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IFAC PapersOnLine 52-27 (2019) 415–420

Adaptive Human Control Model and its Usability in Modeling of Human-in-the-loop Cyber Physical Systems

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Abstract: This paper discusses usability of an adaptive human control model in the context of a simple Human-in-the-loop Cyber Physical Systems (HiLCPS). The first part of the paper characterizes human factor assessment with an emphasis on the modeling of human behavior. This section is followed by a description of the human control model structure, including a definition of the individual components and their roles during the control phases. Exploiting relevant theoretical background, the authors present an example of a human controller comprising the feedback component and two different implementations of a pursuit controller. The parameters of the controllers are obtained from data measured on a flight simulator controlled by a pilot during the defined task. The first results presented in this paper indicate the possibility of use the described human control structure in HiLCPS modeling and its potential for other, more complex experiments within human factor assessment.

Keywords: human perception, HiLCPS, human model, human-machine interface, human brain, human behavior, adaptive human control model, HRA, pursuit controller.

1. INTRODUCTION

Based on the recent trends, the information related to the human factor and its behavior has become very important also for the modern concept of Cyber-Physical Systems involving the human element in the loop; such structures are referred to as Cyber-Physical Human Systems (CPHSs) or Human-in-the-Loop Cyber-Physical Systems (HiLCPSs) (Lee, 2015), (Schirner *et al*., 2013).

Because the role of human in context of the CPS or HiLCPS respectively is essential, there is an effort to model, predict and evaluate human behavior, his/her performance and risk related to the human factor.

Although the researches in the area of human factor are widely discussed, there is not still a sufficient amount of information. Moreover, the steady growth of new trends and technologies requires new approaches and sources of information on possible interactions with humans and their relevant impact. These reasons led to the development of state-of-the-art concepts for describing the human behavior, such as the novel framework for human control modeling defining an adaptive human control model (Mulder, 2017), (Slanina et al. 2017).

This approach seems to be very complex because it considers different levels of human control defined by the widely known Rasmussen's general model (Rasmussen, 1983). Nevertheless, the model defines only the general control structure without specific parameters describing individual controllers.

The aim of this paper is to introduce the basic principles of the modeling and prediction of human behavior in the context of HiLCPSs and to apply the novel framework principles for modeling of human behavior in context of the simple HiLCPS.

2. HUMAN FACTOR IN THE CONTEXT OF THE HiLCPS ISSUE

The HiLCPSs actually represent inclusion of human to the process via mutual communication, especially HMI (Human-Machine Interface) or HCI (Human-Computer Interface), which enable the human interventions to the process (Munir *et al*. 2013).

A human being is a very effective and universal part of the whole system because he/she is able to solve specific tasks and unpredicted situations or problems very fast. Human is also easily adaptable to different situations and conditions changes. On the other hand, human behavior is influenced by many factors, such as fatigue, stress or motivation, which are very important for human performance. Therefore, understanding human behavior is a complex problem where the result depends on many different factors. This procedure is defined mainly by individual capabilities, relevant limitations, and current behavioral patterns, namely, the mental, emotional, and physical state of an individual, as shown in Fig. 1 (Mughni, 2016).

Thus, the key difference between a HiLCPS and a fully autonomous system is presence of human factor whose influence is crucial for the resulting HiLCPS behavior. In order to give guarantees about a HiLCPS, sufficient information and a reasonable model of the human operator are needed (Schirner et al., 2013).

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10.1016/j.ifacol.2019.12.697

Fig. 1. The factors that define and influence human behavior (Mughni, 2016)

3. MODELING AND PREDICTING HUMAN BEHAVIOR BASED ON HRA

The human brain is a complex biological structure responsible for human behavior in various situations. The modeling of human behavior and its prediction is a difficult multidisciplinary issue where the new insights are steadily discovered.

HRA (Human Reliability Assessment) is the science discipline dealing with human factor and its assessment, especially in scope of its reliability. The principle of HRA consists in studying human performance within various operating actions and evaluating the reliability and other important features. It includes more than 50 methods, such as CREAM, THERP, SLIM, ATHEANA, etc. (Bell et al. 2009)

Besides, HRA defines also two basic behavioral models defining information processing by human brain. In both cases, the input signal (stimulus) is perceived by receptors, and then the neural networks are carrying the signal into the brain where it is processed and consequently selected an adequate action. This action is performed by the neuromuscular system. The difference of both models lies in their complexity.

