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Towards A Resilient Control Architecture: A Demonstration of Bumpless Re-Engagement Following an Anomaly in Flight Control

Amir B. Farjadian Postdoctoral Associate, MIT, amirbf@mit.edu
Anuradha M. Annaswamy Senior Research Scientist, MIT, aanna@mit.edu
David Woods Professor, OSU, woods.2@osu.edu

Abstract. A shared flight control framework between an autopilot and a human pilot is proposed to ensure resilient performance following an anomaly. The human pilot is modeled using a perception component and an adaptation component. The concept of Capacity for Maneuver (*CfM*) is used to develop the perception component, and an adaptation component similar to the concepts proposed in the flight control literature is used. The shared control architecture is evaluated in the context of flight control, where an anomaly is modeled as a sudden change in the underlying flight dynamics, with resilient performance defined as reduced command tracking error. Simulation studies show that with no shared control, introduction of an anomaly significantly degrades the resilience, while the proposed shared control results in almost identical performance after the anomaly.

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Introduction. Enhancing automated control capabilities can improve precision, speed, and robustness to well modeled disturbances. Nevertheless, automated processes have limits that define a boundary or envelope. When conditions, context, and disturbances occur that fall outside of this envelope, surprising events can occur and produce a cascade of additional disturbances that exceed the capabilities of automated control (Woods and Sarter 2000). Such anomalies require engagement of human supervisors from other activities to re-assess the situation and intervene quickly and decisively to forestall failures — a form of shared control that can be termed as Bumpless Re-engagement. But today when these human supervisory functions are needed, they are poorly supported, cost intensive, and often slow or erroneous (Woods and Hollnagel 2006). In other words, shared control breaks down, and a shift is required from "textbook" autonomous performance to handling anomalous events with high potential to cascade toward failure.

Current forms of shared control assume a partially autonomous machine does all of the work to handle variability — *until* external demands imposed on the machine exceed the automation's capabilities to handle the situation — *then* control is transferred to people who have to take over when the situation is difficult to handle. This form of shared control virtually guarantees bumpy and late transfers of control that increase the risk of decompensation — inability of a human-machine system to keep pace with growing or cascading demands (Woods 2011). In real cases of human supervision of automation based on this model, the bumpy and late transfers of control have contributed to actual accidents (Job 1998; Woods 2006, Chapter 10).

This paper uses a classic flight control problem to introduce a novel approach to provide improved shared control. The new method is based on the concept of Capacity for Maneuver (*CfM*) – the remaining range or capacity to continue to respond to ongoing and upcoming demands (Woods and Branlat 2011). Control then should seek to minimize the risk of exhausting a unit's capacity for maneuver as that agent responds to changing and increasing demands (risk of saturation).

We are proposing a resilient shared control architecture based on reducing the risk of saturating *CfM* that allows a timely and effective human re-engagement following an anomaly to sustain a desired tracking performance. A problem in flight dynamics is chosen (Hess 2015) to demonstrate the potential benefits of the new architecture as it can involve human-machine interaction in response to anomalous situations (Belcastro et al. 2010; Glussich et al. 2010; Woods and Sarter 2000). Control performance is compared in the case of fully automated flight control with the new shared control architecture, where a model of the human pilot takes over control following an anomaly. The human pilot model uses the new resilient control approach utilizing the information about *CfM*.

Flight Control Problem and Shared Control. Bumpy transfer of control to human pilot following an anomaly can result in loss of control and disastrous consequences. Figure 1 shows a simple block diagram of manual/auto-pilot control of an aircraft, where $Y_c(s)$ denotes the flight dynamics, *M* denotes a flight variable of interest (e.g. flight path angle, or roll angle), and the goal is for *M* to follow the command signal as closely as possible. $G_M(s)$ and $G_A(s)$ denote the mathematical model of the manual pilot and the auto-pilot, respectively, representing the response time and gain characteristics of the two controllers, with s denoting the differential operator d/dt. The goal is the timely and effective switching between $G_M(s)$ and $G_A(s)$ so as to minimize the error between *M* and the command signal (M_{cmd}), especially after the occurrence of an anomaly.

