Immunity-based Flight Envelope Prediction at Post-failure Conditions

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Abstract:

This paper presents the development of a biologically-inspired methodology for flight envelope prediction at post failure conditions. The flight envelope is understood in its most general meaning as the hyper-space of all achievable or desirable relevant variables. The new ranges of these variables at post-failure conditions are the outcomes of the prediction process. Specific algorithms are proposed depending on the affected sub-system and the nature and characteristics of the failure. Actuator, sensor, propulsion system, and structural failures are considered. The proposed methodology is integrated with immunity-based failure detection and identification and benefits from the capabilities of the artificial immune system to address directly the complexity and multidimensionality of aircraft dynamic response in the context of abnormal conditions. A hierarchical multi-self strategy is used, in which low-dimensional projections replace the hyperspace of the self thus avoiding numerical and conceptual issues related to the high-dimensionality of the problem. The methodology is illustrated through numerical examples of envelope prediction under elevator locked failure, yaw rate sensor bias, locked throttle, and partially missing horizontal tail.

I. Introduction

Significant research efforts have been focused in the past few years on the development of flight envelope estimation and protection methodologies for aircraft under damage/failure conditions. These efforts were typically addressing isolated specific problems, considering only a reduced number of aircraft dynamic parameters, and performing abnormal condition evaluation or envelope estimation in a limited manner, mostly outside the general context, which also includes abnormal condition detection, identification, and accommodation. Techniques based on obstacle avoidance for prediction of envelope violation have been proposed [1], within which the control/command margins are estimated by forcing a set of limit parameters to track an adaptive safe-trajectory near the limit boundary. Adaptive flight envelope estimation based on on-line learning neural networks has also been investigated and demonstrated with NASA's Generalized Transport Model aircraft in which the command limits of the controller were constantly adapted to allow the aircraft to fly close to its limit boundary under actuator failures [2]. Analytical methods to identify the aerodynamic performance degradation and its impact on the dynamic flight envelope [3] were proposed and demonstrated for different wing/tail lifting surface damage scenarios. Adaptive control laws have been developed to maintain a structurally damaged aircraft within allowable limits and suppress the dynamic structural mode interaction with the flight control system [4]. Reachable sets and the region-of-attraction analysis have been used for flight envelope assessment [5]. The impact of icing on the performance and its mitigation through increased pilot situational awareness have also been investigated [6].

Addressing the problem of aircraft safe operation under abnormal conditions (AC) in a comprehensive manner [7] involves considering the flight envelope with a generalized meaning, as the hyperspace of all achievable or desirable relevant variables in conjunction with the nature and characteristics of the AC. The flight envelope prediction at post-failure conditions can be viewed as part of a more general AC evaluation process, which includes several distinct aspects such as determining the type of the failure (direct qualitative evaluation) and its magnitude or severity (direct quantitative evaluation). In this context, flight envelope prediction can be defined as an AC indirect quantitative evaluation. Successful flight envelope prediction requires previous AC detection, identification, and direct evaluation.

A highly effective, integrated, and comprehensive solution to the problem of maintaining control of the aircraft and perform the mission at abnormal flight conditions can only be achieved through a holistic approach that considers the multitude of factors involved (aircraft sub-system abnormalities, external hazards, pilot abnormal conditions, aircraft upset conditions), their variability, versatility, and uncertainty [8, 9]. The resulting complexity and multi-dimensionality is enormous. Therefore, an integrated and comprehensive solution to the off-nominal condition detection, identification, evaluation, and accommodation problem for aerospace vehicles requires adequate strategies and tools.

The artificial immune system (AIS) emerged in recent years as a new computational paradigm in artificial intelligence with a variety of applications in areas such as anomaly detection, data mining, computer security, adaptive control, and pattern recognition [10]. Immunity-based fault detection schemes that discriminate between abnormal and normal conditions have been developed [11] inspired by the operation of the biological immune system, which detects exogenous antigens while not reacting to self cells. The versatility, adaptability, and regulatory capabilities of the immune system have inspired the formulation of a comprehensive and integrated immunity-based framework for aircraft abnormal condition detection, identification, evaluation, and accommodation [7,12]. Methodologies for AIS-based detection and identification of a wide variety of aircraft sub-system failures/damages have been designed and implemented [13-15] at West Virginia University (WVU). High-performance AIS-based failure detection and identification schemes have been demonstrated to be capable of handling several categories of sub-system abnormal conditions in flight on a reduced size platform [16]. Testing of the schemes over extended areas of the flight envelope has also been performed successfully [17]. The potential of the AIS paradigm for flight envelope reduction assessment at post-failure conditions has also been investigated with promising results [18].

In this paper, the development of a biologically-inspired methodology for generalized flight envelope prediction at post failure conditions is presented. The prediction process consists of determining ranges of relevant variables at post-failure conditions. Specific algorithms are formulated for several types of actuator, sensor, propulsion system, and structural failures. The proposed methodology is integrated with immunity-based failure detection and identification and benefits from the capabilities of the artificial immune system to address directly the complexity and multi-dimensionality of aircraft dynamic response in the context of abnormal conditions. A hierarchical multi-self strategy is used, in which low-dimensional projections replace the hyperspace of the self thus avoiding numerical and conceptual issues related to the high-dimensionality of the problem.

