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INTERACTING MULTIPLE MODEL–BASED ESTIMATION OF AIRSPEED AND ALTITUDE FROM PITOT–STATIC MEASUREMENTS

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Abstract: *The accurate estimation of aircraft airspeed and altitude using Pitot–static systems is essential for reliable flight control and navigation. Conventional estimation methods, such as the Extended Kalman Filter (EKF), inherently rely on a single dynamic model and may exhibit degraded performance in the presence of sensor degradation and time-varying measurement disturbances. This motivates the development of estimation algorithms capable of accommodating multiple operating conditions.*
This paper investigates an Interacting Multiple Model (IMM) estimator for air-data parameter reconstruction from the Pitot–static measurements. The estimator combines multiple Extended Kalman Filters, each associated with a specific sensor operating condition, including nominal operation, pressure bias, and sensor drift. A mathematical model of the Pitot–static system is developed, incorporating sensor dynamics, measurement noise, bias, and drift effects. The IMM algorithm is implemented in the MATLAB environment and evaluated under representative aircraft flight scenarios.
The performance of the proposed IMM estimator is evaluated through Monte Carlo simulations and compared with that of a conventional EKF estimator. The obtained results demonstrate that the IMM algorithm achieves improved estimation accuracy in the presence of sensor bias and drift while maintaining reliable estimation of flight parameters under different operating conditions. The obtained results indicate the applicability of IMM-based estimation for the improvement of ADC robustness against sensor degradation, while maintaining reliable air-data parameter estimation.

Keywords: *Air Data Computer, Pitot–static system, Extended Kalman Filter, Interacting Multiple Model, Air-data estimation.*

1. INTRODUCTION

The Pitot–static system represents a critical measurement subsystem in an aircraft, providing air-data information required for flight control, navigation, and other avionics functions. Modern aircraft and unmanned aerial vehicles increasingly employ Micro-Electro-Mechanical Systems (MEMS) sensors to perform pressure and temperature measurements due to their compact size, the low power consumption, and compatibility with digital processing architectures. The measurements of static pressure, total pressure, and outside air temperature are processed by the Air Data Computer (ADC) to determine fundamental flight parameters, including airspeed, altitude, vertical speed, and air density [1], [2].

Regardless of these advantages, MEMS-based air-data measurements remain sensitive to several error sources that directly affect estimation accuracy. The most relevant error sources include measurement noise, temperature dependency, sensor bias, long-term drift, nonlinear sensor characteristics, and dynamic effects which are introduced by the pneumatic response of the Pitot–static installation. Furthermore, environmental influences such as vibration, moisture, and partial blockage of the sensing system may degrade measurement quality and reduce the reliability of the estimated air-data parameters [3].

The Air Data Computer integrates measurements from Pitot–static and temperature sensors by employing digital processing and estimation algorithms in order to provide reliable air-data information for aircraft systems. Previous studies have demonstrated the importance of analytical modeling of Pitot–static sensor faults and the estimation-based approaches for the improvement of fault tolerance and reduction of measurement degradation impact [4]–[6]. Among available estimation techniques, the EKF estimator is widely used in nonlinear state estimation applications because of it's capability to handle nonlinear system models with moderate computational complexity. However, the EKF estimator is generally designed around a predefined system model and may experience degraded performance when measurement characteristics or system behavior change due to sensor degradation or abnormal (i.e. unexpected) operating conditions.

To overcome the limitations associated with single-model estimation, multiple-model approaches have also been investigated for systems that are characterized by varying operating conditions. Among these, the IMM algorithm

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represents an established framework for the adaptive state estimation. The IMM algorithm employs several parallel estimators associated with the different system models and updates model probabilities according to consistency between the predicted and the measured outputs, with a goal to facilitate adaptation to changes in system behavior [7]. The theoretical foundation of the IMM approach was introduced by Blom and Bar-Shalom for the systems with Markovian switching parameters, while the subsequent developments extended these multiple-model estimation techniques for variable-structure systems [8], [9].

Previous studies have shown that IMM-based estimators can improve robustness in systems affected by the model uncertainty and changing measurement conditions [10], [11]. Comparative investigations of multiple-model EKF approaches have also shown that estimator performance strongly depends on correct model definition, transition probability selection, and process noise tuning [12].