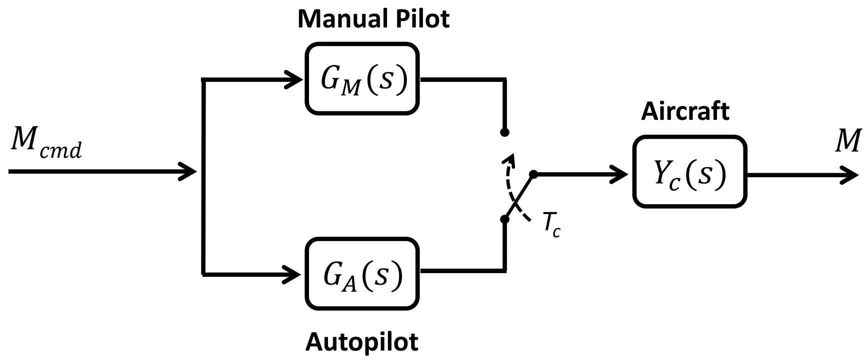

Figure 1: Shared Aircraft Control. The aircraft is controlled by autopilot in nominal case. The pilot takes over control following any special occurrences or anomalies.

Flight control is a well understood and well researched topic in aeronautics, with several textbooks written on the subject (Stevens et al. 2015; and Lavretsky et al. 2012). Basic principles of autopilot design that ensures satisfactory command tracking are laid out in these texts and elsewhere in the literature. Mathematical models of human pilot behavior have also been researched extensively, with seminal contributions by McRuer (McRuer 1980). Detailed models of the pilot behavior, especially at frequencies where stable feedback action is most urgently needed, have been developed (McRuer 1980; Hess 2006, 2009, 2014, 2015). The result is the cross-over model which has been used extensively in autopilot and fly-by-wire designs for nominal flight control. More recently, these models have been studied (Hess 2009, 2014, 2015) to understand a pilot's actions following anomalous events that may produce a significant change in the flight dynamics. The framework we develop in this paper builds on autopilot designs and human pilot models that have been proposed in these earlier works (Hess 2015), and consists of a perception component, which detects the occurrence of an anomaly in a swift and accurate manner, and an adaptation component that prompts the pilot to improve performance. The perception component is built on the notion of resilient control using the actuator's capacity for maneuver (*CfM*). Based on the results of the perception metric, the adaptation component seeks to sustain the tracking error within acceptable limits in the shortest time window. The overall resilient control architecture we propose consists of both the perception and adaptation components. The paper presents results that, with this architecture, the tracking performance remains within the desired boundary even after the occurrence of an anomaly.

Shared Control Architecture. A schematic of the autopilot and the manual pilot action for flight control are shown in Figures 2(A) and 2(B). In this figure, $Y_c(s)$ denotes the aircraft dynamics. E and R denote the perceived position and rate error respectively. The autopilot action consists of measuring a rate $\dot{M}$ and a position M, and using those measurements together with the command and feedback control gains K_r and K_p to compute the necessary compensation, denoted as v. This signal is in turn fed to an actuator in the aircraft, which is a transducer that converts this electronic signal into a desired control surface deflection. Every transducer has physical limits and maximum boundaries which is modeled here by a saturation function (f) mainly affecting the amplitude. The values beyond certain threshold (u_0) will be clamped as they are not effective on the aircraft actuators. The goal of the overall autopilot design, as mentioned earlier, is to design K_r and K_p to achieve desired tracking performance. While the schematic presented in this figure is somewhat simplified, it encapsulates the general principle of an autopilot.

