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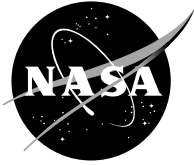
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Abstract

An approach based on the Constant Gain Extended Kalman Filter (CGEKF) technique is investigated for the in-flight estimation of non-measurable performance parameters of aircraft engines. Performance parameters, such as thrust and stall margins, provide crucial information for operating an aircraft engine in a safe and efficient manner, but they cannot be directly measured during flight. A technique to accurately estimate these parameters is, therefore, essential for further enhancement of engine operation. In this paper, a CGEKF is developed by combining an on-board engine model and a single Kalman gain matrix. In order to make the on-board engine model adaptive to the real engine's performance variations due to degradation or anomalies, the CGEKF is designed with the ability to adjust its performance through the adjustment of artificial parameters called "tuning parameters." With this design approach, the CGEKF can maintain accurate estimation performance when it is applied to aircraft engines at off-nominal conditions. The performance of the CGEKF is evaluated in a simulation environment using numerous component degradation and fault scenarios at multiple operating conditions.

Introduction

Aircraft gas turbine engines can be operated with enhanced efficiency while ensuring safe operation if performance parameters, such as thrust and compressor stall margin, are known. Since these performance parameters are not directly measurable during flight, they can only be controlled indirectly through the utilization of measurable variables in the feedback control architecture. This aspect of indirectly controlling performance parameters introduces uncertainty in the engine operation and thus necessitates that additional safety margins be preserved. As a result, aircraft engines are typically operated at conditions where more than sufficient safety margins are available, while efficiency is compromised. However, under extreme conditions and/or events, engine safety margins may also be compromised.

Accurate in-flight estimation of aircraft engine performance parameters is, therefore, desired to advance the

feedback control strategy and consequently enhance aircraft engine safety and efficiency. Some researchers have investigated the application of on-board engine models for the estimation of performance parameters (refs. 1 to 3). An on-board model can be a linear or nonlinear representation of the physical aircraft engine, and it can compute non-measurable parameters. Since an on-board model represents the "nominal" engine, it must be adapted to the performance of the real engine as it deviates from the nominal baseline with time.

A well-known approach for adapting an on-board model to an off-nominal engine is to estimate health parameters using a Kalman filter (refs. 4 to 6). Health parameters, such as efficiency and flow capacity, represent performance deteriorations of engine components. They deviate from the nominal baseline gradually with time due to normal usage and also abruptly due to component fault events. A challenging aspect of this estimation approach is that the number of health parameters is, in general, greater than the number of available sensors. Therefore, only a subset of health parameters can be estimated assuming the others remain unchanged. In reality, all health parameters will change, and this calls into question what will happen to the adapted on-board model if those health parameters not being estimated deviate from the nominal.

In previous research (ref. 7), it was shown that a Kalman filter, designed to estimate a subset of health parameters, could be used to accurately estimate engine sensor outputs even if all health parameters were subject to change. The Kalman filter maintained its accurate sensor matching performance by attributing the shifts in any health parameters to a subset of health parameters being estimated. Consequently, those estimated health parameters no longer represented the actual health parameters; they became tuning parameters to facilitate the output matching performance of the Kalman filter.

In this paper, the approach of tuning is extended to the estimation of engine performance parameters. To accurately estimate engine performance parameters, a constant gain extended Kalman filter (CGEKF) is used. The CGEKF approach (refs. 8 and 9) is similar to the general extended Kalman filter approach (ref. 10) in which a nonlinear model of the plant is used as a part of the Kalman filter. However, unlike the general approach, the linearization of the plant model and the computation of Kalman gains are done off-line. A CGEKF is formed by combining pre-computed single or multiple

Kalman gain matrices and the nonlinear model. A significant advantage of the CGEKF approach is that a large nonlinear operational range can be covered while the computational burden is much less than that of the general extended Kalman filter approach. Its stability, however, must be carefully evaluated since the problem is inherently nonlinear.

In the following sections of this paper, the CGEKF design approach is described, followed by its application to a nonlinear simulation of a large commercial aircraft engine model. Then, the stability and estimation performance of the CGEKF are evaluated in a simulation environment using numerous component degradation and fault scenarios at multiple operating conditions. Finally, a discussion regarding further design enhancement is given, followed by conclusions.

Nomenclature

BST	Booster
FAN	Fan
HPC	High Pressure Compressor
HPT	High Pressure Turbine
LPT	Low Pressure Turbine
P17	Bypass discharge pressure
P25	HPC inlet pressure
PLA	Power Lever Angle
PS3	Combustor inlet static pressure
T25	HPC inlet temperature
T3	Combustor inlet temperature
T4	Combustor temperature
T49	LPT inlet temperature
TMHS23	BST metal temperature
TMHS3	HPC metal temperature
TMHS41	HPT nozzle metal temperature
TMHS42	HPT metal temperature
TMHS5	LPT metal temperature
TMHSBC	Combustor case metal temperature
TMHSBL	Combustor liner metal temperature
VBV	Variable bleed valve
VSV	Variable stator vane
WF36	Fuel flow
XN12	Low-pressure spool speed, measured
XN25	High-pressure spool speed, measured
XNH	High-pressure spool speed, state variable
XNL	High-pressure spool speed, state variable
d	Tuning parameter vector
d_{ref}	Subset of h_{ref}
e	Environmental parameter vector
h	Health parameter vector
h_{ref}	Reference health condition vector
u_{cmd}	Control command vector
v	Sensor noise vector
x	State variable vector
y	Sensor output vector
z	Engine performance parameter vector

Development of Constant Gain Extended Kalman Filter

The overall architecture of the propulsion system integrated with a Constant Gain Extended Kalman Filter (CGEKF) is shown in figure 1. In the general control approach, the Digital Engine Control Unit (DECU) adjusts its actuator commands based on the sensor feedback measurements. Engine outputs such as spool speeds, pressures, and temperatures are measured by the sensors. Based on the information provided by the available sensors, the DECU operates the engine to meet the power demand (thrust) from the aircraft while maintaining the engine operation within the mechanical (e.g., spool speeds), thermal (e.g., combustor temperature), and aerodynamic (e.g., stall margins) limits. Since performance parameters, such as thrust, stall margins, and combustor temperature, are not directly measured during flight, they can only be inferred from the available sensor output values. Because of this aspect of indirectly controlling the performance parameters, it is difficult to operate the engine in an optimal fashion in terms of safety and efficiency.

