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Data-Driven Pilot Behavior Modeling Applied to an Aircraft Offset Landing Task

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Abstract. This paper shows studies for the development of a mathematical model that adequately represents a pilot behavior in the specific task of offset landing, using data-driven modeling techniques. Flight test data was used for the identification procedure. Considerations on the pilot's cognitive process and mathematical modeling possibilities were discussed to select the most appropriate inputs and outputs for the model. This data was used to identify the model using artificial neural network techniques. The models obtained were validated against the identification data and different data not used in the training process to evaluate the quality of the models. Conclusions include the difficulties of showing the generalization capabilities of those non-linear models and further studies.

Keywords: Human factors · Human pilot modeling · Neural networks

1 Introduction

The use of modeling and simulation techniques is rising quickly in every field of engineering as computational power grows and the need for to detect design issues early in the development process rises to shorten lead times, lower costs and increase product maturity. However, for tasks requiring a human operator in the loop, the usefulness of simulation may be reduced. That is because it may be difficult to model human behavior and include it in the simulations. Even if human in the loop simulations are used, this

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N.A. Stanton (ed.), *Advances in Human Aspects of Transportation*,
Advances in Intelligent Systems and Computing 597, DOI 10.1007/978-3-319-60441-1_12

prevents the analyst to run many simulations (such as a Monte Carlo) due to the impossibility of a human (or even a team of humans) to perform hundreds or even thousands of tests points in a feasible time.

For this reason, mathematical representations of the human operator are useful in a variety of scenarios. As stated by Turetta et al. [1], "science is very far from being able to represent all the complex human behavior with mathematical equations, but in some specific cases, it is possible to isolate a specific action that is required for an engineering test."

The first mathematical models of the human pilot were developed by McRuer [2] with linear and quasi-linear models. Those models kept evolving to optimal control models in the 1970s by Wierenga [3] and Kleinman [4], and then to nonlinear models such as Hess's proposal of 'pulsive control behaviour' [5]. Lone and Cooke [6] did an extensive review of those models.

Regarding the use of data driven techniques for modeling the human aircraft pilot, focus has been given on the landing task as it is recognizably the higher workload phase of flight (not considering military tasks). Martens [7] used neural networks to model and evaluate human behavior during landing in a light windshear condition. Mori, Suzuki and others [8, 9, 10] have modeled the pilot approach using stochastic switched linear models for the approach portion, and neural networks to model flare maneuver, which they stated to be highly nonlinear. The experiments performed in this paper are aligned with these observations.

The remainder of this paper is organized as follows. Section 2 contains the behavioral model development rationale. Section 3 presents the results and discussion using the identified models. Finally, the conclusions and further work are the contents of Sect. 4.

2 Model Development

2.1 Offset Landing Task

The offset landing task is indicated by Flight Test Guide for Certification of Transport Category Airplanes, FAA AC 25-7C [12], of the U.S. Department of Transportation, as one of the tasks to be performed during flight test to evaluate the likelihood of airplane pilot couplings, or pilot induced oscillations. This is a phenomenon that occurs when the phase between the pilot inputs and the airplanes dynamic response are in such a way that airplane oscillatory movement may occur causing discomfort or, at higher levels, even loss of aircraft's control.

The task consists in performing the approach to landing with a predetermined localizer offset, and at a given altitude, to correct the offset and land the aircraft. It is an operationally feasible situation that may occur if the airport localizer antenna is poorly regulated and the approach is performed under low visibility operations. In this case, the pilot performs the entire approach with an offset (as s/he is flying using instruments rather than visually) and at the time s/he acquires visual contact with the runway, the correction of the offset is required at a lower altitude than would be desired.