Although IMM-based algorithms have been extensively investigated in applications such as maneuvering target tracking, navigation, and multi-sensor data fusion, their application to Pitot–static air-data estimation with the explicit representation of sensor bias and drift effects has received considerably less attention. In particular, the development of IMM-based estimators that explicitly incorporate sensor bias and drift models within the air-data measurement process has received less attention. Therefore, this represents an important research direction since these degradation mechanisms may directly affect the accuracy and the reliability of ADC outputs.

The main contribution of this work is the development and evaluation of an IMM-based estimator specifically adapted for Pitot–static air-data processing with explicit representation of pressure sensor bias and drift. The proposed approach employs a bank of Extended Kalman Filters representing different sensor operating conditions, including nominal operation, pressure measurement bias, and sensor drift. A mathematical model of the Pitot–static system is developed that incorporates pneumatic sensor dynamics, measurement noise, pressure measurement bias, and drift characteristics. The proposed estimator is implemented in MATLAB and evaluated through Monte Carlo simulations, while its performance is compared with a conventional EKF estimator. The obtained results provide a methodological basis for a further development of robust Air Data Computer estimation algorithms that are capable to maintain improved accuracy under the degraded sensor conditions.

2. PITOT–STATIC SYSTEM MODEL AND SIMULATION FRAMEWORK

2.1. Mathematical Model of the Pitot–Static System and Air-Data Parameter Computation

A mathematical model of the Pitot–static system was established to generate reference air-data parameters and simulate sensor measurements corresponding to ADC operation. The developed model establishes a relationship between flight conditions, atmospheric parameters, and the outputs of the pressure and temperature sensors. The atmospheric parameters were calculated according to the International Standard Atmosphere model [13]. The air temperature at a given altitude is thus defined as:

$$T = T_0 - Lh, \tag{1}$$

where T_0 represents the standard temperature at sea level, L is the temperature lapse rate, and h is the flight altitude. The static pressure is then calculated using the barometric equation:

$$p_s = p_0\left(\frac{T}{T_0}\right)^{\frac{g}{RL}}, \tag{2}$$

where p_0 denotes the standard sea-level pressure, R is the specific gas constant of air, and g represents gravitational acceleration. Based on this, the air density is obtained from the ideal gas relationship:

$$\rho = \frac{p_s}{RT_{at}}. \tag{3}$$

The total pressure measured by the Pitot tube is defined as the sum of static and dynamic pressure:

$$p_t = p_s + \rho\frac{V^2}{2}, \tag{4}$$

where V denotes the true airspeed value. The air-data parameters used for estimator evaluation are calculated from the simulated measurements, while the altitude is obtained from the inverse barometric relationship:

$$h = \frac{T_0}{L}\left[1 - \left(\frac{P_s}{p_0}\right)^{\frac{RL}{g}}\right]. \tag{5}$$

The dynamic pressure is determined as difference of total and static pressure, while the airspeed is calculated as:

$$V = \sqrt{\frac{2q}{\rho}}. \tag{6}$$

The vertical speed is obtained by using the numerical differentiation of the estimated altitude:

$$V_z = \frac{dh}{dt}. \tag{6}$$

The calculated air-data parameters are subsequently used as the reference quantities in order to adequately evaluate the performance of the EKF and IMM estimators.

2.2. Sensor Measurement Model and Representation of Operating Modes

The accuracy of a Pitot–static measurement system is influenced by several non-ideal effects, including sensor response delay, measurement noise, systematic offsets,

and long-term variations. In this work, a specific sensor measurement model was developed to represent different operating conditions required for IMM-based estimation.

The dynamic response of the pressure measurement channels was represented by a first-order system:

$$p_{dyn}(k) = p_{dyn}(k-1) + \frac{\Delta t}{\tau}\left(p_{true}(k) - p_{dyn}(k-1)\right), \quad (7)$$

where p_{true} represents the ideal pressure value, p_{dyn} is the dynamically filtered sensor output, τ represents the sensor response time constant, and Δt is the sampling interval.