The general problem of flight envelope prediction is formulated in Section II. A brief description of the AIS paradigm is provided in Section III. The issue of integrating abnormal condition detection, identification, and evaluation within the AIS paradigm is addressed in Section IV. Algorithms for flight envelope prediction under actuator, sensor, propulsion and structure failures are presented in Sections V through VIII, respectively. Example results are discussed in Section IX. Finally, some conclusions are summarized in Section X, followed by acknowledgements and a bibliographical list.

II. Flight Envelope Prediction at Post-failure Conditions

For the purpose of this research effort, the flight envelope is defined as the hyper-space of all achievable or desirable values of a set $\mathcal{E}$ of *envelope relevant variables* (ERV) v_E . Therefore:

$$\mathcal{E} = \{v_{Ei} \mid i = 1, 2, \dots, N_E\} \quad (1)$$

Let the *feature variables* or shortly *features* be the variables φ_i that completely define the entire system. The set of all features can be expressed as:

$$\mathcal{F} = \{\varphi_i \mid i = 1, 2, \dots, N\} \quad \text{and} \quad \mathcal{E} \subset \mathcal{F} \quad (2)$$

The definition of the feature set $\mathcal{F}$ is a critical element of the AIS implementation. The features must capture the dynamic fingerprint of normal system operation as well as the dynamic fingerprint of all failures considered. For example, the features considered for the purpose of this paper are listed in Table 1.

Table 1. Feature Set

Feature	Description	Feature	Description
H	Altitude	d_e	Longitudinal stick displacement
V	Aircraft ground speed	d_a	Lateral stick displacement
M	Mach number	d_r	Pedal displacement
a_x	Longitudinal acceleration	d_T	Pilot throttle
a_y	Lateral acceleration	p_{ref}	Roll rate command
a_z	Vertical acceleration	q_{ref}	Pitch rate command
α	Angle of attack	r_{ref}	Yaw rate command
β	Sideslip angle	NN_{outp}	Roll acceleration error
ϕ	Roll attitude angle	NN_{outq}	Pitch acceleration error
θ	Pitch attitude angle	NN_{outr}	Yaw acceleration error
p	Roll rate	$MQEE$	Main quadratic estimation error [18]
q	Pitch rate	$OQEE$	Output quadratic estimation error [18]
r	Yaw rate	$DQEE_p$	Decentralized quadratic roll rate estimation error [18]
$\dot{p}$	Roll acceleration	$DQEE_q$	Decentralized quadratic pitch rate estimation error [18]
$\dot{q}$	Pitch acceleration	$DQEE_r$	Decentralized quadratic yaw rate estimation error [18]
$\dot{r}$	Yaw acceleration		

Let the border hyper-surface of the system operating at normal conditions be:

$$\Sigma(\varphi_1, \varphi_2, \dots, \varphi_N) = 0 \quad (3)$$

Let us restrict the definition of the flight envelope at normal conditions to the set of ranges $[v_{Ei \min}, v_{Ei \max}]$ of all envelope variables. If the projection of surface Σ along the axis k defined by φ_k is denoted as $P(\Sigma(\varphi_k))$, then:

$$P(\Sigma(\varphi_k)) = [v_{Ek \min}, v_{Ek \max}] \quad (4)$$

Note that, in general, these ranges can be defined as functions of one or several features. For example, the range of v_{Ek} may be a function of feature φ_l . The projection of surface Σ on the plane (k, l) defined by φ_k and φ_l can be denoted as $P(\Sigma(\varphi_k, \varphi_l))$ and represents the variation of the range $[v_{Ek \min}, v_{Ek \max}]$ with φ_l . The flight envelope at abnormal conditions is then defined as the set of ranges of all ERVs at post-failure conditions: $[v_{Ei \min F}, v_{Ei \max F}]$.

Definition: A *directly involved variable* (DIV) v_δ in the AC is a variable whose alteration or abnormal variation is directly and significantly the result of the AC. They may be part of the feature set or not. If they are not, then a relationship between the DIV and some other variable(s) in the feature set must be established. These variables are referred to as *equivalent directly involved variables* (EDIV), v_ε . For example, consider the case of the left elevator locked failure. The DIV can be defined as the left stab deflection δ_{eL} . It obviously defines the failure; however, it may not necessarily be part of the feature set. Let us assume that the longitudinal stick displacement d_e is part of the feature set. Then we need to formulate a relationship between the left elevator deflection δ_{eL} and the longitudinal stick displacement d_e , or the EDIV, of the form:

$$d_e = f(\delta_{eL}) \quad (5)$$

For each failure considered, a set of variables v_E must be determined that are affected by the failure, that are part of the feature set, and that are flight envelope relevant variables. These variables are the subject of the envelope prediction process. In Table 2, a typical list is provided as an example for a set of AC considered within this paper.