The first model (Fig. 2) considers only a simple approach for description of human response to different stimuli. This model includes the basic principle of information processing described above, extended with feedforward representation of the immediate response without the brain interfering, e.g. reaction to pain. The first generation of HRA methods, such as THERP, ASEP or HEART, that focus mainly on the skill and rule base level of human action, use this model.

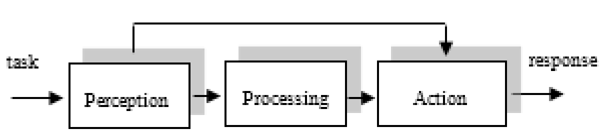


Fig. 2. The simple model of human behavior defined by HRA (Spurgin, 2010)

The second model (Fig. 3) use primarily the second generation of HRA methods. These techniques, such as ATHEANA or CREAM, utilize a complex match of error scenarios to facilitate error identification and quantification.

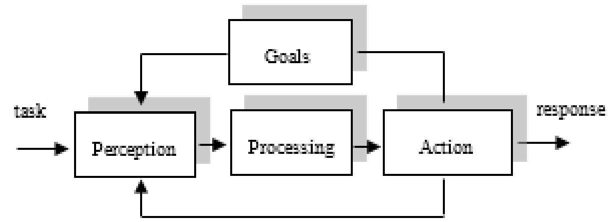


Fig. 3. The complex model of human behavior defined by HRA (Spurgin, 2010)

Although the principle is similar to the previous one, this concept is more complex. It studies also the reverse interactions between actions and perceptions based on cognitive processes using feedback. That approach try to include the role of human cognition, defined as “the act or process of knowing including both awareness and judgement” by an operator. (Bell et al. 2009)

The feature shared by the first and the second generation of HRA together with the corresponding models is the effort to analyze and predict human behavior within different situations for the purpose of the failures prevention. However, all of the methods require sufficient information of entire activities connected to the observed task. This information is often unavailable, and the assessment relies on predefined probabilistic values of parameters for simple operations listed in relevant standards (Bell et al. 2009).

Current trends related to using simulation technologies bring new possibilities also to this field. The principle exploits a suitable simulator of the assessed process, often equipped with data acquisition modules. The provided information is then used to analyze human behavior and his/her reactions within different scenarios. NASA marks this approach as the third generation of HRA methods. (Spurgin, 2010)

The use of simulators enables, apart from obtaining data, the possibility of continuous and deep acquisition of needed habits and their renewal. It allows unifying routine procedures while preserving a wide range of variants of dealing with different random or standard situations (Allerton, 2010).

Moreover, the third generation of HRA methods have aimed at the qualitative assessment of the operator’s behavior and the search for models that describe more accurately the interaction with the controlled system or process.

4. ADAPTIVE HUMAN CONTROL MODEL

The character of the presented HRA models corresponds to the Rasmussen’s general model of human behavior. It consists from several levels for different types of control. These levels are as follows (Rasmussen, 1983):

- the control level (compensatory feedback control),
- the coordination level (control based on rules),
- the organization or cognitive level (control based on knowledge).

