A Dynamic Field Theory Based Pilot Model To Control Aircraft Pitch Attitudes

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Abstract

In this study, a dynamic field theory (DFT) based cognitive model of a pilot performing pitch attitude control of a 3 degree of freedom aircraft model is presented. The cognitive model is validated by comparing the pilot model's pitch attitude hold performance with real flight test results of a human pilot on a real aircraft. A high degree of similarity was observed between the behaviour of the human pilot and the DFT model. The paper contains a brief summary of older control theory based pilot models, describes the similarities between control theoretic and DFT approaches, and shows the DFT pilot's flexibility to adapt to different temporal behaviours.

Keywords: Dynamic field theory, pilot cognitive model, cognitive modelling.

Models of Pilot Cognition and Piloting Tasks

Several mathematical models that emulate a human pilot's abilities to control an aircraft have been proposed in aerospace engineering since 1950s. Most of these are functional models that simply provide a transfer function constructed upon control theoretic principles such as root loci and Bodé plots, which are primarily based on data obtained from questionnaires filled by the pilots or flight test instrumentation. In particular, these models belong to the first among two main modeling paradigms, which focus on performing a specific task by using a pilot transfer function to control some specific aspect of aircraft attitude. Such models treat the pilot as a set of control equations in the control loop of an aircraft function. Although these control models are great engineering efforts, they are primarily geared towards controlling the aircraft as part of an autopilot system, rather than providing tools for understanding human piloting behaviour. The second paradigm employs a cognitively more plausable approach, which will be discussed further after a review of control theory based pilot models.

One of the earliest control theory based pilot models focused on determining the control parameters of vertical take-off and landing (VTOL) aircraft in the United States Air Force Flight Dynamics Laboratory (AFFDL) (Blakelock, 1991). The purpose of this study was to determine the VTOL specification for a future development aircraft with a focus on matching human performance characteristics obtained in conventional aircraft. Since no VTOL aircraft had yet to be built at the time, AFFDL did not have any chance to use real flight test data, so researchers preferred to use a simulated environment to obtain pilot performance parameters as rated by the Cooper-Harper rating scale. This work led to the first control theoretic pilot model in 1960s, which is considered as the *generic pilot model* (Johnson & Pritchett, 2002).

The *crossover model* is one of the two well-known control theory based pilot models. The model takes its name from the crossover frequency which is the frequency where the phase angle of a Bodé plot equals -180° or -π (Blakelock, 1991). The crossover model assumes a simple control loop of pilot-aircraft similar to the one given in Figure 1 below.

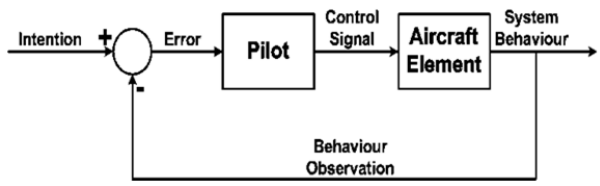

Figure 1. A representation of Crossover Model with a slight modification from Blakelock (1991).

McRuer and Jex (1967) give a crossover model written in frequency domain with parameters *jw* and Blakelock (1991) provides the same model in Laplace domain with variable *s*. In the crossover model's pilot-aircraft loop, we labelled the input as intention, which may refer to a navigation goal originating from the flight plan or a leg of a manoeuvre. In any case, the pilot is mostly interested with the deviation between the intended (or goal) state and the current situation. The crossover model aims to achieve humanly dynamical behaviour by adjusting the time constants to manage the deviation between the current situation and the goal, which is the main reason behind its stability.

However, the model neglects the spatiotemporal behaviour of the neural network underlying the decisions of the pilot. Therefore, one can conclude that such control theoretic models of pilot behaviour are functional engineering models that are not neurobiologically informed. McRuer and Jex (1967) report that such a model holds only around the crossover frequency of its Bodé plot, and this is where the name of the model arises.