Table 2. AC Evaluation Analysis

k_F	Type of Failure	DIV v_δ	EDIV v_ε	Envelope var. v_E
1	Locked elevator	Elevator deflection	Longitudinal stick displacement	$H, M, q, p, \dot{q}$
2	Yaw rate sensor bias	Yaw rate	Pedals displacement	$r, \dot{r}, \beta$
3	Horizontal tail damage	Horizontal tail lift	Longitudinal and lateral stick displacement	$H, M, p, q, \dot{p}, \dot{q}$
4	Reduced effectiveness	Engine thrust	Pilot throttle	a_x, a_z, r, H, M

The set of all features considered for evaluation purposes $\mathcal{F}_E$ will be:

$$\mathcal{F}_E = \{H, M, p, q, r, a_x, a_z, \dot{p}, \dot{q}, \dot{r}, \beta\} = \bigcup_i v_{Ei} \quad i = 1, 2, \dots, N_F \quad (6)$$

In the example presented in this paper, the total number of features considered for evaluation purposes (i.e. flight envelope alteration assessment) is $N_E = 11$. Total number of features is $N = 31$ and the total number of AC considered is $N_F = 4$.

III. The Artificial Immune System Paradigm

The biological immune system (BIS) provides a very complex, highly adaptive, and effective protection of the host organism from external intruders or antigens, such as viruses, bacteria, parasites, etc. The BIS consists of two components: the innate and the adaptive system. The innate system functions as the first line of defense against foreign entities. Through a process known as self/non-self discrimination - in which exogenous entities are referred to as *non-self* while everything belonging to the host organism is known as *self* - the BIS is able to detect antigens while not reacting to the self cells. The self/non-self discrimination process relies on specialized cells called phagocytes. These cells react to biochemical markers of external intruders that differ from the host's biochemical markers. Therefore, the generation of the immunity specialized cells is classified as a negative selection process [19]. The phagocytes transfer information about the antigens to lymph nodes where lymphocytes (T-cells and B-cells) are generated. The lymphocytes, the main component of the adaptive immune system, mark antigens for destruction through cytotoxic T-cells. Figure 1 illustrates this mechanism.

The BIS is the inspiration for the AIS, which mimics the self/non-self discrimination process in order to perform failure detection. Complex systems such as aircraft can be completely characterized by a – possibly – large number of features that capture system dynamics under normal and abnormal conditions [12]. Within the AIS, the concept of biological self/non-self is analogous to regions of the hyper-space defined by the characterizing features at normal and abnormal conditions, respectively. Lower dimensional projections of the self/non-self can be used within a multi-self hierarchical strategy [13] to mitigate the undesirable computational effects of multi-dimensionality. In particular, using clustered 2-dimensional projections allows intuitive analytical and graphical representations of distances, thresholds, and boundaries. Figure 2 shows an example of a self/non-self 2-dimensional projection for two particular aircraft states. The white cluster in the middle correspond to the *Self*, or nominal dynamics., while the gray clusters surrounding the *Self* correspond to abnormal aircraft dynamics or the *Non-Self*. Test data points are included at nominal conditions (left figure) and under failure (right figure). As expected, if flight test data fall within the self, it is considered that the aircraft is at nominal conditions. If the dynamic fingerprint of the flight test data falls outside the self clusters, it is considered that an AC is present.

The 2-D projections of the self/non-self can also be used for identification purposes. The activation of specific projections and specific detectors within each projection may correspond to abnormal dynamics produced only by specific failures. If this information is a priori available, the non-self may be structured such that the activated projection in conjunction with the location of the activated detector provides the identity of the affected subsystem. Alternatively, an artificial dendritic cell mechanism has been recently proposed for both the detection and identification [14]. The mechanism was inspired from the functionality of the biological dendritic cells in the innate immune system and their interaction with the T-cells and antibodies in the adaptive immune system. The proposed mechanism processes the outcomes of the self/non-self discrimination process within the hierarchical multi-self strategy. The migrated artificial dendritic cells have shown their high capability not only in detecting an abnormal condition but also in providing different feature patterns that are useful in identifying the failed subsystem [14].

Figure 1. Negative Selection Mechanism

Figure 2. Nominal (a) vs. Abnormal (b) Dynamic Fingerprint

IV. Integrated AIS-based Abnormal Condition Detection, Identification, and Evaluation (ACDIE)

The *detection* represents the process through which the existence of an AC is assessed or, in other words, a failure within at least one of the aircraft sub-systems has occurred and is recognized as such.

The *identification* or *isolation* process determines which sub-system has failed. Depending on the complexity of the targeted system, the AC identification can be performed in several phases.