2.2 Input and Output Models Considerations

Some variables are fixed for this mathematical model, because they can adversely modify the aircraft dynamic response and increase considerably the complexity of the model. The landing gear is always down and locked and the flaps positions are the same in all test points. CG (center of gravity) position and aircraft weight that can also modify the aircraft dynamic response so it is desirable that they should be fixed or be considered as model inputs. Since a limited amount of test data was available, initially CG and weight variations were not considered, and this resulted in unsatisfactory models. Filtering the test points with only similar weights and CG positions, the model quality improved significantly. Finally, the test points were done with a constant thrust setting, and that no rudder input is used. This means that the outputs of the model are the control column lateral (that controls the ailerons, shown as y1 in the figures) and longitudinal (that controls the elevator, shown as y2 in the Fig. 1 displacements.

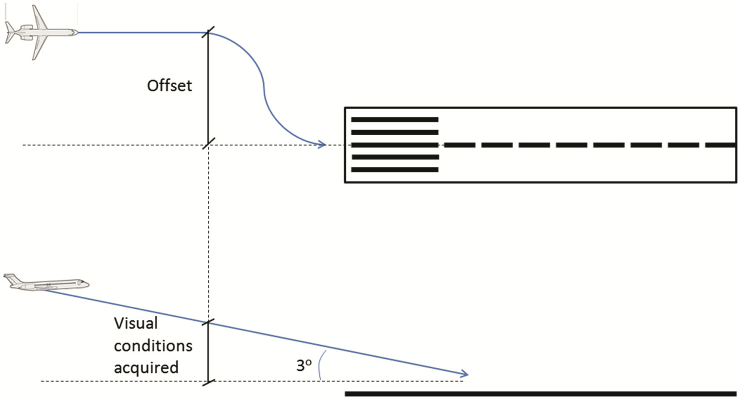

Fig. 1. Offset landing task.

The definition of the model inputs is a more complex task, as multiple factor may influence the pilot behavior in this situation. Mori and Suzuki's [8, 10] analyzed the visual cues the pilot used during approach, and make those cues the inputs of the model. In the end, those cues are a function of airplane position in relation to the runway, airplane speeds and the dimensions of the runway, cockpit seat and windows. Since this work is a data driven approach, it is possible to use directly the airplane position in the algorithm, as it can be transformed into the visual cues by geometric transformations. Therefore, the first inputs for the model were defined as the position of the aircraft in relation to the runway threshold (x, y and z).

Additionally, it is desired that the model is capable of responding to wind gusts, so the wind components in the three directions was also included as model inputs (Xwind, Ywind and Zwind).

Aircraft speed was also considered as an input because it influences the aircraft dynamic response and because the pilot knows that s/he cannot command high angles at low speeds.

The Euler angles were also considered as model inputs because they are highly considered by the pilot during maneuvering, and it is expected that they would reduce the control inputs gain at high angles to avoid stall (pitch, roll and yaw).

At last, it was considered that the load factors in each direction could also be considered as inputs, for a similar reason than the Euler angles, as the pilot would tend to reduce the control inputs gain at high load factors to avoid damage to the airframe (Nx, Ny and Nz). Later, it was observed that those inputs were not necessary as the load factors are not large during this specific operation.

The considerations above defined the model as having the following inputs and outputs:

Inputs:

- Set 1 (coordinates): X, Y and Z coordinates in relation to runway threshold
- Set 2 (winds): Xwind, Ywind and Zwind
- Set 3 (speed): Aircraft speed
- Set 4 (angles): Pitch, yaw and roll angles
- Set 5 (load factors): Nx, Ny and Nz.

Outputs:

- Control column lateral displacement
- Control column longitudinal displacement

The inputs are structured in sets because models with different subsets of those inputs are evaluated. The outputs are the same for all models in this paper.

3 Results and Discussion

3.1 Model Identification Techniques

Initial attempts to use linear mathematical models showed that the dynamic behavior was not captured. Switching to NARX (Nonlinear AutoRegressive with eXogenous input) models and Artificial Neural Networks improved significantly the results at the initial trials, but the models were still having low correlations and R2 coefficients. It was thus defined that artificial neural networks were seemingly more appropriate to fit this kind of problem.