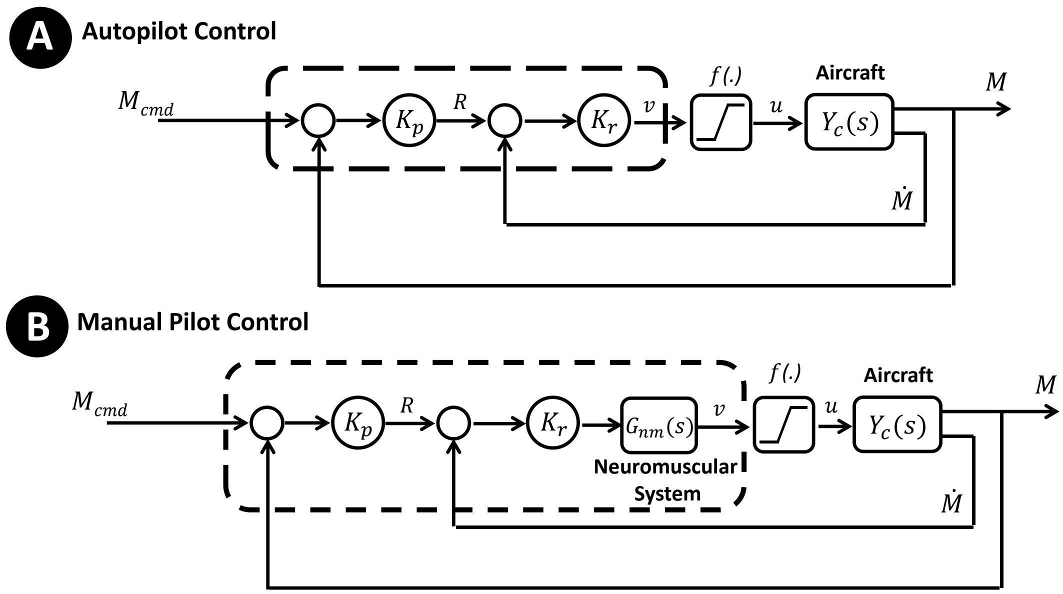

Figure 2: A Schematic of Flight Control Using (A) Autopilot and (B) Manual Pilot Actions (shown in inside dashed rectangles). The goal in both (A) and (B) is to take an action *u* so that the aircraft variable *M* tracks the command signal M_{cmd}.

Figure 2(B) represents the action of a human pilot, following models outlined in (Hess 2006, 2009, 2014, 2015). As shown above, the human pilot can be divided broadly into a perception component followed by an action component. The perception component represents cognitive levels of processing, as the pilot continuously monitors the flight variable *M* as well as its rate of change M, compares them with the desired values, and also identifies an anomaly. The action component uses the perceived errors and scales them into an appropriate signal which is sent to the pilot's neuromuscular system. The outcome of neuromuscular system is a manual action on the control stick, which is then fed to an aircraft actuator via the saturation function.

In special case of an anomaly, an adaptation component is added to the action component in the form of suitable adjustments to the gains K_p and K_r. This combination of perception and action components has been proposed as a pilot model in simulation studies of a linear single/two-axis vehicle model (Hess 2009), to explain the loss of control in a realistic transport aircraft model (Hess 2014) and for single/multi-axis nonlinear aircraft dynamics (Hess 2015).

For the sake of completeness, we describe the perception and adaptation rules proposed in (Hess, 2015) below, both of which are nonlinear. In what follows, $G(s)[z]$ denotes the output of a dynamic system with an input z and a transfer function $G(s)$. The perception model of the human pilot proposed in (Hess 2015) is given by

$$x = G_1(s)[sgn(|R| - |\dot{M}|).(|R| - |\dot{M}|)^2] \tag{1}$$

$$G_1(s) = \frac{1.5^2}{s^2+1.5s+1.5^2} \tag{2}$$

$$K_{trigger} = \begin{cases} 0 & (\sqrt{|x|} < 3.rms\left(\sqrt{|x|}\right)) \cup (t < t_0) \\ 1 & (\sqrt{|x|} \geq 3.rms(\sqrt{|x|})) \cap (t \geq t_s) \end{cases} \tag{3}$$

G_1 denotes a dynamic operator to represent a perceptual lag of the human pilot. $K_{trigger}$ denotes the occurrence of an anomaly, with zero representing a nominal case, and one denoting that an anomaly has occurred. t_0 denotes the instant at which an anomaly occurs. t_s is selected a small time to avoid false positives at the initiation of simulation in nominal condition.

The adaptation model of the human pilot proposed in (Hess, 2015) is given by

$$\dot{K}_r = G_2(s)\left[x_n\, K_{trigger}\right] \tag{4}$$

$$G_2(s) = \frac{1}{s^2+2s+1} \tag{5}$$

$$x_n = G_2(s)\left[\frac{x}{rms(R^2)}\cdot\frac{1}{N}\right] \tag{6}$$

$$\dot{K}_p = \begin{cases} 0.35\dot{K}_r & \dot{K}_r > 0 \\ 0 & \dot{K}_r \le 0 \end{cases} \tag{7}$$

N is the number of response variables being controlled by the pilot in the multi-axis tasks, and G_2 represents an inherent filtering action of the pilot. The action component uses the gains computed as above to produce the stick motion through a conversion into an appropriate input to the neuromuscular system (see Figure 2(B)).