The measured pressure value is defined as:

$$p_{meas} = p_{dyn} + b + d + n, \quad (8)$$

where b represents sensor bias, d represents sensor drift, and n denotes a measurement noise. The measurement noise is modeled as a zero-mean Gaussian process, and the sensor bias is represented as a slowly varying offset:

$$b(k) = b(k-1) + w_b(k), \quad (9)$$

where $w_b(k)$ represents the bias process noise. The long-term sensor drift is modelled by using a random-walk process:

$$d(k) = b(k-1) + w_d(k), \quad (10)$$

where $w_d(k)$ represents the drift process noise.

The IMM-based models differ not only due to the process noise covariance tuning but also due to the assumed sensor degradation dynamics. To enable IMM operation, three sensor operating modes are defined:

- Model 1 – Nominal operating mode, which represents normal sensor operation, and includes measurement noise and dynamic response effects only;
- Model 2 – Bias mode, which represents the sensor condition that is characterized by a constant pressure measurement offset. In simulation used in this work, the pressure bias of 50 Pa is introduced in the time period between 200 s and 300 s; and
- Model 3 – Drift mode, which is used in this work to represent the gradual sensor degradation after 350 s of simulation time. The drift component is generated using a random-walk process in order to reproduce slowly varying sensor characteristics.

The beforehand defined operating modes provide a physical interpretation of the IMM model set and enable adaptive selection between different sensor conditions.

2.3. Simulation Configuration and Measurement Data Generation

An appropriate MATLAB-based simulation environment was developed to evaluate the proposed IMM estimator. A simulation process includes the flight trajectory model, atmospheric calculations, Pitot–static sensor dynamics, measurement noise, and the sensor degradation scenarios.

The total time duration of each simulation is $T_{sim} = 600$ s with the sampling interval defined as $\Delta t = 0.01$ s. The used flight trajectory consists of several climb, level-flight, and descent segments, where altitude and airspeed variations are independently defined according to the selected flight profile.

Based on the generated flight conditions, reference values of altitude, airspeed, temperature, static pressure, and total pressure are calculated. The pneumatic response of the Pitot–static system is represented by first-order dynamics with a different time constants for the pressure channels $\tau_{ps} = 0.1$ s for the static pressure channel and $\tau_{pt} = 0.5$ s for the total pressure channel. The measurement noise is introduced as a Gaussian process with the following standard deviations $\sigma_{ps} = 10$ Pa, $\sigma_{pt} = 5$ Pa and $\sigma_T = 0.5$ K.

The generated sensor measurements are then additionally processed using a second-order Butterworth low-pass filter with a cutoff frequency of 2 Hz to reduce a high-frequency measurement disturbances.

The resulting measurement data are then used as inputs for the both EKF and IMM estimators. Their performance is evaluated under the nominal conditions and during the sensor degradation scenarios that involve bias and drift effects.

The Figure 1 illustrates the simulated and reference Pitot–static sensor outputs used as input data for the evaluation of the EKF and IMM estimators.

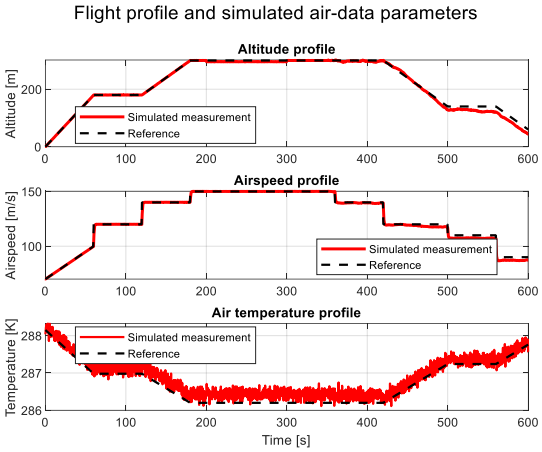


Figure 1. Flight profile and simulated reference air-data parameters used in the Pitot–static system model

3. EXTENDED KALMAN FILTER AND INTERACTING MULTIPLE MODEL ESTIMATION ALGORITHM

3.1. Extended Kalman Filter Formulation for Air-Data Estimation

The Extended Kalman Filter (EKF) is used as a baseline estimator for the evaluation of performance improvement achieved by using the proposed IMM approach. The EKF provides the nonlinear state estimation by linearizing the process and measurement models around the current

operating point. In this work, the estimation is performed directly using Pitot–static pressure measurements, while derived air-data parameters are then obtained from the estimated states. This approach avoids additional filtering of calculated quantities and thus preserves the physical relationships between altitude, airspeed, and atmospheric parameters.