Still, it was necessary to improve the model quality and too many factors were at hand to consider. An optimization approach using all variables was considered, but since it would dramatically increase the complexity of the whole procedure, a sequential strategy has been adopted, namely: analysis of the maneuver, re-evaluation of the inputs with a single landing, evaluation model order and complexity with a single landing and finally evaluation of multiple landings.

3.2 Analysis of the Maneuver

Due to initial difficulty of obtaining a good model, one question that arises was about the complexity of the maneuver and the possibility of modeling it entirely with a single model. As pointed by Mori and Suzuki [8, 10], the flare maneuver is highly nonlinear and represents a completely different behavior than the initial portion of the approach, and this made them divide the initial approach and the flare maneuver into two different models. Even for the initial part of the approach, they used three different linear ARX (AutoRegressive with eXogenous input) models that were switched by a Markov chain depending on the deviation from the intended glide path. The task under study herein is even more complex because it contains the offset correction. Initially, the desire was to model the complete maneuver, but the tryouts indicated that modeling even a normal landing with no flare was a complex task (regarding the neural network generalization capability, as it is shown below). Therefore, it was decided that the evaluation of the flare would be left for further studies, and focus would be given on the offset correction only. All data below 20 m of height above ground level was removed from the data sets to remove the flare behavior.

3.3 Reevaluation of the Inputs - Single Landing

Although all the inputs described in Sect. 2.2 influence the pilot inputs, it may be possible to model the behavior with fewer inputs to simplify the model and save computational cost. It is shown that for a single landing identification, a neural network with 10 neurons and fifth order of delays could deliver an almost perfect correlation and R2 with the actual data, indicating an over fitted model. So, to evaluate the contribution of the variables, models with a fixed order of 3 and complexity of 5 neurons (single layer and sigmoid activation functions) were generated for the same landing, using a different set of inputs. This was made to allow the observation of the variation in the model quality with the inputs sets variation. The results are seen in Figs. 2, 3, 4, 5 and Table 1.