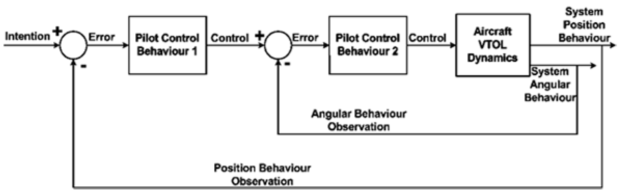

Figure 2. A schematic representation of the paper pilot. The paper pilot differs from the crossover pilot by incorporating not only the position but also the angular situation of the aircraft into the control loops.

The *Paper Pilot* is another seminal model like the crossover model, which employs the McRuer and Jex model as an inner loop. Hence, it is a far more complex model in comparison with the crossover model (Anderson, 1970; Anderson, Connors & Dillow, 1970). A schematic representation of the paper pilot model is provided in Figure 2. There are two control loops, one being inside and in contact with the aircraft dynamics, and one being outside serving as an outer loop oriented towards position behaviour. The use of such inner and outer control loops are still commonly used in aircraft control modelling.

The paper pilot model uses a performance-based approach for the determination of model parameters (Anderson, 1969). The use of the transfer function from the crossover model eased the development of the paper pilot. It is named as paper pilot possibly because it depends on the evaluation of pilot performance with questionnaires. In the model, the most important parameters are the gain and the lead time constants, which are selected to optimize the model performance by minimizing attitude errors.

The crossover model described above can control a single parameter, and thus controlling multiple parameters instantaneously requires the use of multiple crossover models. The paper pilot model has an advantage in comparison with the crossover model, as it uses both position and angular parameters to control the displacement. This parallels to the real situation in an aircraft where the pilot generally controls the angular movements and the thrust level (i.e. speed for displacement). Therefore, the paper pilot is far more realistic as a model as compared to the crossover model.

The main weakness of the paper pilot is its performance dependency. Since the model parameters are adjusted using the model performance iteratively, the model is very much dependent on the physical aircraft model. In other words, the pilot model performance changes with the aircraft model. So paper pilot is a task dependent model that differs from a human pilot who can learn to fly any type of aircraft with a performance depending on training hours.

The *optimal pilot model* is developed to overcome the task dependency (i.e. dependency to aircraft dynamics) of the paper pilot (Pollard, 1975). As it can be seen in Figure 3, in contrast to prior models the main improvement is the addition of the angular control element to the control loop, which is one of the primary controls performed by a human pilot. The optimal pilot goes one step further by adding a simulation of humanly behaviour in the form of an estimation-control loop. Therefore, the optimal pilot model can be considered as the first attempt in capturing the pilot's cognitive abilities in a computational model, even though it is not biologically informed and it is still essentially a control model.

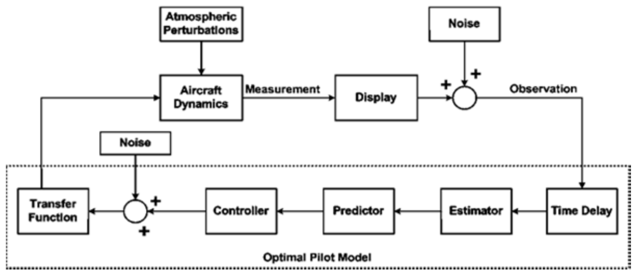

Figure 3. A schematic of the optimal pilot model.

Similar to the paper pilot, the optimal pilot also depends on a pilot rating function (PR), which is used to evaluate the model performance with current parameters like previously cited gain or time constants. One major difference between the older model and the optimal pilot is that the noise due to neuromuscular or perceptual factors is aimed to be included in the model via noise input addition. White noise is typically employed to ensure that errors are distributed equally around the target value (Blakelock, 1991).

More recently, Johnson and Pritchett (2002) proposed a *generic pilot model* that can be both used as a simulated pilot in engineering and scientific applications as well as an autopilot controller. This model can be considered as one of the newest and most generalized of all control theoretic models. Although this study is newer than the previously described approaches by three decades, Johnson and Pritchett's model is also based on McRuer and Jex (1967).