As shown in the figure, the CGEKF uses two sets of input signals: sensor measurements and control commands. Given these inputs, the CGEKF estimates the state variables, sensor outputs, and non-measurable performance parameters. If the CGEKF is able to accurately estimate performance parameters, those estimated values can be fed into the DECU, as indicated by the dashed line, for the enhancement of engine operation.

A critical aspect in designing a CGEKF is to make it robust to off-nominal engine behavior caused by both degradation and anomalies. Component degradation is a natural phenomenon which occurs to all aircraft engines as a result of normal usage. The level of component degradation worsens gradually with time, and consequently the engine performance deviates gradually from its nominal level. Component faults similarly result in off-nominal engine performance, but they occur abruptly due to anomalous events such as foreign or domestic object damage. Sensors and actuators may also exhibit anomalous behavior due to the presence of bias and drift. Without robustness to component degradation and anomalies, it is possible to encounter a scenario where incorrect estimation by the CGEKF leads mission-critical elements (e.g., control system, flight crew) to take incorrect action.

In this paper, a CGEKF is designed so that it is robust to component degradation and component faults. Its robustness to actuator biases is also investigated. In the presence of a sensor fault, the CGEKF tends to accurately estimate all sensor outputs, including the faulty measurement, without recognizing that a fault exists. In the meantime, as a result of a sensor fault, the estimation accuracy of the performance parameters becomes poor. As such, the CGEKF is not able to handle sensor faults by itself, and therefore CGEKF performance against sensor faults is not investigated in this paper, assuming that sensor faults are handled by an in-flight sensor fault detection and isolation system. In the following section, the design process of the CGEKF is discussed in detail.

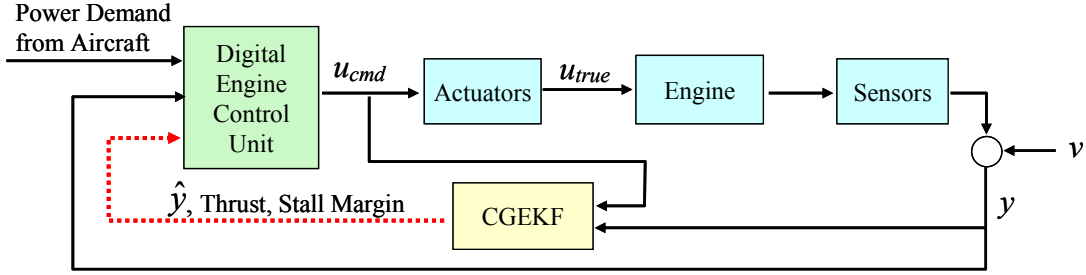


Figure 1.—Architecture of Propulsion System Integrated with CGEKF.

CGEKF Design Approach

The design approach of a CGEKF is exactly the same as that of general linear Kalman filter. First, a nonlinear plant model is linearized at operating points, and then Kalman gains are computed based on the linear representations of the plant model. When implemented, however, Kalman gains are integrated with the nonlinear model instead of linear models. The nonlinear model of an aircraft engine is represented by the following equations:

$$\begin{aligned}\dot{x} &= f(x, h, u_{cmd}, e) \\ y &= g_y(x, h, u_{cmd}, e) + v \\ z &= g_z(x, h, u_{cmd}, e)\end{aligned}\quad (1)$$

where x , h , u , and e represent the vectors of state variables, health parameters, control command inputs, and environmental parameters, respectively. A health parameter, such as compressor efficiency or flow capacity, indicates the “health” of an engine component. For given input values, the nonlinear functions f , g_y , and g_z generate the vectors of state derivatives \dot{x} , sensor outputs y , and non-measurable performance parameters z , respectively. The sensor outputs are corrupted by a white noise vector v . By linearizing the engine model, the following state-space equations are obtained:

$$\begin{aligned}\dot{x} &= A(x - x_{ss}) + L(h - h_{ref}) + B(u_{cmd} - u_{ss}) \\ y - y_{ss} &= C_y(x - x_{ss}) + M(h - h_{ref}) + D_y(u_{cmd} - u_{ss}) + v \\ z - z_{ss} &= C_z(x - x_{ss}) + N(h - h_{ref}) + D_z(u_{cmd} - u_{ss})\end{aligned}\quad (2)$$

where A , B , C_y , C_z , D_y , D_z , L , M , and N are the state-space matrices with appropriate dimensions. The subscript “ss” indicates the steady-state point at which the engine model is linearized. The vector h_{ref} represents a reference health condition. The health parameters deviate gradually or abruptly from this reference over the lifetime of engine operation. As can be seen in the above equations, health parameter deviations cause the state derivatives, sensor outputs, and performance parameters to deviate from their nominal condition values. One approach to make the estimation capability of a Kalman filter adaptive to health parameter deviations is to estimate the health parameter vector in addition to the state variable vector. If all

health parameters can be accurately estimated, the state variables, sensor outputs, and performance parameters are also accurately estimated regardless of the health parameter deviations. However, to estimate all health parameters, the number of available sensors must be at least equal to the number of health parameters (ref. 11). In general, this condition is not met, especially for commercial aircraft engines.

If the objective of utilizing a Kalman filter is to accurately estimate sensor outputs regardless of health parameter deviations, this objective can be met by estimating a subset of health parameters. In reference 7, it was shown that a Kalman filter designed to estimate a subset of health parameters actually “tuned” these selected health parameters instead of estimating their actual values in the presence of deviations in all health parameters. Through this tuning, the Kalman filter maintained its sensor output estimation accuracy. The estimated health parameters, however, no longer represented the actual health condition; they simply became tuning parameters to facilitate the output matching performance of the Kalman filter. In the present research, this tuning approach is investigated further to determine whether it will enable the Kalman filter to accurately estimate performance parameters in addition to sensor outputs.