The adaptation rules in Eqs. (4)-(7) essentially enable a change from nominal values of K_r and K_p to new values. This ad-hoc adaptive framework has been developed based on the expert's experience in choosing gain values for the simplified command following model (Hess 2006). Inspired by this method (Hess 2015), we introduce a perception algorithm different from (1)-(3) that is based on actuator's capacity for maneuver (*CfM*) as a trigger for detecting the occurrence of an anomaly, so as to meet the goal of ensuring resilience. This perception algorithm is described below:

$$C(t) = u_0 - \left(\frac{1}{t}\int_0^t u(\tau)^2 d\tau\right)^{\frac{1}{2}},\ t > 0 \tag{8}$$

The perception trigger is defined as:

$$K_t = \begin{cases} 0 & |F_0| < 1 \\ 1 & |F_0| \ge 1 \end{cases} \tag{9}$$

$$F_0 = G_1(s)[F(t)] \tag{10}$$

$$F(t) = \frac{\dot{C}(t)-\mu}{3\sigma} \tag{11}$$

The parameters μ and σ are chosen based on statistical properties of the *CfM* during nominal operation of the aircraft and also to ensure prompt anomaly detection.

Using the perception algorithm proposed above in Eqs. (8)-(11) and the same adaptation model as in Eqs. (4)-(7), the shared control architecture that we propose in this paper proceeds as follows. Under nominal conditions, an autopilot is in place, as described in Figure 2(A). The pilot implicitly monitors the perception trigger defined in Eq. (9) and, when K_t becomes one, takes over the control. The perception rule also triggers the adaptive component specified in Eqs. (4)-(7) so as to improve the pilot's performance. The overall shared architecture is then shown to result in a satisfactory performance in terms of maintaining the same tracking error, E_{rms} (defined in Eq. (17)) before and after the anomaly, and therefore strong resilience.

Validation of the Shared Control Architecture. The anomaly that we simulate is the same as in (Hess 2015), and corresponds to a change in the aircraft dynamics $Y_c(s)$ as follows.
The initial aircraft dynamic is modeled by

$$Y_c = \frac{1}{s(s+10)} \tag{12}$$

and it is assumed that when an anomaly occurs, the aircraft dynamics changes suddenly to

$$Y_c = \frac{e^{-0.2s}}{s(s+5)(s+10)} \tag{13}$$

The command signal that needs to be tracked is selected following (Hess 2015) as a combination of sinusoids, given by

$$M_{cmd}(t) = 0.033\sin(0.06\pi t) + 0.041\sin(0.14\pi t) + 0.047\sin(0.26\pi t) + 0.047\sin(0.46\pi t) \tag{14}$$

The saturation function that represents magnitude limits in the actuator is defined as

$$f(.) \coloneqq \begin{cases} u = v & |v(t)| \le u_0 \\ u = u_0 sgn(v) & |v(t)| > u_0 \end{cases} \tag{15}$$

with $u_0 = 10$.

The human neuromuscular system is modeled also as in (Hess 2006, 2009, 2014 and 2015) with a transfer function G_{nm} given by

$$G_{nm} = \frac{100}{s^2 + 2(0.707)10s + 100} \tag{16}$$

N is 1; t_s is set as 10s; and the statistical parameters of *CfM* were chosen as $\mu = 0$, and $\sigma = 0.036$. These values were selected based on the nominal response of $C(t)$ observed over a 500s window and also to provide prompt and enough trigger to the pilot.

Results. A 500s simulation was considered in the presence of an anomaly at *t* = 50s, when the aircraft model was switched from model (12) to (13). Two case studies were carried out:
Case 1) Autopilot control: The aircraft was controlled by autopilot for an entire period *T* = 500s
Case 2) Shared control: The autopilot is engaged for the first 50s when an anomaly occurs and the control is transferred to manual pilot. In both cases, the gains (K_p, K_r) were set to (3, 10) for the autopilot as well as the initial values of manual pilot immediately following the anomaly. Cases 1) and 2) were simulated using Eqs. (4)-(16) described above. The final values for (K_p, K_r) in the manual pilot were (7.2, 22.1).

Figure 3 shows the details and performance of the shared controller in comparison with the autopilot. The shared controller shows lower tracking error which is almost as good as performance prior to anomaly. The *CfM* in (8), perception metric in (10), triggering signal in (9) and parameter adaptation of manual pilot in (4) and (7) are plotted. At t = 50 s the anomaly is introduced which is detected by the perception variable (F_0) and prompted by the trigger variable (K_t). This results in an initial adaptation in parameters (K_p, K_r). Consequently the perception process prompts three more instants of parameter adaptation to improve performance. The autopilot acting alone was not capable of either adaptation or managing utilization of the available *CfM*.