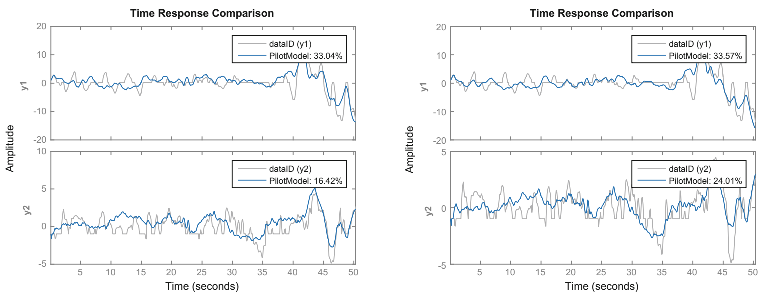

Fig. 2. Left: all inputs sets - Right: no winds set

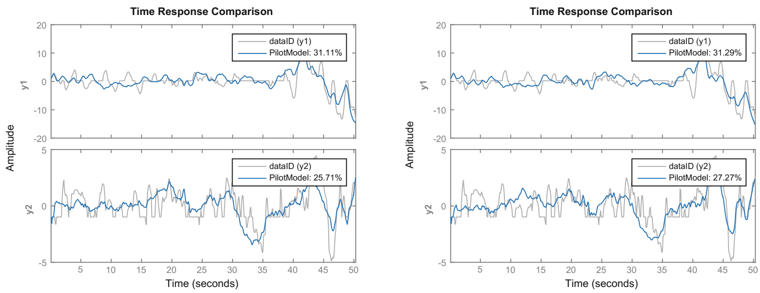

Fig. 3. Left: no angles set - Right: no speeds set

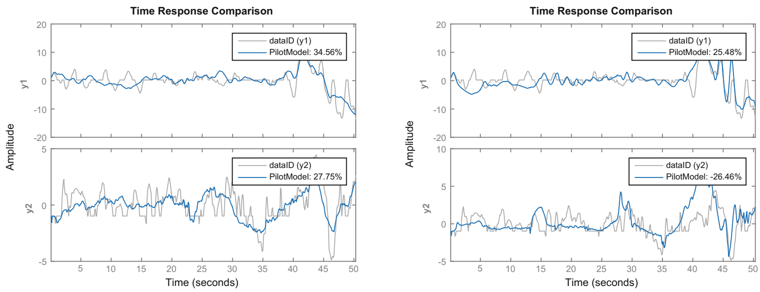

Fig. 4. Left: no load factors set - Right: coordinates only

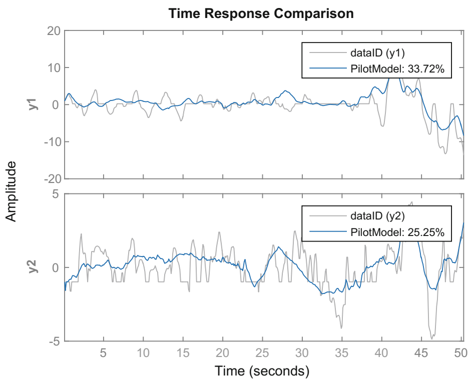

Fig. 5. Coordinates and angles only

Initial analysis suggested that it could be possible to use only the coordinates, but that model lost the capability of fitting y2 (longitudinal stick input). The reason for this result is traced to the pilots' need to know - at least - the angle of attack in order to calculate his maximum longitudinal stick input. It could be argued that adding only the pitch angle to the net would resolve this issue, but since the maneuver contains the offset correction that calls for large bank and roll angles, it is wise to include all the three angles as net inputs (as the angles are dynamically coupled). Table 1 shows that a model using the coordinates and angles only showed results as good as the one with all variable sets. From this point on in this paper, all models are using those sets of inputs.

Table 1. Quality of models varying with inputs set.

Inputs	Correlation:y1	R2:y1	Correlation:y2	R2:y2
All inputs set	0.750	0.552	0.663	0.302
No winds	0.761	0.559	0.668	0.423
No angles	0.730	0.525	0.676	0.448
No speeds	0.733	0.528	0.695	0.471
No load factors	0.758	0.571	0.695	0.478
Coordinates only	0.703	0.445	0.416	0
Coordinates/angles	0.773	0.561	0.675	0.441

3.4 Model Order and Complexity - Single Landing

When identifying a model for a single landing and comparing the model to its data, it was observed that a perfect match could be obtained for any specific landing. Figure 6 shows that the metrics improve with higher orders and a greater number of neurons, with the median approaching 100% with ninth order or 9 neurons. It also shows that there is a significant spread between different landings, meaning that for a specific landing, a good model may be obtained with a simpler model. This is an interesting result and prompts the question of how it is possible to quantify the human variability. In other words: what is the variance of human behavior in that specific task? This metric, if developed, could be applied to help validate a human model, meaning that maybe a model does not have a particularly good fit to the test data, but it can still be considered as a "human like" behavior, due to this variance.

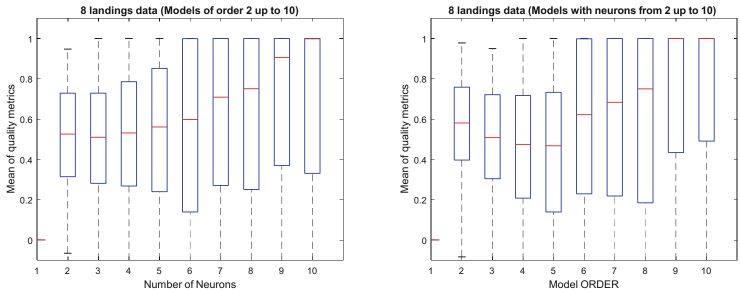

Fig. 6. Evolution of the mean of the model quality metrics (R2 and Correlations) with model order and number of neurons.