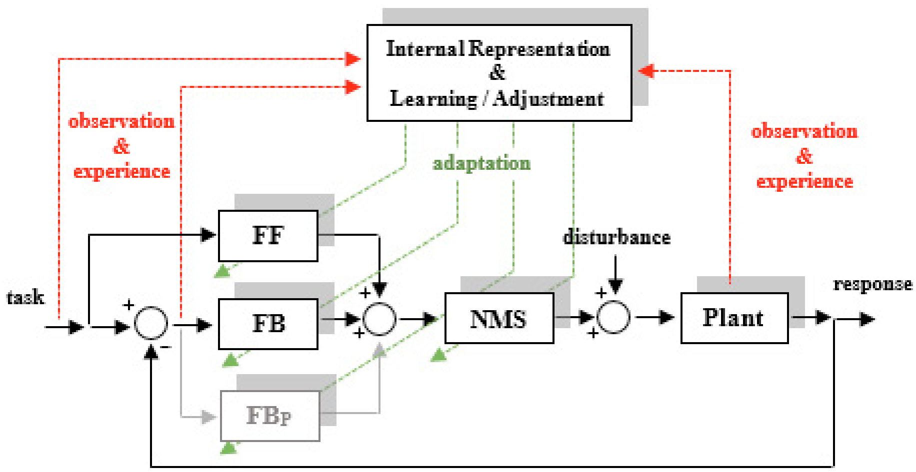


Fig. 4. The adaptive human control model according a novel framework (Mulder, 2017)

The Rasmussen's model is generally valid for all human control activities. Although it does not bring a more specific description of human performance or his/her abilities, it was base for the new models that are continuously designed and verified. One of those models is also the adaptive human control model proposed in frame of the novel framework for human control modeling; see Fig. 4 (Mulder, 2017).

This idea consists of several parts (controllers) and loops describing the approach to human control.

The basic part of the whole control system is the feedback controller FB related to the compensatory control. The main task of this loop rests in fast reaction to changes and compensation of control error $e(t)$. For these purposes, the equalization form of the McRuer model (McRuer, 1974) with the lead-time constant T_L, the lag-time constant T_I, gain K_{FB} and reaction delay τ is frequently used, see (1).

$$FB(s) = K_{FB} \cdot \frac{T_L s + 1}{T_I s + 1} \cdot e^{-\tau s} \tag{1}$$

The lag time constant T_I is related to the implementation of learned stereotypes and routines. The lead-time constant T_L corresponds to the experience of the pilot, reflecting the pilot's ability to predict a near future control input, i.e. to predict the situation that may occur. The relationship between T_L and T_I (the equalization part) together with the gain K_{FB} reflects human adaptation to the controlled element. The reaction delay τ indicates the delay between eye perception and the brain response. These parameters correspond to the stimuli perception, information processing and selecting suitable control action, as defined by the simple HRA model (Fig. 2).

The second part is the feed-forward controller FF. This controller ensures the pursuit or preview control mode, which is focused on minimizing the control error $e(t)$ from the set-point. (McRuer, 1974). In case of simple tasks, this type of control is obviously used also for correction of the sudden changes or unpredictable situation instead of the FB controller (Roesener et al. 2018).

The last (but not least) part of the human controller is the cognitive part responsible for cognitive processes, namely, learning, internal data representation and control optimization or adjustment. The modeling of this controller is very difficult because of the different strategies of each human and is mostly modeled using neural networks and probabilistic approaches (Jiang et al., 2019).

Based on the above-mentioned information, the human-control process can be divided into two or three phases (McRuer, 1974), (Mulder, 2017).

Within the first phase, the FB controller is mainly active, because fast compensation of the set-point change is required.

During the second phase, there is an effort to minimize the control error $e(t)$, and the pursuit or FF controller is majorly active. However, with complex dynamics of the controlled element, we can advantageously model the pursuit controller as a complement to the FB controller, e.g. FB_P.

The third phase lies in strategy planning and optimization and it is often modeled together with the second phase in case of easier tasks.

The resulting control action is performed through the neuromuscular system (NMS) and an actuator. Describing function for NMS is based on the McRuer's precision model and is generally defined as a second order LTI system with frequency ω and damping ξ , see (2) (McRuer, 1974).

$$NMS(s) = \frac{K_{NM}}{(s^2 + 2 \cdot \xi_{NM} \cdot \omega_{NM} \cdot s + \omega_{NM}^2)} \tag{2}$$

Thus, the individual controllers represent, together with the neuromuscular system, a general adaptive human control model defined within the novel framework for human control modeling (Mulder, 2017).