The linear Kalman filter equation that incorporates the tuning parameters (a subset of health parameters) is given as follows:

$$\begin{aligned}\begin{bmatrix} \dot{\hat{x}} \\ \dot{\hat{d}} \end{bmatrix} &= A_{aug} \begin{bmatrix} \hat{x} - x_{ss} \\ \hat{d} - d_{ref} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} (u_{cmd} - u_{ss}) + K(y - \hat{y}) \\ \hat{y} - y_{ss} &= C_{aug} \begin{bmatrix} \hat{x} - x_{ss} \\ \hat{d} - d_{ref} \end{bmatrix} + D_y (u_{cmd} - u_{ss}) \\ \hat{z} - z_{ss} &= \begin{bmatrix} C_z & N_d \end{bmatrix} \begin{bmatrix} \hat{x} - x_{ss} \\ \hat{d} - d_{ref} \end{bmatrix} + D_z (u_{cmd} - u_{ss})\end{aligned}\quad (3)$$

where

$$A_{aug} = \begin{bmatrix} A & L_d \\ 0 & 0 \end{bmatrix}, \quad C_{aug} = \begin{bmatrix} C_y & M_d \end{bmatrix}$$

The vectors \hat{x} and \hat{y} represent the estimates of the state variables and sensor outputs, respectively. The vector d contains the tuning parameters, and d_{ref} is a subset of h_{ref}

corresponding to those tuning parameters. The matrices L_d , M_d , and N_d are selected columns of L , M , and N respectively, and their columns correspond to the tuning parameters. The matrix K represents the Kalman gain. In order for the Kalman gain to converge, the matrix pair (A_{aug}, C_{aug}) must be observable.

The linear Kalman filter is composed of a linear plant model, represented by state-space matrices and steady-state value vectors, and the corresponding Kalman gain. To construct a CGEKF, the linear plant model is simply replaced by the nonlinear model of equation (1), as shown in the following CGEKF equation:

$$\begin{aligned} \begin{bmatrix} \dot{\hat{x}} \\ \dot{\hat{d}} \end{bmatrix} &= \begin{bmatrix} f(\hat{x}, d, u_{cmd}, e) \\ 0 \end{bmatrix} + K(y - \hat{y}) \\ \hat{y} &= g_y(\hat{x}, d, u_{cmd}, e) \\ \hat{z} &= g_z(\hat{x}, d, u_{cmd}, e) \end{aligned} \quad (4)$$

As can be seen in the above equation, the tuning parameters are embedded in the Kalman filter design. If sensor outputs deviate from nominal condition values due to component degradation and/or faults, the Kalman filter will attribute the cause of sensor output deviations (i.e., deviations in health parameters) to the tuning parameters, so that the residuals $(y - \hat{y})$ will remain small.

An advantage of the CGEKF approach (eq. 4) over the linear Kalman filter approach (eq. 3) is its capability to cover a wide operating range. For the linear Kalman filter approach, a single Kalman filter cannot cover the typical range of operating conditions that aircraft engines will experience. Consequently, piece-wise Kalman filters must be designed at different operating conditions, and then they must be interpolated through scheduling parameters which indicate the specific condition at which an engine is operating at a given time. For the CGEKF approach, a single or a few Kalman gain matrices are sufficient to cover the entire engine operating envelope as indicated in reference 9. This is a significant advantage in terms of design complexity.

Moreover, the CGEKF approach can capture the nonlinearity of aircraft engine operation under the influence of anomalies. For instance, when an engine experiences component faults, the control system adjusts the actuator positions based on the sensor feedback measurements in order to meet its objective (e.g., to maintain fan speed at the commanded value). Because of this control adjustment, in addition to component faults, the engine moves to a new operating condition which may be a significant deviation from the nominal condition. Piece-wise linear Kalman filters, designed along the operating line of the nominal condition, can not capture such off-nominal behavior of an aircraft engine due to closed-loop control effects in the presence of anomalies (ref. 7).

The CGEKF approach, however, also has disadvantages. The CGEKF is much more computationally intensive than the linear approach since the nonlinear plant model must be executed in real-time. Moreover, the nonlinear approach may

not be as numerically robust as the linear approach as mentioned in reference 9. Therefore, the stability of the CGEKF must be carefully evaluated. In the following sections, the CGEKF approach is applied to the nonlinear simulation of a large commercial aircraft engine, and its performance and stability are evaluated.

Application of CGEKF Technique to an Aircraft Engine Simulation

In this section, the CGEKF technique is applied to an aircraft engine simulation. A description of the engine simulation is given first. Then the CGEKF design-specific issues are discussed.

Engine Model

The engine model used in this paper is a nonlinear simulation of an advanced high-bypass turbofan engine, a typical power plant for large commercial aircraft. This engine model has been constructed as a Component Level Model (CLM), which consists of the major components of an aircraft engine. The CLM represents highly complex engine physics while having the capability to run in real-time. Engine performance deviations from the nominal baseline are modeled by adjustments to efficiency and flow capacity scalars of the following five components: Fan (FAN), Booster (BST), High-Pressure Compressor (HPC), High-Pressure Turbine (HPT), and Low-Pressure Turbine (LPT). A total of 10 adjustments are called health parameters. These health parameters are used to represent component degradation and faults. The engine state variables, health parameters, actuator variables, environmental parameters, and performance parameters are shown in table 1.

There are two sets of sensor suites to be used in this study. These two sets are shown in table 2 along with the standard deviation of the sensor noise given in percent of steady-state values at the ground maximum power condition.

TABLE 1.—ENGINE MODEL VARIABLES

State Variables	XNL, XNH, TMHS23, TMHS3 TMHSBL, TMHSBC, TMHS41 TMHS42, TMHS5
Health Parameters	FAN efficiency, FAN flow capacity BST efficiency, BST flow capacity HPC efficiency, HPC flow capacity HPT efficiency, HPT flow capacity LPT efficiency, LPT flow capacity
Actuators	WF36, VBV, VSV
Environmental Parameters	Altitude, Mach Number Ambient Temperature
Performance Parameters	Thrust, FAN stall margin, BST stall margin, HPC stall margin, T4

Sensor set no. 1 is the standard sensor suite available to the digital engine control unit of this engine. Sensor set no. 2 is composed of sensor set no. 1 and one additional sensor: P17.

TABLE 2.—SENSOR SETS AND SENSOR STANDARD DEVIATION (σ IN PERCENT OF STEADY-STATE VALUES AT GROUND MAXIMUM POWER CONDITION)

Sensor Set no. 1	Sensor Set no. 2	σ (%)
XN12	XN12	0.25
XN25	XN25	0.25
-----	P17	0.50
P25	P25	0.50
T25	T25	0.75
PS3	PS3	0.50
T3	T3	0.75
T49	T49	0.75

During a preliminary study of a linear Kalman filter design, it was found that the P17 sensor is crucial to relate FAN component performance to thrust. Without this sensor, a linear Kalman filter was not able to generate an accurate thrust estimate when the health parameters for the FAN component were shifted. Therefore, there is a limit on the achievable accuracy for thrust estimation if sensor set no. 1 is used. Sensor set no. 2 is used to investigate the benefits of having the P17 sensor.