A resilient performance metric was defined as the root mean square value of the tracking error $e(t)$:

$$E_{rms} = \left(\frac{1}{T}\int_0^T e(\tau)^2 d\tau\right)^{\frac{1}{2}} \tag{17}$$

$$e(t) = M_{cmd}(t) - M(t) \tag{18}$$

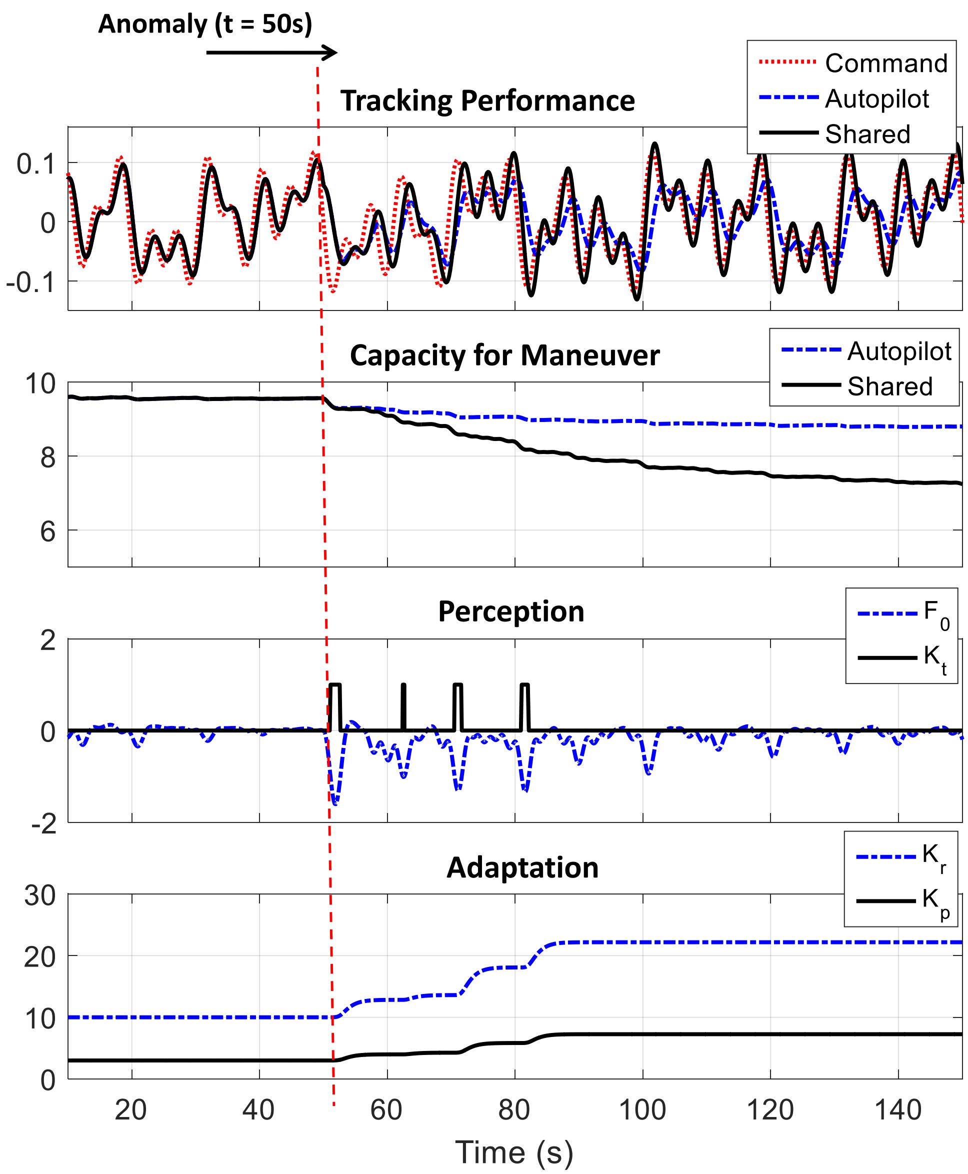

Figure 3: Shared Control versus Autopilot. Top Panel: Tracking Performance: Command following of autopilot vs. shared control. **Middle Panel 1:** Capacity for Maneuver (*CfM*) in autopilot control and shared control. **Middle Panel 2:** Perception: *CfM*-based identification and triggering signal to re-engage and adapt the human pilot. **Bottom Panel:** Adaptation: Parameter adaption in manual pilot prompted by perception rule.

Summary of the tracking performances from Case 1) and Case 2) is provided in Table 1. In both cases, the E_{rms} during in the first 50 seconds, and over the next 450 seconds after the anomaly (*t* = 50s) are provided. It is clear that in Case 1), the tracking error increases by 80% whereas in Case 2), the tracking error is maintained almost at the same level as before the anomaly.