Most of the described controllers are usually implemented in the linear form. Human behavior, however, is generally non-linear, primarily because of the different types of limitations to be identified, mathematically described and included in the resulting behavioral model. The others, which can not be easily mathematically described, are commonly summarized as a remnant function and modeled e.g. using an additive noise (Lone & Cooke, 2013). The most significant nonlinearities are the threshold element connected with the properties of human sensing or saturation. In large part, these together with the reaction delay and value of parameters of the equalization element, represent a group of fundamental physical limitations for the human being.

5. APPLYING THE NOVEL FRAMEWORK PRINCIPLES INTO SIMPLE HiLCPSs

As an example of HiLCPS description, the interaction between a human and the flight simulator will be presented. In fact, a system where a human being (pilot) is controlling the simulated aircraft flight is a feedback control loop similar to that shown in Fig. 4. The used flight simulator is a relatively complex device with many control elements, displays, computational resources and communications, including the relation to the real environment and human or pilot. The whole system thus represents a certain type of HiLCPS.

Many experiments have been performed to assess pilots' abilities, current skills and training level, and other relevant aspects (Boril et al. 2017). These studies analyzed mainly the basic properties of human behavior, albeit only via parameters of the FB controller. Based on the defined simple control task (reaction to the step change in the aircraft altitude under the preset conditions described in (Jirgl et al. 2018)), we evaluated probable ranges of the FB parameters.

The feedback controller (FB) is only one part of the human behavior model defined by the novel framework. The FB is responsible for the compensatory control and describes the dynamic properties in particular. Further, this simple form finds use as the only model to simulate human behavior or approximate the human control action; however, as regards complex dynamics control, a simple FB controller can be insufficient as an approximation of the real control action.

Flight or simulated longitudinal flight control of a King Air C90B aircraft performed on a stationary flight simulator can provide a suitable example.

5.1 Modeling Human Behavior with an FB Controller

In our experiment, the pilot's control task was defined as a longitudinal flight within the following initial conditions: altitude $H_0 = 2{,}900$ ft, longitudinal velocity $v_0 = 170$ mph, Mach number $M_0 = 0.23$, engine thrust $\delta_{P0} = 600$ lb; the relevant angle of attack α_0, pitch angle υ_0, and their derivations were approximately equal to zero. The linearized state-space model of the longitudinal flight for the above-mentioned conditions had been developed and described in (Jirgl et al. 2015). The system matrix roots (poles) represent dynamic properties of the controlled element and correspond to the phugoid oscillations ($\omega_{ph} = 0.103$rad.s^{-1}, $\zeta_{ph} = 0.021$), short-period oscillations ($\omega_{sp} = 3.88$ rad.s^{-1}, $\zeta_{sp} = 0{,}463$) and to integrative character of the longitudinal flight ($\lambda \rightarrow 0$). This system dynamic is typical for these types of aircraft (Fossen, 2011).

At the defined moment, a request for a step change of about 300 ft occurred, and the task of the pilot was to respond to this change within the shortest time and as accurately as possible. The signals representing the altitude H and the pilot's control action, namely, stick deflection dv, were logged and then employed to identify the parameters of the simple FB controller, specified in formula (1) to describe the pilot's behavior during the corresponding situation. The model parameters identification was carried out by using MATLAB-System Identification Toolbox.

The results of modeling human behavior with an FB controller are demonstrated in the following example. Based on the described approach, the FB parameters of a selected pilot were evaluated as $K_{FB} = 0.24$, $T_L = 2.5$ s, $T_I = 0.7$ s and $\tau = 0.65$.

The FB controller was then extended with appropriate nonlinearities (such as saturation and dead zone) and noise effect. The NMS was modeled according to (2) with the standard parameters ($\omega_{NM} = 10$ rad.s^{-1} and $\xi_{NM} = 0.6$) (McRuer, 1974). The results of the modeled control loop with the FB controller, NMS, and longitudinal flight model compared with the original data (representing a measurement with the selected pilot) are in Fig. 5.