Engine control is performed based on sensor set no. 1 (i.e., the P17 sensor has no influence on control action). For the major portion of a typical flight profile, the corrected low-pressure spool speed is regulated by the control system. In the current control architecture, the power level angle (PLA) is converted to desired corrected low-pressure spool speed (an indicator of thrust). The control system adjusts three actuation values to cause the corrected measured low-pressure spool speed to match the desired value.

Kalman Gain Design Condition

A steady-state Kalman gain is computed based on state-space matrices derived at a specific operating point. Single or multiple Kalman gain matrices generated off-line are then used to construct a CGEKF. In this paper, a single Kalman gain matrix is used. The major significance of the CGEKF approach is that, as shown by Safonov et al. (ref. 8), a non-divergent nonlinear estimator can be designed for systems with substantial nonlinearity even when a relatively crude linear representation is used for computing a Kalman gain. The non-divergence proof in reference 8 is derived based on the assumption that the plant model varies as a function of known or observed variables. In the present paper, the true plant varies as a function of health parameters, but the plant model uses a subset of health parameters which are “tuned” rather than “estimated.” Therefore, the operating condition of the plant model will differ from that of the true plant, thus violating the previously stated assumption. However, the powerful non-divergence aspect of the CGEKF approach is investigated empirically by covering a wide operating range just using a single Kalman gain matrix. The design operating point for computing the Kalman gain is set to the ground maximum power condition as was done by Sugiyama (ref. 9), while the reference health condition (h_{ref} in eq. 2) is set to the nominal or

“healthy” baseline. It should be noted that the selection of design condition is left to engineering judgment, and the performance of the CGEKF will vary with selected design conditions.

Selection of Tuning Parameters

The selection of tuning parameters is a critical part in the CGEKF design process. It is desirable to find a subset of health parameters which can capture the major influence of all 10 health parameters. The selection of tuning parameters for the case of engine-to-engine variation (i.e., relatively small deviations in all health parameters) was investigated by Brunell et al. (ref. 12). In this reference, an index, which indicates the level of observability and sensitivity, was determined for each health parameter through singular value decomposition of state-space matrices (eq. 2). Based on the index values, a subset of health parameters to be estimated was selected. The same technique was applied in the present paper; however, some issues were encountered. First, a subset of health parameters selected from this approach varied significantly with operating point. Since a wide operating range is covered by a CGEKF, it is difficult to determine a “global” subset of health parameters from the current approach. Another issue that needs to be considered is the highly nonlinear aspect of the present problem. In the present problem where component degradation and faults are considered, all health parameters are shifted beyond the level of engine-to-engine variation. When a subset of health parameters is estimated in the presence of such relatively large shifts, the estimated values often become large and exceed the linear range. The approach based on singular value decomposition of state-space matrices is not able to capture this nonlinear aspect of the problem. Therefore, some engineering judgment is still needed to select tuning parameters.

Table 3 shows the two sets of tuning parameters for the CGEKF designed with sensor sets no. 1 and 2. It can be seen that the CGEKF design with sensor set no. 1 does not use the health parameters of the FAN component. During a preliminary evaluation of the CGEKF performance, it was noted that the use of either FAN health parameter as a tuning parameter causes instability when component degradation is present. Without the P17 sensor, it appears that the CGEKF is not able to converge either FAN health parameter to a steady-state condition, and consequently the system becomes unstable.

TABLE 3.—TUNING PARAMETERS FOR TWO CGEKF DESIGNS

CGEKF Design with Sensor Set no. 1	CGEKF Design with Sensor Set no. 2
BST flow	FAN flow
HPC efficiency	BST flow
HPC flow	HPC efficiency
HPT efficiency	HPC flow
HPT flow	HPT efficiency
LPT flow	HPT flow
	LPT flow

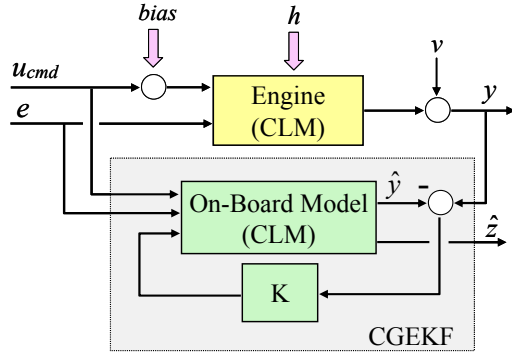


Figure 2.—Simulation Setup for CGEKF Evaluation.

Implementation of CGEKF in the Simulation Environment

The simulation setup to run the CGEKF is shown in figure 2. The nonlinear engine model (CLM) is used to represent both actual engine and on-board model. Off-nominal health conditions of an actual engine are modeled by shifting all 10 health parameters of the nonlinear engine model from the healthy baseline. It is assumed that the health condition of the actual engine is unknown. The reference health condition of the on-board model is set to the healthy baseline at which a Kalman gain was computed. (Again, the selection of the reference health condition is up to the designer.) The CGEKF is implemented by integrating the “healthy” on-board model and the single Kalman gain matrix. When the CGEKF is applied to the nonlinear engine model at off-nominal health conditions, the on-board model is adapted to the performance of the “degraded” engine through the adjustment of tuning parameters. In addition to component degradation, actuator biases can also be injected to simulate off-nominal operation. The nonlinear engine model and the CGEKF are set to run in a discrete fashion with a 0.02-second time step.

Performance Evaluation of CGEKF

In this section, the stability and the estimation accuracy of the CGEKF are evaluated. The evaluation is conducted first at the nominal condition and then at various off-nominal conditions. As shown in figure 2, off-nominal conditions are modeled by the following two types of engine variation sources: 1) component degradation, and 2) actuator biases. For each engine variation source type, 100 cases are created by randomly shifting the vector elements of health parameters and actuator biases. For each case, the nonlinear engine model and the CGEKF are run through ground-idle, takeoff, climb and then cruise phases of a typical flight (Altitude: 0.0 ~ 35,000 ft, Mach: 0.0 ~ 0.84). The flight duration is 2500 seconds. Stability of the CGEKF is evaluated through a total of 200 simulation runs (2 engine variation source types × 100 cases) of the typical flight profile.