Once a failure has been detected and correctly identified, the AC *evaluation* process must address three aspects. One is of a qualitative nature and involves determining the type of the failure. The other two aspects are of a quantitative nature and can be defined as direct and indirect. The direct failure evaluation consists of estimating the magnitude or severity of the failure. The indirect failure evaluation includes the re-assessment of the flight envelope and prediction of the limitations and constraints on relevant parameters inflicted by the presence of the failure. The outcome of the indirect quantitative evaluation process typically represents a set of new ranges at post failure conditions of the variables v_E that define the flight envelope, in its most general meaning. This process is the focus of this paper. The development of schemes for indirect quantitative failure evaluation (IQE) is based on Table 2. Specific algorithms must be developed for all targeted variables v_E in conjunction with the nature and type of the failure. The general block diagram of the integrated ACDIE process is presented in Figure 3.

Figure 3. Integrated Abnormal Condition Detection, Identification, and Evaluation

Failure detection, identification, and direct evaluation must be successfully completed for flight envelope prediction. Therefore, the sets of DIV (v_δ), EDIV (v_ε), and envelope relevant variables (v_E) are pre-determined.

For IQE, a relationship between v_ε and v_δ must be known:

$$v_\varepsilon = f_{\varepsilon\delta}(v_\delta) \quad \text{such that} \quad v_{\varepsilon i} = f_{\varepsilon\delta i}(v_\delta), \quad i = 1, 2, \dots, N_\varepsilon \quad (7)$$

The self can be viewed as a generalized flight envelope based on features φ_i . Assume that each failure $f_i \in F$, $i = 1, 2, \dots, N_F$, produces a set of N_{Γ_i} constraints Γ_i on a set of known variables X_i , where:

$$\Gamma_i = \{\gamma_{i1} \quad \gamma_{i2} \quad \dots \quad \gamma_{iN_{\Gamma_i}}\} \quad (8)$$

$$\gamma_{ij} = \gamma_{ij}(X_i) = 0, \quad i = 1, 2, \dots, N_F \text{ and } j = 1, 2, \dots, N_{\Gamma_i} \quad (9)$$

The variables X_i must be part of the feature set. Let us assume that the alteration of the flight envelope is assessed in terms of a set $Y \subset \mathcal{F}$ of N_Y variables y_i . Typically, the constraints Γ_i are not completely known, otherwise they would specify any alteration of the variables y_i and the problem would be solved. The solution is equivalent to determining a new self at post-failure conditions based on a set of features Y . If $Y = \mathcal{F}$ then a solution is found if perfect structuring of the non-self is possible, which in the most general case is not. If $N_Y < N$, then the flight envelope alteration assessment is equivalent to obtaining the N_Y -dimensional projection of the N -dimensional non-self region corresponding to the targeted failure f_i . Again, if structuring of the non-self for f_i is available, then the problem is solved. If not, we can still obtain the N_Y -dimensional projection of the self. In many cases, depending on the failure, the constraints Γ_i , and the set Y , we can infer the relative position of the N_Y -dimensional projections of the non-self and the self. For example, let us consider a stuck elevator failure (the left or right elevator is locked at a constant deflection δ_{e0}). The effects on aircraft pitch rate q must be assessed. Therefore, $x_I = \delta_e$, $y_I = q$, and $\gamma_I \equiv \delta_e - \delta_{e0} = 0$. Due to the nature of this failure, it can be inferred that the values of the pitch rate at post failure conditions will be in the range of normal conditions corresponding to δ_{e0} . In other words, the projection of the non-self on the 2-dimensional plane (x_I, y_I) falls inside the projection of the self. For such situations, a “new” self $\bar{S}$ or altered envelope at post failure conditions can then be defined as the set of all self-clusters c_i that satisfy constraint Γ_i :

$$\bar{S} = \{c_i \mid c_i \text{ satisfies constraints } \Gamma_i\} \quad (10)$$

The concept is illustrated in Figure 4 on a generic 2-dimensional self projection.

Figure 4. Post-Failure Flight Envelope Estimation Using the AIS Paradigm

V. Prediction of Flight Envelope with Actuator Failures

Let us assume that the deflection of the left elevator $\delta_{eL}(t)$ is locked at a constant value δ_{eLF} . The derivation will refer to the left surface, but it applies similarly to the right as well. For this case, we can specify:

$$v_\delta = [v_{\delta I}] = [\delta_{eL}], \quad \text{left elevator deflection, positive downwards} \quad (11)$$

$$v_\varepsilon = [v_{\varepsilon I}] = [d_e], \quad \text{longitudinal stick} \quad (12)$$

Let a typical set of envelope relevant variables be:

$$v_E = [H \quad M \quad p \quad q \quad \dot{q}] \quad (13)$$

The relationship between DIV and EDIV is assumed to be:

$$d_e = f_e(\delta_{eL}) = f_e\left(\frac{\delta_{eL} + \delta_{eR}}{2}\right) \quad (14)$$

Let the post failure left elevator deflection be a value determined through direct quantitative evaluation:

$$\delta_{eL}(t) = \delta_{eLF} \quad (15)$$

The nominal range for d_e is:

$$d_{e\max} = f_e\left(\frac{\delta_{eL\max} + \delta_{eR\max}}{2}\right), \quad d_{e\min} = f_e\left(\frac{\delta_{eL\min} + \delta_{eR\min}}{2}\right) \quad (16)$$