The generic pilot model is popularly employed as an autopilot system in modern aircraft systems. A human pilot controls the aircraft with no direct contact with the position or attitude. The change in the position of an aircraft is the result of the speed, moments, inertia, current angles of the body etc. Similarly the angular control of the body is not directly performed, but rather the pilot controls the body movements via changing the positions of flight control surfaces. The control parameters in an aircraft control system can be divided into two layers. A layer of parameters is in direct contact with the aircraft body, and a layer formed by higher-level parameters operates at a more global level. In other words, this organisation is similar to Marr's (1982) three levels of analysis where the body of the aircraft resembles the biological layer, the direct parameters resemble the representation layer which are in direct contact with the biological layer, and finally the indirect parameters resemble the computational level which are shaped by the pilot's intentions or mission parameters e.g. climb to a specific altitude, go to a specific place etc.

Researchers have been in search of an adaptive or dynamic aircraft attitude control capability for several decades due to the difficulty of predicting environmental effects in open (uncontrolled) atmosphere. This necessity motivated the second paradigm in pilot modelling, which can be referred as *neural* or *dynamic* approaches. Such models are reported in various publications and are generally providing autopilot capabilities to control real or simulated aircraft dynamics. Some examples include Enns and Si's (2004) helicopter flight control with Neural Dynamic Programming, Kaneshige and Burken's (2008) neural network based in-flight control model of a real F-15 aircraft, and neutrally informed intelligent models developed in NASA (Motter, 2008). Although these approaches offer very effective and successfully tested autopilot models, none of them are based on dynamic field theory

In this study, we opted for employing an intention layer to supply the pilot model with a goal. Such a layer can be formed with a self-excitory dynamic neural field with a very low decaying time constant so that the pilot never forgets his intention. Using a reference field or model to create an intention is first proposed by Kaneshige, Bull and Totah (2000), where 3 functions are used as reference models for pitch, roll and yaw rates of the aircraft. Dividing the intention into 3 components as reference models of behaviour in this way provides a useful and easy method to implement such a model. We have similarly used 3 different dynamic neural fields holding or memorizing the pilot's intention patterns, which will be described further in subsequent sections. Note that the Kaneshige, Bull and Totah (2000) model uses neural networks with s-domain transfer functions to control the aircraft, so dynamic neural fields are not used in this approach. While Kaneshige et al. continuously compare the reference models with current rates and form the next action based on their difference, this loop can be assumed as a negative feedback line to achieve stability.

To sum up, existing pilot models in aviation industry are predominantly control theoretic models that focus more on control dynamics than cognitive processes underlying a human pilot's performance. In this paper, we propose a Dynamic Field Theory based approach to extend this line of work by incorporating biologically plausible layers that modulate cognitive processes underlying pilot behaviour. The next section provides an overview of Dynamical Field Theory. This is followed by a description of the physical aircraft model used in this study and the DFT based architecture developed to model pilot behaviour. The paper concludes with our preliminary findings regarding the model's performance on an altitude hold task, which is contrasted with real human pilot data.

Dynamical Field Theory

Neural field studies starting from late 1950s take the firing rates as the primary state variable with the assumption that neuron populations are embedded in coarse-grained areas (Meijer and Coombes, 2013). Beurle, Wilson, Cowan and Amari have laid the mathematical groundwork for neural field modelling. Beurle's (1956) work on large scale neuron population excitation behaviour was extended with inhibitory capabilities contributed by Wilson and Cowan (1972) and Amari's (1977) Mexican hat type kernels, which altogether provided a mathematical model for characterizing neural population activity.