Estimation accuracy of the CGEKF at off-nominal conditions is also evaluated using the same 100 cases for each

engine variation source type. For each run, a 100-second time history of the estimation error is taken from each of the ground-idle, climb, and cruise phases. Using 100-second time histories from 100 cases, the mean and the maximum estimation errors are computed.

At the end of this section, the responses of the CGEKF to abrupt shifts in health parameters (component faults) are investigated.

Evaluation 1: Engine at the Healthy Condition

The CGEKF is first applied to the nonlinear engine model at the healthy condition (no component degradation). The estimation performance of the CGEKF of this nominal case establishes the baseline with which the performance at off-nominal cases can be compared. For the evaluation of the estimation accuracy, the following absolute percent estimation errors are computed for the sensor outputs and the engine performance parameters:

$$y_{error} = 100 \cdot \left| \frac{\hat{y} - y_{true}}{y_{true}} \right| \quad (5)$$

$$z_{error} = 100 \cdot \left| \frac{\hat{z} - z_{true}}{z_{true}} \right|$$

where the vectors y_{true} and z_{true} are true engine outputs (no noise) and performance parameters, respectively, generated by the engine model. A 100-second time history of the absolute estimation error is taken from each of the ground-idle, climb, and cruise phases of the typical flight profile. Then, the mean and the maximum of absolute percent estimation errors are computed for each 100-second segment. The result of the estimation performance is shown in table 4 for the two CGEKF designs using sensor sets no. 1 and 2.

It can be seen that both CGEKF designs accurately estimate the sensor outputs. Since both the nonlinear engine model and CGEKF are set to the nominal health condition, the estimation error is due to the sensor noise. The largest maximum sensor output estimation errors for sensor set no. 1 and 2 are 0.44 percent (T3) and 0.52 percent (T49), respectively. For the performance parameters, both CGEKF designs accurately estimate thrust, FAN stall margin, and T4. It can be seen that the estimates of BST and HPC stall margins are not as accurate as those of the other performance parameters.

The estimation accuracy varies with the operating condition, and this variation is due to two factors. First of all, the true values used in equation (5) for normalization vary with operating condition. For instance, XN12 is higher at cruise than at ground-idle. Thus, a smaller percent estimation error in the cruise phase versus the ground-idle phase does not mean that the actual error is smaller. The second factor is that the Kalman gain was computed at a specific operating point: ground maximum power condition. None of the three operating conditions used in the evaluation exactly match the design point. The ambient condition of the ground-idle is identical to

TABLE 4.—MEAN AND MAXIMUM ABSOLUTE PERCENT ESTIMATION ERROR FOR HEALTHY ENGINE (MAXIMUM ERROR IN PARENTHESES)

	CGEKF Design with Sensor Set no. 1			CGEKF Design with Sensor Set no. 2		
	ground	climb	cruise	ground	climb	cruise
XN12	0.05 (0.25)	0.02 (0.08)	0.02 (0.09)	0.06 (0.28)	0.02 (0.07)	0.02 (0.08)
XN2	0.02 (0.09)	0.03 (0.09)	0.02 (0.07)	0.02 (0.08)	0.03 (0.10)	0.02 (0.08)
P17	-----	-----	-----	0.01 (0.02)	0.04 (0.13)	0.04 (0.15)
P25	0.02 (0.04)	0.06 (0.22)	0.06 (0.27)	0.03 (0.08)	0.07 (0.25)	0.08 (0.31)
T25	0.02 (0.07)	0.02 (0.07)	0.02 (0.10)	0.02 (0.08)	0.02 (0.08)	0.03 (0.11)
PS3	0.09 (0.37)	0.08 (0.29)	0.08 (0.31)	0.07 (0.19)	0.06 (0.22)	0.05 (0.19)
T3	0.08 (0.44)	0.08 (0.32)	0.08 (0.34)	0.09 (0.49)	0.09 (0.34)	0.09 (0.36)
T49	0.08 (0.41)	0.06 (0.24)	0.07 (0.27)	0.11 (0.52)	0.08 (0.29)	0.08 (0.35)
Thrust	0.08 (0.43)	0.03 (0.14)	0.03 (0.12)	0.19 (0.64)	0.05 (0.22)	0.06 (0.21)
FAN Stall Margin	0.03 (0.13)	0.16 (0.57)	0.15 (0.63)	0.10 (0.40)	0.21 (0.71)	0.21 (0.89)
BST Stall Margin	0.30 (1.09)	1.19 (4.74)	1.21 (5.17)	0.47 (1.69)	1.38 (5.36)	1.46 (6.04)
HPC Stall Margin	1.04 (4.97)	1.17 (4.77)	1.24 (5.19)	0.93 (4.62)	1.20 (4.80)	1.24 (5.06)
T4	0.11 (0.55)	0.08 (0.34)	0.09 (0.36)	0.13 (0.65)	0.10 (0.39)	0.10 (0.41)

the design point, but the power setting of the design point is closest to that of the climb phase.

Evaluation 2: Engine at Degraded Conditions

All health parameters of an aircraft engine deviate from the healthy baseline with time due to wear and tear on engine components. In the real environment, the level of such deviations will differ from engine to engine depending on how and where an engine was operated. In this section, the CGEKF is applied to the nonlinear engine model at degraded conditions. One hundred degradation cases are created by randomly shifting all 10 health parameters. The deviation values are uniformly distributed over the range from 1 to 5 percent, and this level of deviation is beyond the typical level of engine-to-engine variation due to manufacturing tolerance. With a given degradation, the nonlinear engine model is run through the typical flight profile described earlier. The given degradation is fixed throughout the flight. Since degradation causes shifts in the sensor outputs and the control system uses the sensor outputs to adjust its commands, the closed-loop system response is unique for each degradation case.

When applied to a degraded engine, the estimates of the CGEKF upon initialization do not match the actual values because the CGEKF has been designed for an engine at the healthy condition. This mismatch results in large residuals

$(y - \hat{y})$, and the CGEKF tries to reduce the residuals by adjusting tuning parameters. If the CGEKF is able to maintain small residuals throughout the flight profile, it means that the influence of component degradation can be captured by tuning parameter adjustments at any point along the operating path. For 100 degradation cases, the CGEKF was stable throughout the flight profile. Thus, the influence of component degradation was successfully captured to the level where stability is maintained.