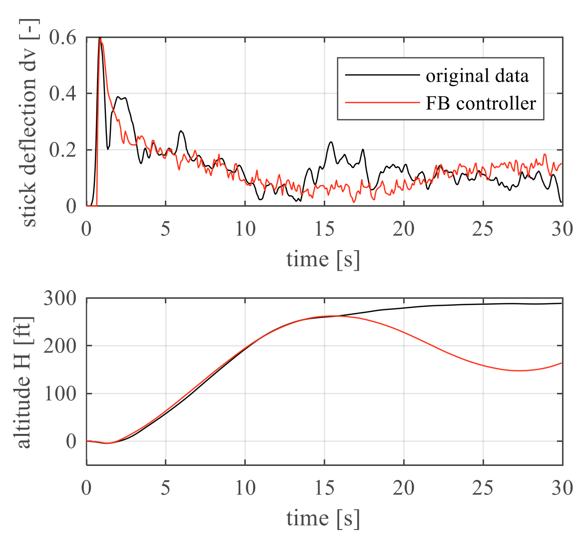


Fig. 5. A comparison of the measured and modeled data using the FB controller within zero initial conditions (without the offset of H = 2,900 ft).

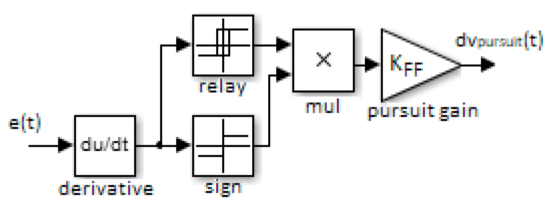
The compared original (measured) data and control loop simulation by using the FB controller and linearized model of the longitudinal flight indicate that the controller is valid for time $t < 15$ s in this case. This control stage can be characterized as phase 1, or compensatory control. To obtain a comparable response throughout the entire time interval, a more complex human model should be used.

5.2 Extension of the FB Controller by using the Pursuit Controller

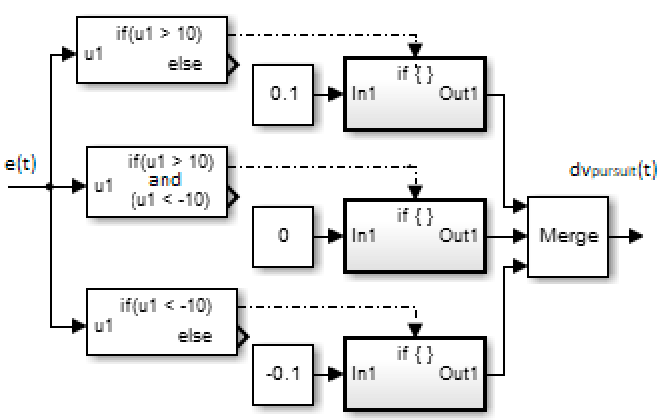
As illustrated in Fig. 2 and described in the related chapter, the whole human behavior model consists of several important parts, which can be modeled individually or together as a complex model. There are different approaches to this issue.

The FB controller is most often modeled by using McRuer's model; the pursuit controller can be then modeled as a common feedforward (FF) or, in case of more complex dynamics of the controlled element, we can advantageously model the pursuit controller as FB_P feedback controller.

For these purposes, either the relay controller (Fig. 6 - a) or the controller based on applicable rules (Fig. 6 - b) were used as a complement to the FB controller described above. Both these controllers respond to the control error instead of the set point (it corresponds to the FB_P controller), and are applied especially in the steady state (the second control phase); functionally, they focus mainly on minimizing the control error $e(t)$ from the set point. This function is implemented as a conditioned working range $e(t)$ = (-50;50) ft.



a)



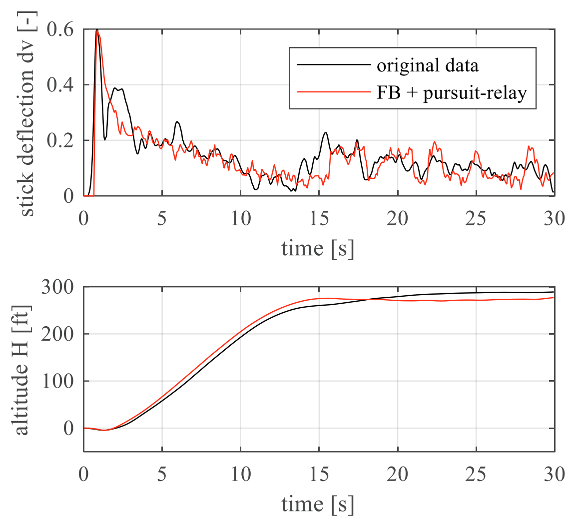
b)

Fig. 6. The pursuit controller implementation.