The state vector of the EKF is defined as:

$$\mathbf{x}_k = [h_k \quad V_k \quad T_k \quad b_{p_s,k} \quad b_{p_t,k}], \tag{11}$$

where h_k represents altitude, V_k is airspeed, T_k is air temperature, while b_{ps} and b_{pt} denote the biases of the static and the total pressure sensors, respectively. The nonlinear state transition model is expressed as:

$$\mathbf{x}_k = f(x_{k-1}) + \omega_k, \tag{12}$$

where w_k represents the process noise with covariance matrix **Q**. The flight parameters are assumed to remain constant within a single sampling interval, while the pressure sensor biases are modeled as slowly varying stochastic processes $b_{ps,k} = b_{ps,k}+w_{bps}$ and $b_{pt,k} = b_{pt,k}+w_{bts}$. The measurement vector is defined using the directly available Pitot–static sensor outputs:

$$\mathbf{z}_k = [p_{s,k} \quad p_{t,k} \quad T_k], \tag{13}$$

and the nonlinear measurement equation is given by:

$$\mathbf{z}_k = h(x_k) + \upsilon_k, \tag{14}$$

where v_k represents zero-mean Gaussian measurement noise with covariance matrix **R**.
The EKF prediction step is performed according to:

$$\begin{aligned} \hat{\mathbf{x}}_{k|k-1} &= f(\hat{\mathbf{x}}_{k-1}), \\ \mathbf{P}_{k|k-1} &= \mathbf{F}_k \mathbf{P}_{k-1} \mathbf{F}_k^T + \mathbf{Q}, \end{aligned} \tag{15}$$

where $\mathbf{F}_k$ is the state transition Jacobian matrix. Since the selected process model assumes that the flight parameters remain constant within the same sampling interval, while sensor biases follow a random-walk process, the state transition matrix is approximated by the identity matrix. The measurement update is calculated using the Kalman gain:

$$\mathbf{K_k} = \mathbf{P}_{k|k-1}\mathbf{H}_k^T \left[\mathbf{H}_k \mathbf{P}_{k-1} \mathbf{H}_k^T + \mathbf{R_k}\right]^{-1} \tag{16}$$

where $\mathbf{H}_k$ represents the measurement Jacobian matrix defined as:

$$\mathbf{H}_k = \begin{bmatrix} \frac{\partial p_s}{\partial h} & 0 & 0 & -1 & 0 \\ \frac{\partial p_t}{\partial h} & \frac{\partial p_t}{\partial V} & \frac{\partial p_t}{\partial T} & 0 & -1 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \tag{17}$$

where $\frac{\partial p_t}{\partial h} = \frac{\partial p_s}{\partial h} + \frac{1}{2}V^2 \frac{\partial \rho}{\partial h}$, $\frac{\partial \rho}{\partial h} = \frac{1}{RT}\frac{\partial p_s}{\partial h}$ and $\frac{\partial p_s}{\partial V} = \rho V$, $\frac{\partial p_s}{\partial h} = -\frac{g}{RT} p_s$,

The updated state estimate is obtained as:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{z}_k - h(\mathbf{x}_{k|k-1})), \tag{18}$$

while the covariance matrix is updated according to:

$$\mathbf{P_k} = (\mathbf{I} - \mathbf{K_k}\mathbf{H}_k)\mathbf{P}_{k|k-1}. \tag{19}$$

The EKF estimator described above represents the single-model estimation approach used as a reference for the comparison with the proposed IMM estimator.