Another interesting result, can be seen in Fig. 7, notice that the fourth order model has a better fit than the sixth order one, the eight order model has an even worse fit, and finally the tenth order model has an over fitted response. However, notice that in the eighth order model, the fit is almost perfect in the beginning of the maneuver, diverging at the middle. This indicates that there are two different behaviors contained in the data, and this model is able to fit the first behavior (which is the normal approach sequence). By the middle of the data, the second behavior appears and the model is no longer good (which is the offset correction). This shows that the strategy adopted by Mori and Suzuki in 2010 of having different models for different behaviors in the same maneuver is interesting because it allows using simpler models, rather than capturing different behaviors in a more complex model.

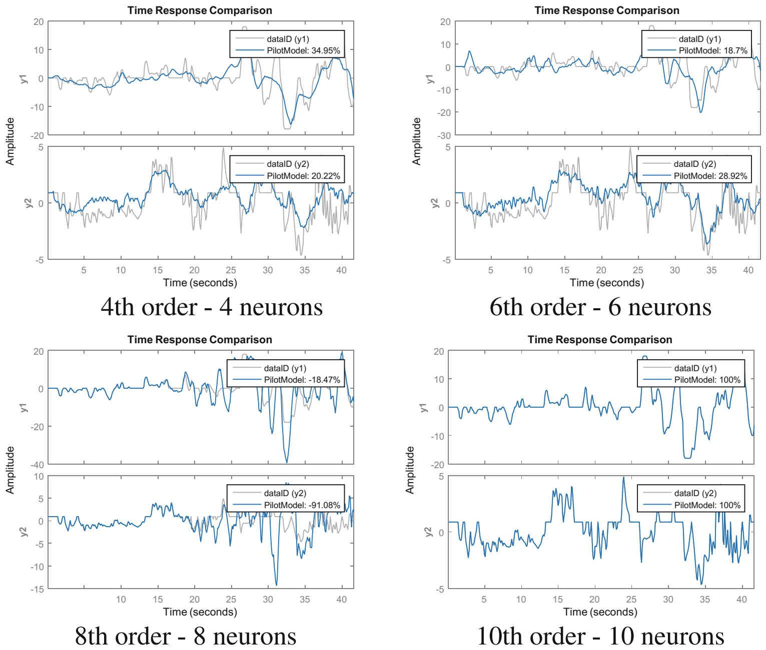

Fig. 7. Evolution of fit of a single landing with order and neurons number increase.

3.5 Evaluation of Multiple Landings

As seen above, when comparing the obtained models with the data sets used in the network training, it is possible to obtain good models with a considerably low complexity such as fourth order and four neurons (correlations around 70% and R2 around 45%). However, to be able to use the model in, for example, Monte Carlo simulations with large variations in the variables such as wind conditions offset size etcetera, the model should have considerable generalization capabilities. That is, the ability to reproduce human-like behavior in scenarios that did not appear in the training data set. This appeared to be a challenging problem, as even very complex models could not show good correlations when exposed to landing data that was not considered in the training set. Additionally, just increasing the model complexity started to prove an unfeasible option as the computational cost grows very quickly. As a measure of this cost, using an Intel(R) Core(TM) i7-4810MQ CPU @ 2.80 GHz with 16 GB RAM (Random Access

Memory), the learning process to obtain a single model from data merged from 7 landings with fourth order and four neurons took 10.22 s. The model from the same data but with tenth order and 10 neurons took 137.40 s.

In order to observe the generalization, the combination of 7 landings (out of 8) to be compared with the remaining one was made, with neurons and order varying from 2 to 15 (resulting in 1568 different models). This training process for all those models took 71 h.

Figure 8 shows that the results quality decrease significantly when compared to the data of a single landing (Fig. 6). This result indicates the need of a strategy change to obtain a model with good generalization capabilities. In addition, Fig. 8 shows that apparently there is no observable improvement in the quality of the model even when the order/quantity of neurons increases up to 15.