The CGEKF maintained its stability under the influence of component degradation. However, it is reasonable to expect that the level of estimation accuracy will become worse, compared to the estimation accuracy of the nominal condition case, unless the influence of component degradation is completely accounted for. To investigate estimation performance, the estimation accuracy of the CGEKF is evaluated through the following process. From each degradation case, a 100-second time history of the absolute estimation error in equation (5) is taken from each of the ground-idle, climb, and cruise phases. Then, the mean and the maximum of absolute percent estimation errors of 100 degradation cases, each of which consists of a 100-second time history, are computed for each flight segment. The result of the estimation performance is shown in table 5 for the two CGEKF designs using sensor sets no. 1 and 2.

Again, both CGEKF designs are successful in accurately estimating sensor outputs. The largest maximum sensor output

TABLE 5.—MEAN AND MAXIMUM ABSOLUTE PERCENT ESTIMATION ERROR FOR 100 CASES OF DEGRADED ENGINES (MAXIMUM ERROR IN PARENTHESES)

	CGEKF Design with Sensor Set no. 1			CGEKF Design with Sensor Set no. 2		
	ground	climb	cruise	ground	climb	cruise
XN12	0.05 (0.24)	0.02 (0.09)	0.02 (0.10)	0.05 (0.27)	0.02 (0.07)	0.01 (0.07)
XN2	0.02 (0.10)	0.03 (0.15)	0.02 (0.10)	0.02 (0.10)	0.02 (0.16)	0.02 (0.09)
P17	---	---	---	0.01 (0.03)	0.04 (0.17)	0.05 (0.21)
P25	0.02 (0.07)	0.07 (0.30)	0.06 (0.28)	0.03 (0.09)	0.06 (0.33)	0.07 (0.31)
T25	0.04 (0.11)	0.42 (0.80)	0.34 (0.67)	0.04 (0.12)	0.42 (0.79)	0.34 (0.66)
PS3	0.08 (0.36)	0.07 (0.34)	0.07 (0.29)	0.08 (0.32)	0.04 (0.31)	0.04 (0.18)
T3	0.08 (0.45)	0.08 (0.37)	0.08 (0.37)	0.09 (0.50)	0.08 (0.39)	0.09 (0.39)
T49	0.08 (0.45)	0.06 (0.27)	0.06 (0.30)	0.10 (0.56)	0.07 (0.30)	0.07 (0.35)
Thrust	1.47 (2.96)	3.44 (6.88)	2.91 (5.80)	0.20 (0.66)	0.08 (0.43)	0.07 (0.31)
FAN Stall Margin	0.77 (1.47)	5.92 (12.29)	4.88 (10.15)	0.11 (0.47)	0.74 (2.12)	0.77 (2.13)
BST Stall Margin	0.32 (1.58)	2.08 (11.61)	1.72 (10.62)	0.47 (1.69)	2.13 (12.47)	1.83 (11.58)
HPC Stall Margin	1.07 (5.98)	3.11 (10.11)	2.49 (8.57)	0.94 (5.45)	3.10 (10.22)	2.48 (8.58)
T4	0.10 (0.57)	0.10 (0.40)	0.09 (0.39)	0.12 (0.68)	0.10 (0.44)	0.10 (0.43)

estimation errors for sensor set no. 1 and 2 are 0.80 percent (T25) and 0.79 percent (T25), respectively. The benefit of having the P17 sensor can be seen in the estimation accuracy of thrust and FAN stall margin. Especially for thrust estimation, the level of estimation accuracy under degraded conditions is comparable to that of the healthy engine case. As mentioned earlier, the P17 sensor is crucial for relating the FAN performance to thrust. Without this sensor, the estimation accuracy that the CGEKF can achieve is limited.

The estimation accuracy for BST and HPC stall margins gets worse compared to the healthy engine case. The difficulty of estimating these stall margins may be due to the fact that the sensors and the tuning parameters being used are not appropriate. In the current CGEKF approach, 10 health parameters are mapped into a subset of health parameters (tuning parameters) through the matching of sensor output estimates to the measurements. Since the influence of 10 health parameters can not be fully captured by the tuning parameters, some information is lost in the reconstruction of the performance parameter estimates. It is considered that the lost information is critical for the estimation of BST and HPC stall margins.

Although some of the performance parameters are not accurately estimated, those estimates with high accuracy have some potential to improve the engine performance through their utilization in the control algorithm. For instance, with the spool-speed control used in this study, degradation causes deviation in thrust from the nominal target value. This thrust

deviation is about 2 percent on average at steady-state cruise conditions. Since the average thrust estimation error for the CGEKF design with sensor set no. 2 (0.07% in table 5) is much smaller than the average thrust deviation, direct control of estimated thrust can result in better thrust tracking performance than the spool-speed control. Through direct thrust control, benefits such as avoiding asymmetric thrust can be achieved.

Evaluation 3: Healthy Engine with Biased Actuators

In the real environment, there are many elements, other than those health parameters considered in this paper, which deviate from their nominal baseline conditions over the lifetime of engine operation. Some examples of such elements are seal leakage, combustor efficiency, and actuator biases. (Sensor biases are not considered here, as discussed earlier.) These elements can cause the engine to operate at off-nominal conditions, but they are not directly accounted for in the current CGEKF design process. In this section, actuator biases are used to evaluate the CGEKF performance at off-nominal conditions other than those “anticipated” off-nominal conditions due to component degradation and/or faults.