3.2. Interacting Multiple Model Estimator Configuration

The IMM estimator is introduced as an extension of the single-model EKF approach described in the previous section. Unlike the conventional EKF, which assumes a fixed system behavior, the IMM algorithm employs a bank of parallel EKF estimators with the different process noise characteristics in order to represent possible (i.e. here observed) sensor operating conditions.
In this work, three beforehand defined operating modes of the Pitot–static system are considered, which correspond to the nominal operation, sensor bias, and sensor drift conditions. In each mode the EKF formulation presented in Section 3.1 is employed, while a different process noise covariance matrices $\mathbf{Q}_1$ $\mathbf{Q}_2$, and $\mathbf{Q}_3$ are assigned in order to adjust the estimator sensitivity to the corresponding sensor behavior.
The IMM model set is therefore defined as:

$$\mathbf{M} = \{M_1 \quad M_2 \quad M_3\}, \tag{20}$$

where each model has an associated EKF estimator and model probability μ_i. The transition between operating modes is described by the Markov transition probability matrix:

$$\mathbf{\Pi} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{bmatrix}, \tag{21}$$

where π_{ij} represents the probability of transition from model i at the previous time step to model j at the current time step.

At each sampling instant, the IMM estimator performs state interaction, model-conditioned EKF filtering, model probability update, and fusion of individual estimates. In the interaction step, the initial conditions for each EKF are obtained by combining the state estimates and the covariance matrices from all models according to their previous probabilities and the Markov transition matrix. The predicted probability of model j is calculated as:

$$c_j(k) = \sum_{i=1}^{N} \pi_{ij}\mu_i(k-1), \tag{22}$$

where μ_i(k−1) denotes the probability of model i at the previous time step. Corresponding mixing probabilities are determined by:

$$\mu_{ij}(k) = \frac{\pi_{ij}\mu_i(k-1)}{c_j(k)}. \tag{23}$$

These probabilities are used to compute the mixed initial state and covariance for each EKF prior to the prediction and correction steps described in Section 3.1. After the EKF update, the consistency of each model with the current measurements is evaluated using the innovation vector and innovation covariance. The likelihood function of the j-th model is calculated as:

$$\Lambda_j(k) = \frac{1}{\sqrt{(2\pi)^m |S_j(k)|}} \exp(D), \qquad D = -\frac{1}{2} \nu_j^T(k) S_j^{-1}(k) \nu_j(k), \tag{24}$$

where $\nu_j(k)$ is the innovation vector, $S_j(k)$ is the innovation covariance matrix, and m denotes the dimension of the measurement vector. The model probabilities are then updated according to Bayes' rule:

$$\mu_j(k) = \frac{\Lambda_j(k) c_j(k)}{\sum_{i=1}^{N} \Lambda_i(k) c_i(k)}. \tag{25}$$

Finally, the overall IMM estimate is obtained as the weighted combination of the individual EKF estimates:

$$\hat{\mathbf{x}}_{IMM}(k) = \sum_{i=1}^{N} \mu_j(k) \hat{x}_j(k), \tag{25}$$

while the corresponding covariance matrix is computed as

$$\mathbf{P}_{IMM}(k) = \sum_{i=1}^{N} \mu_j(k)\mathbf{E}, \qquad \mathbf{E} = \mathbf{P}_j(k) + \left(\hat{\mathbf{x}}_j(k) - \hat{\mathbf{x}}_{IMM}(k)\right)\left(\hat{\mathbf{x}}_j(k) - \hat{\mathbf{x}}_{IMM}(k)\right)^T. \tag{26}$$

The resulting model probabilities provide an indication of the most likely sensor operating condition at the each sampling instant, while weighted state estimate combines the advantages of all candidate models. Consequently, the here proposed IMM estimator preserves the estimation accuracy during the nominal operation, and also improves robustness under sensor bias and drift conditions.

The numerical values of the process noise covariance matrices, transition probability matrix, and initial model probabilities used in the simulations are presented in the following section.

4. SIMULATION RESULTS AND DISCUSSION

For the statistical evaluation of the proposed IMM estimator, 100 Monte Carlo simulation runs have been performed under the nominal operating conditions as well as in the presence of sensor bias and sensor drift, using different realizations of process and measurement noise. The simulation parameters adopted throughout this study are summarized in Table 1.