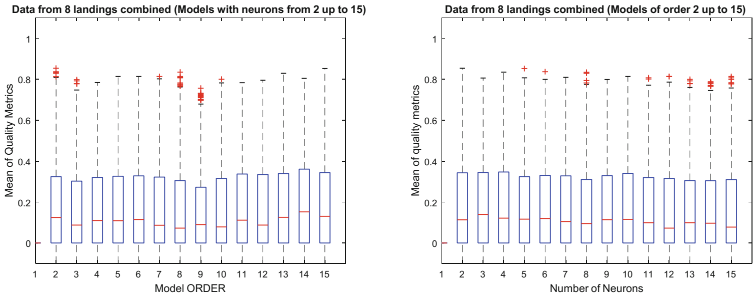

Fig. 8. Evolution of the mean of the model quality metrics (R2 and Correlations) with model order and number of neurons for models identified with 7 landings compared to an eighth one.

Changing the reference for model caused observable changes in the quality of the model. Figure 9 shows an example for the lateral stick input correlation only (but other metrics show a similar behavior). Notice that when landing 1 is used as a reference, the quality is always below 40%, while when the reference is landing 8, the quality is around 70%. Taking landing 2 as a reference, it is possible to see a relation between the increase in the order and the increase in model quality. This shows the complexity of the problem and that further analysis is required. Maybe some landings are outliers, or maybe they contain some characteristic that are not present in the other landings, causing the generalization to decrease when they are not used in the learning process. If that is the case simply increasing the number of landing available for training may solve the issue, but at this point, such data was not available.

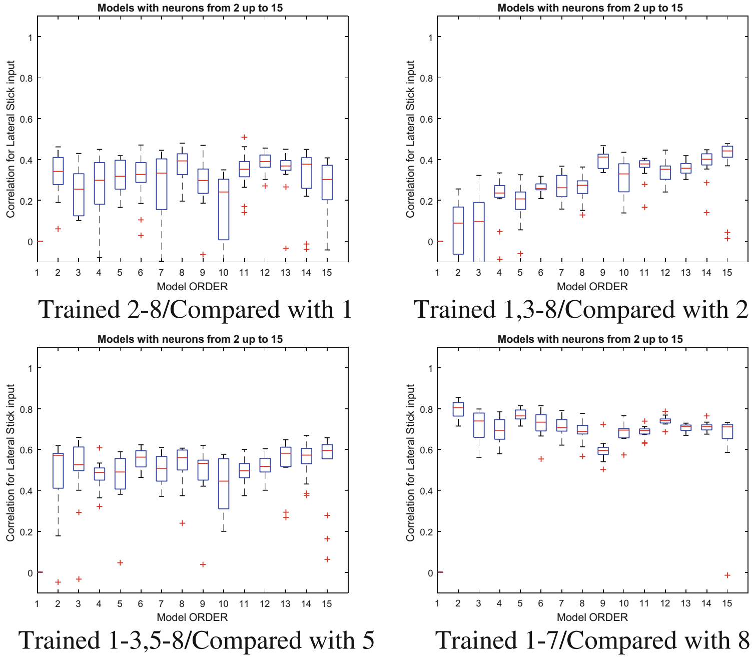

Fig. 9. Comparison of quality of the model (Correlation only) when changing the reference landing for comparison

4 Conclusions

In conclusion, it is possible to model a single landing using a neural network structure, but producing a network capable of reproducing different landings apparently requires further studies. Increasing the number of landings available for training is one obvious possibility but it has operational difficulties related to obtaining and filtering the data.

Other further studies include using an optimization algorithm considering all variables to discover the contributions of each variable and to try to obtain a model with better generalization capabilities. Another possibility is to design a specific experiment to make the identification, as this study was conducted with reused data from tests that were designed for other purpose. This would allow better signal/noise relations in some variables that could uncover interesting results. A possibility would be to start the modeling procedure with a simple normal landing with no offset, and then include growing offsets in the maneuver in such a way that is possible to obtain better understanding of how the offset modifies the pilot behavior.

Other future research is studying the variance of human behavior as suggested in item 3.4 would be a good addition to help validate human models.

Acknowledgements. This study is partially supported by the National Council of Scientific and Technologic Development of Brazil (CNPq) under Grant 150238/2017-7.

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