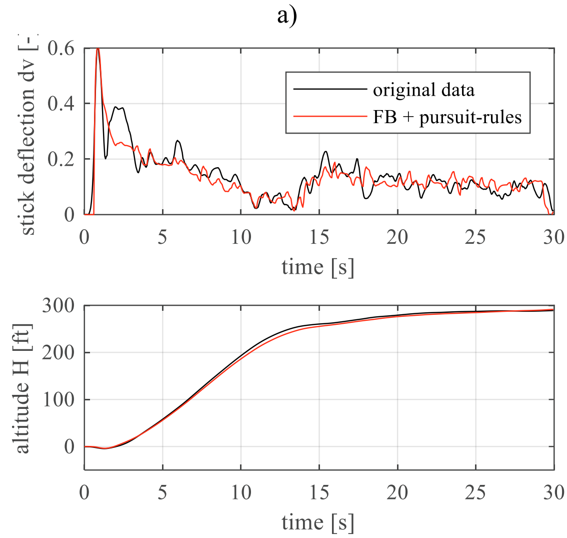
The pursuit controller implemented as the relay controller (Fig. 6 – a) enables reaction to the control error $e(t)$ derivation by using relay characteristics with the sign function for the positive or negative control action. This solution is simplified because the gain K_{FF} is experimentally set as the constant value of 0.1.

The other solution (Fig. 6 – b), exploiting the rules-based controller, evaluates the rules (observable in the figure) for the control error ranges and responds with a relevant control action. The working region is predefined for the interval $e(t)$ = (-50;50) ft, similarly to the previous case. This solution additionally comprises a dead zone $e(t)$ = (-10;10) ft related to the inaccuracy of reading the altitude indicator by pilot.

All the parameters, ranges, and properties of the individual controllers were set experimentally, with an emphasis on sufficient approximation of the measured response. In both cases, the pursuit controller is in parallel configuration to the FB controller (with described parameters) as FB_P. The resulting control action is then implemented through the NMS and contains white noise. A comparison of the solutions is outlined in Fig. 7.



a)



b)

Fig. 7 The selected original (measured) data approximated by using the FB controller and a) the relay pursuit controller b) the rules-based pursuit controller.

6. CONCLUSION

The aim of this paper was to describe an advanced approach towards human behavior modeling (referred to as adaptive human control model) and to demonstrate the method's applicability in the context of a simple HiLCPS. For these purposes, the main idea of human-based task processing was characterized, together with a definition of the individual components forming the human behavioral model. Based on the novel theory, we proposed a general model structure to cover the individual control phases including the FB controller and the pursuit controller. The parameters of the FB controller were identified from the data measured on a flight simulator controlled by a selected pilot during the defined task. The pursuit controller was then tuned with an emphasis on suitable approximation of the data representing the appropriate measured pilot's control action.

The results obtained via combining the FB and the pursuit controllers exhibited relatively accurate approximation of the responses measured on the pilot-controlled flight simulator. The configuration of the pursuit controller was then verified by utilizing other measured data (for other pilots); in this context, the first results of the rule-based controller indicated the possibility of using this approach to model the human/pilot behavior during more complex control tasks. However, it is needed to employ more experiments to generalizing the described principle. One of the key features is the fixed parameters might have to be replaced with a more flexible approach (with respect to the novel framework), e.g., a fuzzy logic system or artificial intelligence; this approach is subject of our onward research. The results can be then used for basic estimating and predicting human performance and limitations in terms of HiLCPSs.