After failure, the range for d_e becomes:

$$d_{e\max F} = f_e\left(\frac{\delta_{eLF} + \delta_{eR\max}}{2}\right), \quad d_{e\min F} = f_e\left(\frac{\delta_{eLF} + \delta_{eR\min}}{2}\right) \quad (17)$$

Note that this is a rather virtual or equivalent range, since the stick in the cockpit can still be moved within the nominal range, only the effects are different. With this post-failure range, new ranges for all v_E may be obtained from the 2-D projections, if there is a mutual constraint (cause/effect relationship) between the two features involved in the projection. Otherwise, special consideration must be given. For example, the asymmetry induced by a locked elevator failure produces undesired roll moments and rates that must be typically compensated by aileron deflections, thus reducing roll command authority. It will be stipulated that the elevator failure induces an aileron pseudo-failure, involving a non-zero aileron trim at δ_{aPF} necessary to compensate for the rolling effect of the locked elevator. The compensating aileron deflection can be approximated using the balance of the rolling moment:

$$\delta_{aPF} = -\frac{C_{l\delta_{eL}}}{C_{l\delta_a}}(\delta_{eLF} - \delta_{eR}) \quad (18)$$

Let a generic aileron deflection be defined as $\delta_a = \delta_{aL} - \delta_{aR}$ and the relationship with the EDIV, $d_a = f_a(\delta_a)$.

Then the nominal lateral control range is:

$$d_{a\max} = f_a(\delta_{a\max}), \quad d_{a\min} = f_a(\delta_{a\min}) \quad (19)$$

Under elevator failure, the new range for the lateral control is:

$$d_{a\max F} = f_a\left[\delta_{a\max} + \frac{C_{l\delta_{eL}}}{C_{l\delta_a}}(\delta_{eLF} - \delta_{eR})\right], \quad d_{a\min F} = f_a\left[\delta_{a\min} + \frac{C_{l\delta_{eL}}}{C_{l\delta_a}}(\delta_{eLF} - \delta_{eR})\right] \quad (20)$$

Note that this is equivalent to shifting the range of d_a in one direction or the other (depending on the sign of the stab failure), while maintaining the same span, if linearity properties are considered for f_a . The new range of d_a can be used with the (d_a, p) projection to determine the effects on p of the elevator failure.

VI. Prediction of Flight Envelope with Sensor Failures

The analysis of the sensor failures relies on the specifics of the control system that uses the sensor information. For the purpose of demonstrating the methodology, it is assumed that the control augmentation system is commanding angular rates and relies on a model following architecture. Based on stick displacements, the control system determines first a “desired” angular rate response as dictated by handling qualities reference models. Then, actuator deflections are determined to track the desired angular rate response. Angular rate sensors must be used in the feedback loop. The abnormal condition considered next consists of biased output of yaw rate sensor. Under these circumstances, the following main elements can be specified:

$$v_{\delta} = [v_{\delta I}] = [r_{meas}], \quad \text{measured yaw rate} \quad (21)$$

$$v_{\varepsilon} = [v_{\varepsilon I}] = [d_r], \quad \text{pedals displacement} \quad (22)$$

A typical set of relevant affected variable is:

$$v_E = [r \quad \dot{r} \quad \beta] \quad (23)$$

At nominal conditions, the desired or reference yaw rate is $r_{ref} = F_I(d_r)$, where F_I represents the yaw channel reference model. The yaw rate measurement is assumed to be perfect at nominal conditions, for simplicity:

$$r_{meas} = r_{act} \quad (24)$$

and the commanded yaw rate is given by a control law of the form:

$$r_{cmd} = F_2(r_{ref} - r_{act}) \quad (25)$$

At failure condition, the reference is unchanged; however:

$$r_{measF} = r_{act} + r_{bias}, \quad r_{cmdF} = F_2(r_{ref} - r_{act} - r_{bias}) \quad (26)$$

As a result of the failure, an undesired additional yaw rate command is produced, which can be expressed with some simplifying assumptions, at steady state, as:

$$\Delta r_{cmd} = r_{cmdF} - r_{cmd} = -r_{bias} \quad (27)$$

In other words, the control laws will rotate the aircraft in the opposite direction of the sensor bias. This effect must be compensated using rudder command; therefore, the control authority on the yaw channel will be affected by restricting the excursion of the cockpit controls by the amount d_{rF} equal to what is necessary to command a yaw rate equal to the bias:

$$d_{rF} = F_I^{-1}(r_{bias}) \quad (28)$$

The new equivalent range of d_r is:

$$d_{rmaxF} = d_{rmax} - d_{rF}, \quad d_{rminF} = d_{rmin} - d_{rF} \quad (29)$$

With the new range of pedals displacement after failure, corresponding new ranges for all v_E may be obtained from appropriate 2-D projections.