Below is the Amari equation which is used to model the firing behaviour of a cortical area, nuclei or column on a functional basis (Amari, 1977).

$$\tau \frac{du}{dt} = -u(x,t) + h + S(x,t) + \int dx'\, w(x - x')\, f\,(u(x',t)) \qquad 1$$

In the equation above, the term $w(\Delta x)$ is the interaction kernel and is convolved with a threshold function $f\,(u(x',t))$ which is used to supress the kernel's excitory parts in case the system dynamics are below a preselected threshold. τ is the time constant for the population dynamics. $u(x, t)$ is the field activity function. The output of the U function provides the activity value. H is the resting level of the model, whereas $S(x, t)$ are the input(s).

$w(\Delta x) = w(x - x')$ is the interaction kernel representing each neuron's excitory or inhibitory relation from the neuron at the origin with a distance $x - x'$. $f\,(u(x',t))$ is the threshold function.

Below is the equation defining a kernel example.

$$w(x) = A\, e^{\frac{-(x-x')^2}{2\sigma_1^2}} - w_{inh} \qquad 2$$

Equation 2 provides a relation of neural interaction between neural fields depending on their distal separation, i.e. it is a function of a spatial parameter. Notice that the activity relation here is simply independent of time but it is a function of the separation between the fields' physical distances and forms a Gaussian with standard deviation σ. A is the excitation constant which will vary with a Gaussian behaviour over distances between fields. w_{inh} is a constant value of inhibitory effect between neural fields.

$$f\,(u(x',t)) = \frac{1}{1 + e^{-\beta(u(x',t)-u_0)}} \qquad 3$$

Above given eq. 3 is the threshold function in form of a sigmoid.

The DFT method allows model builders to implement networks of neural fields to create logical or spatiotemporal decisions. One can adjust kernel parameters to modify a spatiotemporal parameter. For example, the observation of the distance from an object can be represented by the activity position of the field in the spatiotemporal axis and the saliency of the activity amplitude of the same field.

The Aircraft Model

A 3 degrees of freedom (3DoF) model was selected to model the aircraft in this study. The selected 3DoF model suits particularly well for understanding long-term navigation behaviour, and similar models have been used in previous studies (e.g. Carretero, Nieto & Cordon, 2013). A 3DoF model neglects the moments inputs of the aircraft model, does not contain angular rates modelling and Euler rates. Our model will include a point mass aircraft with a linear drag model. The mass of the aircraft is decreasing proportional to the thrust used due to the fuel consumption. Below is the mathematical summary of the 3DoF aircraft model. Since phugoids or dutch rolls are not aimed to be captured in our application, a higher degree model is not considered.

$$\frac{d}{dt}\begin{bmatrix} X \\ Y \\ h \\ V \\ \varphi \\ \gamma \\ W \\ T \end{bmatrix} = \begin{bmatrix} V\cos(\varphi)\cos(\gamma) + w_x \\ V\sin(\varphi)\cos(\gamma) + w_y \\ V\sin(\gamma) + w_z \\ \frac{g}{W}[(T\cos(\theta-\gamma) - D) - W\sin(\gamma)] \\ \frac{g\sin(\rho)}{W\,V}[L + T sin(\alpha)] \\ \frac{g}{W\,V}[(L + T\sin(\theta-\gamma))\cos(\rho) - W\cos(\gamma)] \\ -C\,T \\ 0 \end{bmatrix} \quad (4)$$

Equation 4 contains the rate of change of the fundamental model parameters in time. The parameters used in Equation 4 are defined as follows.

X: Longitudinal axis position of the aircraft (along body axis position). Y: Lateral axis position of the aircraft (cross body axis position). h: Altitude of the aircraft upon flat earth Cartesian coordinate system (the normal axis position). V: The speed of the aircraft upon flat earth Cartesian coordinate system. φ: Aircraft current heading angle. γ: Aircraft flight path angle. This angle is the angle between the flat earth surface and the aircraft velocity vector. W: The weight of the aircraft plus the weight of the fuel. In normal conditions, fuel is expected to decrease proportional to the thrust applied by the engines to the aircraft. T: Constant aircraft thrust supplied by the engines. g: The gravitational acceleration. Flat earth model is used, g can be assumed constant. wx, wy, wz: Components of wind vector, i.e. the speed of wind in North and East direction and finally the third one is in normal axis. θ: Aircraft pitch angle; the angle between the flat earth surface and the aircraft nose. ρ: Aircraft roll angle; i.e. the angle between the lateral axis of the aircraft and the flat earth surface. L: The lift force. In this model L will be taken equal to a proportion of W with a coefficient of (1/cos(ρ)). D: The Drag induced on the body of the aircraft due to the airspeed. α: Angle of attack; i.e. the angle between the aircraft mean chord line (longitudinal axis of the aircraft) and the velocity vector. Sideslip or skid effects are all neglected.

