-to-Air Ratios. In GT11, the Ratio was 1:32; while in GT12, the Ratio was maintained at 1:36. This Fuel-to-Air Ratios mean that more fuel was injected into GT11, while more air was injected into GT12 due to higher load demand for GT11. During simulations, the Filter model automatically generated its Gain (K) as well as the Positive Definite Matrix (P) needed for smooth prediction and filtering respectively. Temperature estimates attained stability at 100min and 80min for GT11 and GT12 respectively. The more the filtering capability, the more the time taken to attain stability. The unwanted signal frequencies were decoupled from the measurement earlier, and suppressed along the X-axis (time) in blue colour, as illustrated in Figure 2 and Figure 5 for GT11 and GT12 plant models respectively. It was realised that the higher the noise, the higher the values of K and P. Since more Noise signals were introduced into GT12 than GT11, the K and P matrices had higher values for GT12 than for GT11 models respectively. Figure 3 and Figure 6 represent the early stages of the Noise signals, while Figure 4 and Figure 7 illustrate their conditions after filtration.

V. CONCLUSION

To achieve accurate estimates, some trade-offs had to be performed among the parameters. This model did not introduce the Temperature After Turbine (*T2*) into its dataset as various proprietary models. The essence of obtaining two sets of plant data from GT11 and GT12 was to check the filter performance on two different instances. The Kalman Filter has responded accurately during fuel gas increase along with Compressor Discharge Temperature variations. The use of Kalman Filter model with real-time process data for estimation of Gas Turbine Inlet Temperature has been validated. In earnest, Kalman Filter is simple, accessible and closely accurate.

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