Table 1. Simulation parameters

Parameter	Value
P_0	diag(10^2,10^2,1^2,50^2,50^2)
R	diag(10^2,5^2,0.5^2)
Q_1	diag(0.5^2,0.2^2,0.05^2,0.01^2,0.01^2)
Q_2	diag(0.5^2,0.2^2,0.05^2,1.5^2,1.5^2)
Q_3	diag(0.5^2,0.2^2,0.05^2,0.05^2,0.05^2)
μ_0	$[0.98,0.01,0.01]^T$
Π	[0.995 0.004 0.001; 0.010 0.985 0.005: 0.005 0.010 0.985]

Figure 2 shows that both estimators accurately follow the reference altitude and velocity during nominal operation. However, in the presence of sensor degradation, the IMM estimator achieves better agreement with the reference values compared with the EKF. Unlike the single-model EKF estimator, the IMM estimator adapts the estimation process according to the most probable sensor operating condition, and thus reduce the influence of bias and drift effects.

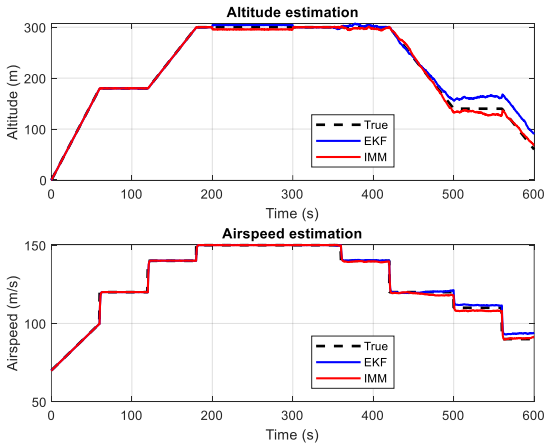


Figure 2. Comparison of EKF and IMM estimates

The Monte Carlo simulation results presented in Figure 3 confirm the robustness of the proposed IMM estimator. For all the analyzed parameters, here proposed IMM approach achieves the lower root mean square error (RMSE) values when compared with the EKF estimator, with the most significant improvements being obtained in case of the altitude estimation.

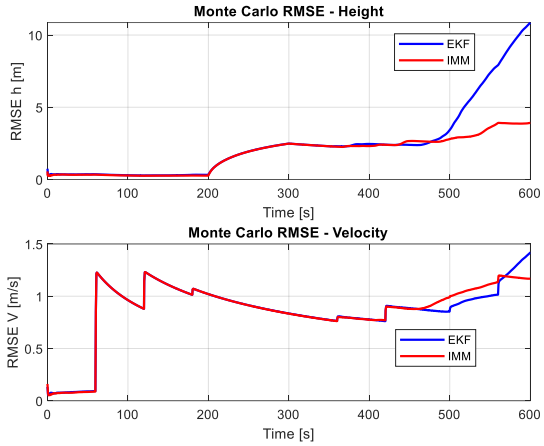


Figure 3. RMSE comparison obtained from Monte Carlo simulations

The quantitative comparison that is presented in Table 2 confirms the advantages of here proposed IMM estimator over the conventional EKF estimator approach. The lower RMSE values are achieved for all analyzed parameters, which indicates the improved estimation accuracy while algorithm stability is also maintained. It shuld be stressed, that the most significant improvement is observed in the case of altitude estimation, which confirms effectiveness of here observed multi-model approach under the sensor degradation conditions.

Table 2. RMSE comparison

State	EKF RMSE	IMM RMSE	Improvement
Altitude (m)	2.4433	1.7859	26.9%
Airspeed (m/s)	0.8669	0.7742	8.3%

5. CONCLUSION

This paper presents an air data parameter estimator based on the IMM algorithm and a bank of EKFs for the different operating regimes of a pitot-static system. The proposed approach includes nominal operation, sensor bias, and drift models, with the adaptive mode selection based on the estimated model probabilities.

The observed nonlinear Pitot–static system model include sensor dynamics, measurement noise, bias, and drift effects that were used for estimator evaluation. The obtained Monte Carlo simulations results show that the IMM approach reduces estimation errors compared with the conventional EKF while preserving stable operation under degraded sensor conditions. Our future work will focus on incorporating additional degradation models and validation of the proposed approach by using real-time experimental flight test data.

Acknowledgments

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