Table 1. Summary Results.

Simulation Case	Control Method	E_{rms} (0-50s)	E_{rms} (50-500s)
1	Autopilot	0.029	0.053
2	Shared	0.029	0.030

Summary and Conclusion. A shared flight control architecture that includes an autopilot and a human pilot is proposed to ensure resilient performance following an anomaly. The architecture includes a new perception component and an adaptation component proposed elsewhere in the flight control literature (Hess 2015). The anomaly consists of a sudden change in the aircraft dynamics. It was shown through simulation studies that our shared control architecture is capable of detecting the anomaly and triggering the pilot to re-engage and take over the control. The adaptive component is then engaged in the form of suitable adjustments to control gains. The final control performance is shown to result in the same desired tracking error before and after the anomaly. The human pilot used more of the available capacity for maneuver to keep up performance following the anomaly. The non-shared control resulted in a significant performance degradation and did not utilize the available *CfM*.

The results reported here represent our first step in developing new methods for resilient shared control. In future studies, we will utilize *CfM*-based metrics not only for the perception component but also the adaptation component. The adaptation component will be developed in a more systematic way to provide the desired performance as well as higher *CfM*. How these shared controllers can reduce the risk of saturation and show graceful extensibility in face of surprising events will be explored (Woods 2015).

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References

Belcastro, C.M. and Foster, J.V. 2010. August. Aircraft loss-of-control accident analysis. *Proceedings of AIAA Guidance, Navigation and Control Conference*, Paper No. AIAA-2010-8004. Doi: 10.2514/6.2010-8004.

Glussich, D. and Histon, J. 2010. Human/automation interaction accidents: implications for UAS operations. *In Digital Avionics Systems Conference (DASC)*. 2010 IEEE/AIAA 29th (pp. 4-A). Doi: 10.1109/DASC.2010.5655352.

Hess, R.A. 2015. Modeling Human Pilot Adaptation to Flight Control Anomalies and Changing Task Demands. *Journal of Guidance, Control, and Dynamics*, pp.1-12, Doi: 10.2514/1.G001303.

Hess, R.A. 2014. A model for pilot control behavior in analyzing potential loss-of-control events. Proceedings of the Institution of Mechanical Engineers, Part G: *Journal of Aerospace Engineering*, p.0954410014531218, Doi: 10.1177/0954410014531218.

Hess, R.A. 2009. Modeling pilot control behavior with sudden changes in vehicle dynamics. *Journal of Aircraft*, 46(5), pp.1584-1592, Doi: 10.2514/1.41215.

Hess, R.A. 2006. Simplified approach for modelling pilot pursuit control behaviour in multi-loop flight control tasks. Proceedings of the Institution of Mechanical Engineers, Part G: *Journal of Aerospace Engineering*, 220(2), pp.85-102. Doi: 10.1243/09544100JAERO33.

Job, M. 1998. *Air Disaster Volume 3*. Australia: Aerospace Publications. p. 155. ISBN 1 875671 34 X.

Lavretsky E, Wise K. 2012. *Robust and adaptive control: with aerospace applications*. Springer Science & Business Media.

McRuer, D., 1980. Human dynamics in man-machine systems. *Automatica*, 16(3), pp.237-253. Doi: 10.1016/0005-1098(80)90034-5.

Stevens, B.L., Lewis, F.L. and Johnson, E.N. 2015. *Aircraft Control and Simulation: Dynamics, Controls Design, and Autonomous Systems*. John Wiley & Sons.

Woods, D. D. (2015). Four Concepts for Resilience and their Implications for Systems Safety in the Face of Complexity. *Reliability Engineering and System Safety*, 141, 5-9. published online: 3 APR 2015 | doi:10.1016/j.ress.2015.03.018.

Woods, D. D. and Branlat, M. (2011). How Adaptive Systems Fail. In E. Hollnagel, Paries, J., Woods, D.D., and Wreathall, J., Eds., *Resilience Engineering in Practice* (pp. 127-143), Aldershot, UK: Ashgate.

Woods, D.D. and Sarter, N. (2000). Learning from Automation Surprises and Going Sour Accidents. In N. Sarter and R. Amalberti (Eds.), *Cognitive Engineering in the Aviation Domain* (pp.327-354). Hillsdale NJ: Erlbaum.

Woods D. and Hollnagel E., 2006. *Joint cognitive systems: Patterns in cognitive systems engineering*. CRC Press.