VII. Prediction of Flight Envelope with Propulsion Failures

Left or right engine throttle locked is the failure considered for the propulsion system, which is assumed to consist of two jet engines. The following elements can be specified for this case:

$$v_{\delta} = [v_{\delta I}] = [\delta_{TL}], \quad \text{left throttle/fuel valve displacement} \quad (30)$$

$$v_{\varepsilon} = [v_{\varepsilon I}] = [d_T], \quad \text{collective throttle} \quad (31)$$

Let a set of envelope relevant target variables be:

$$v_E = [a_x \quad a_z \quad r \quad H \quad M] \quad (32)$$

The relationship between DIV and EDIV is assumed to be:

$$d_T = f_{\delta I}(\delta_{TL}) = k_T \delta_T = k_T \frac{\delta_{TL} + \delta_{TR}}{2} \quad (33)$$

If the left throttle is locked, then after failure $\delta_{TL}(t) = \delta_{TLF}$, where δ_{TLF} is determined through direct quantitative evaluation. The nominal range for d_T is typically:

$$d_{Tmax} = k_T \frac{\delta_{TLmax} + \delta_{TRmax}}{2} = 100\%, \quad d_{Tmin} = k_T \frac{\delta_{TLmin} + \delta_{TRmin}}{2} = 0\% \quad (34)$$

After failure, the range for d_T becomes:

$$d_{TmaxF} = k_T \frac{\delta_{TLF} + \delta_{TRmax}}{2} = k_T \frac{\delta_{TLF} + 100}{2}, \quad d_{TminF} = k_T \frac{\delta_{TLF} + \delta_{TRmin}}{2} = k_T \frac{\delta_{TLF}}{2} \quad (35)$$

Note that this is a rather virtual or equivalent range, since the throttle lever in the cockpit is assumed to still be capable of moving within the nominal range, only the effects are different. With the new range after failure, new ranges for all v_E may be obtained from 2-D projections, if there is a direct cause/effect relationship between the two features involved in the projection. The yaw rate effects need to receive some special attention since they are different whether the left or right engine fails and this difference is not captured by the virtual control range at post-failure. Due to asymmetry, a throttle failure will create an undesired yawing moment depending on the distance of

the engines with respect to the aircraft centerline. This effect can be compensated using rudder deflection, thus reducing yaw control authority. The rudder trim position is shifted at a deflection δ_{rPF} necessary to compensate for the yawing effect of the locked throttle. The compensating rudder deflection can be approximated using the balance of the yawing moment:

$$\delta_{rPF} = -\frac{C_{n\delta_{TL}}}{C_{n\delta_r}}(\delta_{TLF} - \delta_{TR}) \quad (36)$$

Assuming that $d_r = k_r \delta_r$, the nominal directional control range results to be:

$$d_{rmax} = k_r \delta_{rmax}, \quad d_{rmin} = k_r \delta_{rmin} \quad (37)$$

Under throttle failure, the new range for the directional control is:

$$d_{rmaxF} = k_r(\delta_{rmax} - \delta_{rPF}), \quad d_{rminF} = k_r(\delta_{rmin} - \delta_{rPF}) \quad (38)$$

The new range of d_r can be used with the (d_r, r) projection to determine the effects on r of the throttle failure. This range can be expressed in terms of the failed surface and the throttle of the healthy engine as follows:

$$d_{rmaxF} = k_r[\delta_{rmax} + \frac{C_{n\delta_{TL}}}{C_{n\delta_r}}(\delta_{TLF} - \delta_{TR})], \quad d_{rminF} = k_r[\delta_{rmin} + \frac{C_{n\delta_{TL}}}{C_{n\delta_r}}(\delta_{TLF} - \delta_{TR})] \quad (39)$$

VIII. Prediction of Flight Envelope with Structural Failures

Let us assume that the left horizontal tail (similar analysis applies for the right side) has sustained damage that produces alterations of its capability to generate lift and hence pitching moment. In this case, we can specify:

$$v_\delta = [v_{\delta 1}] = [\Delta C_{L_{HL}}], \text{ lift alteration due to left horizontal tail damage} \quad (40)$$

$$v_\varepsilon = [v_{\varepsilon 1} \ v_{\varepsilon 2}] = [d_a \ d_e], \text{ lateral and longitudinal stick displacements} \quad (41)$$

Flight envelope relevant variables may be considered to be:

$$v_E = [H \ M \ p \ q \ \dot{p} \ \dot{q}] \quad (42)$$

The assumption will be made that the left elevator can still be deflected; however, the respective control derivative may be affected, such that:

$$\Delta C_{L_{HL}} = \Delta C_{L_{HL0}} + \Delta C_{L_{\delta_e}} \delta_e \quad (43)$$

It is also assumed that both $\Delta C_{L_{HL0}}$ and $\Delta C_{L_{\delta_e}}$ are negative representing a reduction of the horizontal tail capability to produce lift. For longitudinal balance, this lift variation must be compensated by an additional positive elevator deflection:

$$\Delta \delta_e = -\frac{\Delta C_{L_{HL}}}{C_{L_{\delta_e}} - \Delta C_{L_{\delta_e}}} \quad (44)$$

For lateral balance, a compensatory rolling moment must be produced using aileron, such that:

$$\Delta C_{L_{HL}} \cdot \frac{l_{LHT}}{b} = C_{l_{\delta_a}} \Delta \delta_a \quad (45)$$

where $l_{LHT} < 0$ is the distance from the left horizontal tail aerodynamic center to the plane of symmetry. Then:

$$\Delta \delta_a = \frac{\Delta C_{L_{HL}} \cdot l_{LHT}}{b C_{l_{\delta_a}}} \quad (46)$$

Note that $\Delta C_{L_{HL}}$ and l_{LHT} must be estimated as part of the failure direct evaluation process.