ACKNOWLEDGEMENT

The research was financially supported by Brno University of Technology. Part of the work was carried out with the support of core facilities of CEITEC – Central European Institute of Technology. This work was supported by the projects: FV30037 Research and development of new control systems for purchasing platforms, Ministry of Industry and Trade, Czech Republic, FV40196 Research and development of the monitoring of immobile persons who are tethered to the bed in terms of risk of suffocation – decubitus, Ministry of Industry and Trade, Czech Republic, FV40247 Cooperative robotic platforms for automotive and industrial applications, Ministry of Industry and Trade, Czech Republic, TF04000074 Digital representation of Assets as a configurable AAS for OT and IT production systems, Technology Agency of the Czech Republic, TH02030921 The sophisticated wireless network with elements of IoT for plant protection and water management, Technology Agency of the Czech Republic, FEKT-S-17-4234 Industry 4.0 in automation and cybernetics, Internal Grant Agency of Brno University of Technology, 783119-1 SECREDAS Product Security for Cross Domain Reliable Dependable Automated System, H2020-ECSEL, EU. The above-mentioned grants and institutions facilitated efficient performance of the presented research and associated tasks.

REFERENCES

Allerton, D. J. (2010). The impact of flight simulation in aerospace. *The Aeronautical Journal*, **114(1162)**, pp. 747-756.

Bell, J. & Holroyd, J., 2009. *Review of human reliability assessment methods*, Buxton: HSE Books.

Boril, J., Jirgl, M. & Jalovecky, R. (2017). Using Aviation Simulation Technologies for Pilot Modelling and Flight Training Assessment. *Advances In Military Technology*, **12(1)**, pp. 147-161.

Fossen, T. (2011). Mathematical Models for Control of Aircraft and Satellites. Norwegian University of Science and Technology, January 2011. - 37 p.

Jiang, H., Tian, H. & Hua, Y. (2019). Model predictive driver model considering the steering characteristics of the skilled drivers. *Advances in Mechanical Engineering*, **11(3)**.

Jirgl, M. & Jalovecky, R., 2015. Analysis of the Dynamic Properties of Longitudinal Flight Based on the Measurement on the Flight Simulator. In *Transport Means - Proceedings of the International Conference*. Kaunas Univ Technol, Kaunas, LITHUANIA, pp. 290-293.

Jirgl, M., Bradac, Z. & Fiedler, P. (2018). Human-in-the-Loop Issue in Context of the Cyber-Physical Systems. In *IFAC-PapersOnLine*. pp. 225-230.

Lee, E. (2015). The Past, Present and Future of Cyber-Physical Systems: A Focus on Models. *Sensors*, **15(3)**, pp. 4837-4869.

Lone, M. & Cooke, A., 2013. Pilot-model-in-the-loop simulation environment to study large aircraft dynamics. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, pp.555–568.

McRuer, D.T. & Krendel, E.S., 1974. Mathematical Models of Human Pilot Behavior, London: AGARD AG-188.

Mughni, W. (2016). *Human Factors in Aviation*. Aviation Institute of Management.

Mulder, M., Pool, D. M., Abbink, D. A., Boer, E. R., Zaal, P. M. T., Drop, F. M., et al. (2017). Manual Control Cybernetics: State-of-the-Art and Current Trends. *IEEE Transactions On Human-Machine Systems*, pp. 1-18.

Munir, S., Stankovic, J. A., Ljang, C. -J. M., & Lin, S. (2013). Cyber Physical System Challenges for Human-in-the-Loop Control. In Presented as part of the 8th International Workshop on Feedback Computing. San Jose, CA: USENIX.

Rasmussen, J., 1983. Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and Other Distinctions in Human Performance Models. In IEEE Transactions on Systems, Man, and Cybernetics, pp.257–266

Roesener, C. et al. (2018). Modelling Human Driver Performance for Safety Assessment of Road Vehicle Automation. In: *21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, pp. 735-741.

Schirner, G., Erdogmus, D., Chowdhury, K., & Padir, T. (2013). The Future of Human-in-the-Loop Cyber-Physical Systems. *Computer*, **46(1)**, pp. 36-45.

Slanina, Z., Mikolajkova, S., & Vala, D. (2017) Human vehicle interaction. In AIP Conference Proceedings, **1836**, pp. 020050-1 - 6.

Spurgin, A. J. (2010). *Human reliability assessment: theory and practice*. Boca Raton: CRC Press.