One hundred cases of actuator anomalies are created by randomly selecting the bias values for three actuators. The bias values are uniformly distributed over the range of ± 10 percent of the steady-state actuator command values at the ground-idle condition. With a given set of actuator biases, the

TABLE 6.—MEAN AND MAXIMUM ABSOLUTE PERCENT ESTIMATION ERROR FOR 100 CASES OF HEALTHY ENGINE WITH BIASED ACTUATORS (MAXIMUM ERROR IN PARENTHESES)

	CGEKF Design with Sensor Set no.1			CGEKF Design with Sensor Set no.2		
	ground	climb	cruise	ground	climb	cruise
XN12	0.05 (0.26)	0.02 (0.09)	0.02 (0.11)	0.06 (0.30)	0.02 (0.09)	0.02 (0.10)
XN2	0.02 (0.09)	0.03 (0.17)	0.02 (0.11)	0.02 (0.09)	0.03 (0.18)	0.03 (0.14)
P17	---	---	---	0.01 (0.02)	0.04 (0.14)	0.04 (0.18)
P25	0.02 (0.07)	0.06 (0.30)	0.06 (0.31)	0.03 (0.11)	0.07 (0.35)	0.08 (0.37)
T25	0.02 (0.12)	0.02 (0.12)	0.03 (0.14)	0.02 (0.13)	0.03 (0.12)	0.03 (0.15)
PS3	0.08 (0.40)	0.08 (0.34)	0.09 (0.36)	0.07 (0.32)	0.06 (0.33)	0.06 (0.26)
T3	0.08 (0.45)	0.08 (0.35)	0.08 (0.34)	0.09 (0.49)	0.09 (0.36)	0.09 (0.36)
T49	0.08 (0.50)	0.06 (0.25)	0.07 (0.29)	0.11 (0.63)	0.08 (0.30)	0.08 (0.37)
Thrust	0.59 (1.64)	0.40 (0.96)	0.89 (1.89)	0.76 (2.06)	0.47 (1.15)	1.01 (2.22)
FAN Stall	1.00	0.48	0.89	1.08	0.37	0.65
Margin	(2.11)	(1.55)	(2.43)	(2.49)	(1.37)	(2.12)
BST Stall	6.54	7.49	12.16	6.53	7.52	12.18
Margin	(17.05)	(23.36)	(42.54)	(17.58)	(23.83)	(43.34)
HPC Stall	25.02	4.99	10.64	25.02	5.00	10.64
Margin	(54.43)	(15.33)	(26.15)	(54.24)	(15.39)	(25.97)
T4	0.11 (0.68)	0.10 (0.49)	0.10 (0.45)	0.14 (0.80)	0.11 (0.53)	0.11 (0.49)

nonlinear engine model is run through the typical flight profile described earlier. The biases are kept constant throughout the flight.

When applied to the healthy engine with biased actuators, the estimates of the CGEKF upon initialization do not match the actual values because the CGEKF has been designed for an engine at the nominal condition where no actuator bias is present. Again, this mismatch results in large residuals $(y - \hat{y})$, and the CGEKF tries to reduce the residuals by adjusting tuning parameters. If the CGEKF is able to maintain small residuals throughout the flight profile, it means that the influence of actuator biases can be captured by tuning parameter adjustments at any point along the operating path. For 100 cases of actuator anomalies, the CGEKF was stable throughout the flight profile.

The estimation accuracy of the CGEKF is evaluated using the same process described in the previous section for the degraded engine case. From each actuator anomaly case, a 100-second time history of the estimation errors is taken from each of the ground-idle, climb, and cruise phases. Then, the mean and the maximum of absolute percent estimation errors of 100 anomaly cases, each of which consists of a 100-second time history, are computed for each flight segment. The result of the estimation performance is shown in table 6 for the two CGEKF designs using sensor sets no. 1 and 2.

Both CGEKF designs are successful in accurately estimating sensor outputs. This ability to accurately estimate sensor outputs in the presence of actuator biases was also observed in reference 7 where the piece-wise linear Kalman filters with tuning parameters were designed at a cruise condition. The largest maximum estimation errors for sensor set no. 1 and 2 are 0.5 percent (T49) and 0.63 percent (T49), respectively.

The level of estimation accuracy for thrust, FAN stall margin, and T4 is still fairly good. For actuator anomaly cases, the benefit of having the additional P17 sensor can not be observed. This is understandable since the P17 sensor measures bypass pressure while the actuators mainly influence core operation. The estimation accuracy for BST and HPC stall margins are much worse than in the degraded engine case. As discussed in the previous section, the combination of sensors and tuning parameters being used may not be appropriate for the estimation of BST and HPC stall margins. Moreover, these stall margins are very sensitive to the VBV and VSV actuator positions, and the influence of the actuator biases can not fully be captured by the tuning parameters.

It should be noted that the actuator bias terms could have been treated as tuning parameters, as long as the number of tuning parameters does not exceed the number of sensors. Through such an implementation, the estimation accuracy of

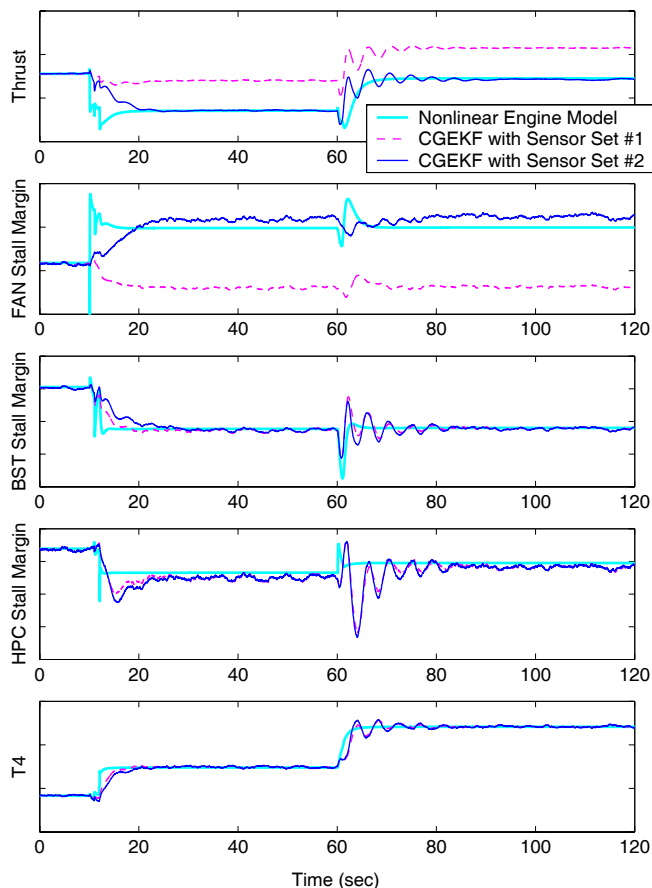


Figure 3.—Responses of Nonlinear Engine Model and CGEKF Designs to Component Faults.

the CGEKF may be improved. However, it is impossible to treat all elements that can deviate from the nominal as tuning parameters. The result in this section reveals the performance of the CGEKF when it encounters unanticipated off-nominal conditions.