The relationships between DIV and EDIV are assumed linear, $d_e = k_e \delta_e$ and $d_a = k_a \delta_a$. After failure, the ranges for d_e and d_a become:

$$d_{emaxF} = d_{emax} - k_e \Delta \delta_e \quad \text{and} \quad d_{eminF} = d_{emin} - k_e \Delta \delta_e \quad (47)$$

$$d_{amaxF} = d_{amax} - k_a \Delta \delta_a \quad \text{and} \quad d_{aminF} = d_{amin} - k_a \Delta \delta_a \quad (48)$$

The new ranges for a longitudinal subset of v_E may now be obtained from corresponding 2-D projections of d_e . Similarly, new ranges for a lateral-directional subset of v_E may be obtained from corresponding 2-D projections of d_a .

IX. Example of Post-Failure Envelope Prediction Results

To illustrate the proposed methodology, the self for a supersonic fighter aircraft has been developed within the AIS paradigm based on motion-based flight simulator tests over a wide flight envelope [12]. The features presented in Table 1 have been used for building the self. A total of 11 nominal tests lasting between 15-20 minutes each at Mach numbers ranging between 0.5 and 0.9 and altitudes between 2,000m and 10,000m have been performed in the WVU flight simulator. Nominal ranges for flight envelope relevant variables have been determined based on simulator tests. Verification tests under AC have been performed for each specific subsystem failure attempting to achieve the same tasks and level of maneuverability as in the nominal tests.

To achieve desirable performance of the post-failure envelope prediction methodology, data points acquired through properly designed verification tests under abnormal conditions must stay within the predicted range and be close to the predicted limits. Therefore, for performance evaluation, three metrics have been defined attempting to capture the level of prediction confidence, the level of possible range exceedance, and the level of predicted range conservativeness. The first evaluation criterion is expressed by a prediction rate (PR) calculated as the percentage of all verification data points ERV_{val} that fall inside the predicted range. If the predicted range of any ERV is denoted as $R_{ERV} = [ERV_{min}, ERV_{max}]$, then the total number of validation points N_V is the sum of points inside (N_R) and outside ($N_{\bar{R}}$) the predicted range. Therefore, the prediction rate is calculated as:

$$PR = \frac{N_R}{N_V} \cdot 100 \quad (49)$$

The level of possible range exceedance is assessed as the relative maximum amount by which points in the verification data set exceed the predicted range. The predicted range exceedance index (REI) is defined as:

$$REI = \frac{\max_{N_{\bar{R}}} [\min(|ERV_{val} - ERV_{max}|, |ERV_{val} - ERV_{min}|)]}{|ERV_{max} - ERV_{min}|} \cdot 100 \quad (50)$$

The values of the previous two evaluation metrics must be considered in conjunction with a margin index (MI) that is expected to capture the level of predicted range conservativeness. MI is defined as:

$$MI = \frac{\max_{N_R} [\min(|ERV_{val} - ERV_{max}|, |ERV_{val} - ERV_{min}|)]}{|ERV_{max} - ERV_{min}|} \cdot 100 \quad (51)$$

Table 3 presents the predicted post-failure flight envelope ranges under an elevator failure along with the corresponding nominal ranges and the performance metrics defined above. The failure considered consists of left elevator locked at 8 degrees. Two different verification tests have been performed covering the altitude range of the nominal tests for Mach between 0.7 and 0.9. The results show alterations of the ranges of pitch rate, pitch acceleration, and roll rate as expected. Note that the reduced range of Mach and altitude considered when building the self is not affected by this elevator failure. The verification points are well within predicted ranges for all variables considered, as captured by REI, except for pitch acceleration. The variation of this variable experiences a short-duration sudden peak at the failure occurrence moment. The low values of MI show that the predicted limits of the respective variables are not unrealistically large. The large MI value recorded for Mach number is due to the fact that the verification tests do not cover the range between 0.5 and 0.7, which was included in the self. This is one example of a situation when large values of MI reflect the incompleteness of the verification tests rather than flaws in the range prediction process.