Evaluation 4: CGEKF Response to Component Faults

The CGEKF was evaluated in the previous sections using constant off-nominal engine variation sources; component degradation and actuator biases were constant throughout the flight profile. In this section, the CGEKF response to component faults is investigated. A component fault is modeled by abruptly shifting the health parameters of an engine component. Similar to the case of component degradation, the sensor outputs will shift from their nominal condition values when an engine experiences component faults. The shifts in sensor outputs cause the control system to adjust its commands, so the closed-loop system will move to a new operating condition through a transient period. During the transient operation, the CGEKF must remain stable.

This test is done at ground-idle, climb, and cruise operating conditions. Each of the 10 health parameters is

abruptly shifted by 5 percent from the healthy baseline sequentially over a time interval of 5 seconds. A 5 percent abrupt shift in all health parameters represents quite severe damage to an engine, and such a scenario may never happen in the real environment. However, this scenario of severe damage is used to check the stability of the CGEKF.

At three operating conditions, both CGEKF designs with sensor sets no. 1 and 2 were stable. Figure 3 shows the time history of the responses generated by the nonlinear engine model and two CGEKF designs with sensor sets no. 1 and 2 at the cruise condition. In this particular case, the health parameters of the FAN, BST, and HPC components were abruptly shifted sequentially in the time interval between 10 and 12 seconds, and the health parameters of the HPT and LPT components were abruptly shifted sequentially in the time interval between 60 and 61 seconds. At the cruise condition, the control system tries to maintain the corrected low-spool speed at the demanded condition. As discussed before, the CGEKF designed with sensor set no. 1 is not able to accurately estimate thrust and FAN stall margin when the health parameters for the FAN component are shifted. The CGEKF design with sensor set no. 2 exhibits accurate estimation performance. This difference in the estimation accuracy indicates the significance of the P17 sensor for estimating thrust.

Discussion

The evaluation of the CGEKF performance in the previous section indicated the effectiveness of using tuning parameters for the adaptation of the on-board model to aircraft engines at off-nominal conditions. Through the adjustment of tuning parameters, the CGEKF accurately estimated sensor outputs in the presence of component degradation or actuator anomalies. This ability to maintain accurate estimation performance at off-nominal conditions was also extended to the estimation of the performance parameters. Without using tuning parameters, any mismatch between the actual engine and the on-board model will corrupt the estimation performance. To validate this point, the evaluation in the previous section was repeated for the “general” CGEKF which was designed with no tuning parameters. The general CGEKF performed better than the “adaptive” CGEKF when it was applied to the nonlinear engine model at the healthy condition. However, when the general CGEKF was applied to the nonlinear engine model at off-nominal conditions, its estimation performance became significantly worse: both sensor outputs and performance parameters were poorly estimated. Unlike the adaptive CGEKF, the general design does not have any freedom to adjust itself in the presence of component degradation or anomalies, and thus the influence of such off-nominal engine-variation sources directly effect estimation performance.

Although the CGEKF demonstrated its capability to maintain stability and estimate both measurable and non-measurable engine parameters, further investigation is needed

to improve the CGEKF performance. During the evaluation of the CGEKF, it was noted that the accuracy of performance parameter estimation is influenced by the sensors and tuning parameters used. In the current problem where in-flight application is pursued, the sensors to be used may be limited to those sensors currently implemented. However, the designer does have freedom in the selection of tuning parameters. The tuning parameters used in this paper were selected based on engineering judgment, and the non-divergence property was shown empirically to be maintained with appropriate tuning parameters. It is desirable to develop an analytical approach to find an optimal set of tuning parameters that will maintain the non-divergence property and minimize the estimation errors for a given set of sensors.

Other areas for investigation that may help to improve the estimation accuracy include the optimal selection of the Kalman gain design point, or the utilization of multiple Kalman gain matrices. It was observed in the evaluation results that the estimation accuracy of the CGEKF varies with operating condition. The variation in the estimation accuracy is partially due to the fact that a single Kalman gain matrix designed at a specific operating condition was used. In this paper, the ground maximum power condition was used as the design point. It is reasonable to consider that this selected design point may not be the optimal point at which estimation errors over the flight envelope are minimized. Thus, it is desirable to repeat the evaluation process using Kalman gains computed at different design points and then to assess the influence of the design points on the CGEKF performance. Through such an investigation, the optimal design point may be determined. An alternative approach which may also improve the CGEKF performance is the utilization of multiple Kalman gain matrices. By using multiple Kalman gain matrices, each of which provides best estimation performance at its design point, the CGEKF performance over the entire flight envelope may be improved. Since this approach increases the design complexity, such as selection of appropriate design points and interpolation of multiple Kalman gain matrices, the trade-offs between the increased complexity and the performance improvement must be studied.

Finally, it should be noted that the performance level that the CGEKF can achieve is limited by the available sensors. For instance, it was shown that the CGEKF was not able to accurately estimate thrust without the P17 sensor. If the ability to accurately estimate thrust outweighs the cost of sensor installation, the P17 sensor may be added or may replace an existing engine sensor.

Conclusion

An approach based on the Constant Gain Extended Kalman Filter (CGEKF) technique was investigated for the in-flight estimation of non-measurable performance parameters of aircraft engines. A CGEKF was developed by combining an on-board engine model and a single Kalman gain matrix. In

order to make the on-board engine model adaptive to a real engine whose performance will deviate from the nominal baseline over its lifetime of operation, the CGEKF was designed with the ability to adjust its performance through the adjustment of artificial parameters called “tuning parameters.” With this design approach, the CGEKF attributes any component performance deviations due to degradation and/or faults to tuning parameters so that it can maintain accurate estimation performance at off-nominal health conditions.

The evaluation of the CGEKF performance was conducted in a simulation environment using a nonlinear simulation of a large commercial aircraft engine model. The stability and estimation accuracy of the CGEKF were evaluated at multiple operating points using component degradation, actuator biases, and component faults. The CGEKF exhibited excellent stability. Despite the fact that the Kalman gain was designed at a specific operating point, the CGEKF was stable throughout a typical flight profile. The CGEKF was also able to estimate the performance parameters with fairly good accuracy at off-nominal health conditions. Some performance parameters such as thrust and combustor temperature were estimated with higher accuracy than the others. It is considered that the difference in the estimation accuracy is strongly affected by the sensors and tuning parameters being used. To further improve the estimation performance of the CGEKF, a technique to select an optimal set of tuning parameters is desired.

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