Table 3. Predicted Flight Envelope and Performance Metrics Under Elevator Failure

ERV	Nominal Range	Post Failure Range	PR [%]	REI [%]	MI [%]
H	[2012, 9929]	[2012, 9929]	100.0	0.0	8.0
M	[0.526, 0.95]	[0.526, 0.95]	99.9	1.6	32.9
q	[-0.225, 0.183]	[-0.141, 0.105]	100.0	2.6	0.0
$\dot{q}$	[-0.383, 0.386]	[-0.23, 0.32]	99.7	24.6	0.0
p	[-0.94, 1.08]	[-0.90, 0.79]	100.0	0.0	1.0

The predicted post-failure flight envelope ranges under the yaw rate sensor failure are presented in Table 4. The failure consists of a 0.5 degree bias in the yaw rate sensor output. Four different verification tests have been performed covering the entire altitude and Mach ranges of the nominal tests. The results show alterations of the ranges of yaw rate and yaw acceleration, as expected. Although an affected rudder would be expected to impact

sideslip capability, this effect is not captured because the sideslip range considered for normal operation was already limited within the capability under failure of such low severity. The verification points are all within predicted ranges for all variables considered with only insignificant exceedance, as reflected by REI. The simultaneous occurrence of non-zero values of REI and MI reflect the situation when one limit of the predicted range is exceeded and the other is not reached during the verification tests. The relatively low values of MI lead to the conclusion that the predicted limits of the respective variables are not unrealistically large.

Table 4. Predicted Flight Envelope and Performance Indices Under Yaw Rate Sensor Failure

ERV	Nominal Range	Post Failure Range	PR [%]	REI [%]	MI [%]
r	[-0.064, 0.062]	[-0.08, 0.0477]	100.0	1.0	10.7
$\dot{r}$	[-0.117, 0.126]	[-0.093, 0.128]	100.0	4.8	5.8
β	[-9.6, 9.8]	[-9.6, 9.8]	100.0	0.7	16.9

Table 5 presents the predicted post-failure ranges of relevant variables with left engine throttle locked at idle. One verification test has been performed covering an altitude range between 6,000m and 10,000m for Mach numbers between 0.7 and 0.9. The results show alterations of the ranges of the longitudinal and vertical acceleration, and roll rate, as expected. Note that the reduced range of Mach and altitude considered when building the self is not affected by this failure. The verification points are well within predicted ranges for all variables considered. Only few points exceed the predicted ranges by small relative amounts, as captured by REI. The relatively large values of MI are the result of the verification test not completely covering the maneuver range of the self-generating data.

Table 5. Predicted Flight Envelope and Performance Metrics Under Engine Failure

ERV	Nominal Range	Post Failure Range	PR [%]	REI [%]	MI [%]
a_x	[-0.344, 0.597]	[-0.344, 0.353]	99.92	4.77	20.43
a_z	[-2.46, 3.05]	[-2.46, 2.16]	99.60	10.34	10.43
r	[-0.0637, 0.0621]	[-0.0637, 0.0393]	99.95	5.31	21.52
H	[2008, 9933]	[2008, 9933]	95.02	3.44	49.98
M	[0.526, 0.950]	[0.526, 0.950]	100	0.0	54.11

Table 6 presents the predicted post-failure flight envelope ranges under a horizontal tail damage affecting 60% of the left surface. One verification test has been performed covering an altitude range between 6,000 and 10,000m and a Mach number range between 0.7 and 0.9. The results show alterations of the ranges of pitch rate, pitch acceleration, roll rate, and roll acceleration, as expected. Note that the reduced range of Mach and altitude considered when building the self is not affected by this horizontal tail damage. Both PR and REI indicated good performance. Relatively large values of MI seem to indicate that the maneuvers performed were not as aggressive as for the nominal conditions. Note that the ranges of Mach and altitude for the verification test were limited, explaining the large values of MI for these two variables.

Table 6. Predicted Flight Envelope and Performance Metrics Under Horizontal Tail Failure

ERV	Nominal Range	Post Failure Range	PR [%]	REI [%]	MI [%]
H	[2012, 9929]	[2012, 9929]	99.0	2.0	40.3
M	[0.526, 0.95]	[0.526, 0.95]	98.5	0.8	35.5
q	[-0.225, 0.183]	[-0.327, 0.165]	100.0	0.0	38.2
$\dot{q}$	[-0.383, 0.386]	[-0.37, 0.355]	100.0	0.0	9.1
p	[-0.94, 1.08]	[-0.925, 1.09]	100.0	0.0	18.1
$\dot{p}$	[-2.95, 3.10]	[-2, 3.13]	100.0	0.0	24.5

X. Conclusions

A framework within the AIS paradigm has been formulated for the prediction of flight envelope alteration at post-failure conditions. The proposed methodology has been demonstrated with promising results through simulation for failures affecting actuators, sensors, and the propulsion system, and damages of horizontal tail.

The prediction of altered ranges of relevant variables at post-failure conditions requires prior abnormal condition detection, identification, direct evaluation, and failure specific algorithms. A set of such simplified algorithms have been formulated and demonstrated successfully.

The AIS-based methodology for flight envelope prediction creates the premises for the development of an integrated and comprehensive solution to the problem of safe aircraft operation under abnormal conditions.

A set of metrics for performance evaluation of the proposed methodology has been defined. Limitations of these metrics due to the nature and extension of the verification tests have been identified and illustrated through numerical simulation examples.

It is expected that the proposed methodology will facilitate the design of on-board augmentation systems to increase aircraft survivability and improve operation safety.

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