The model described above is implemented in C++ and connected to our pilot model as a plugin which is implemented in the CEDAR framework (Lomp, 2013) using a DFT approach.

The Architecture

The general architecture of our setup is the same as in Figure 1. Unlike the crossover model that controls a single parameter, the DFT pilot model is used to control multiple aircraft behaviours by using 2 control inputs (Figure 4).

In this study, 3 axis behaviour of the aircraft model is controlled via two inputs, namely the pitch and heading correction. The model will focus on emulating the performance of a human pilot who intends to hold the pattern of flight stable. Only the pitch results will be summarized in this paper. The roll control is left out of the scope of this paper. Figure 4 summarizes the control flow for each control parameter.

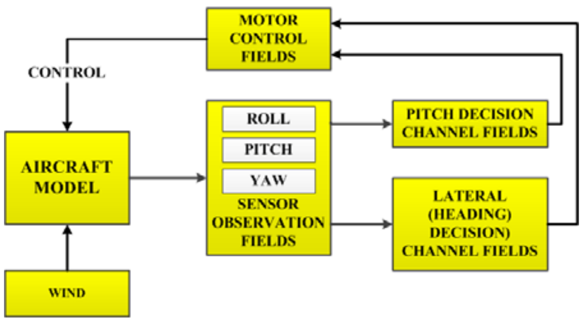

Figure 4. The architecture for the DFT Pilot Model.

The intention layer, which is not shown in Figure 4, is used to generate a constant behaviour to hold the aircraft at initial attitude. The reason behind the use of the intention layer is to provide the pilot model a goal structure. In this preliminary study we aimed to provide a DFT model that is deliberately oriented towards performing level flight. The architecture is used to control the aircraft on holding the initial heading and altitude. Due to the unavailability of the roll control channel, the aircraft roll attitude is not held under control and left freely to oscillate due to the control behaviour. Since a 3DoF aircraft model is used, each attitude channel can be assumed independent and harmless upon aircraft pitch performance. Since there is an intention layer to hold the aircraft in a selected path or pattern, our DFT based architecture bears a strong similarity to the models proposed by Johnson and Pritchett (2002) and Kaneshige, Bull and Totah (2000). One major architectural difference between our approach and the existing models is that our intention layer is formed by a neural field, whose decaying time constant is adjusted to a numerically larger value which is normally not used for decision fields, so that the activity of the field is almost non-decaying, even when an input is not applied or an applied input is removed (see Appendix). Notice Amari equation is in an integro-differential form and time constants can be adjusted to shape the differential field produced by the equation. Hence, the intention layer can be considered to function like a working memory component. A block diagram of the pitch decision channel is given in Figure 5.

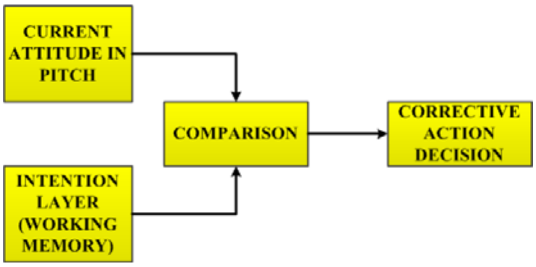

Figure 5. A representation of pitch decision channel.

In the CEDAR implementation, the aircraft model's output is connected to the perceptual neural fields (sensory fields used for observing the aircraft dynamics), which transform the spatial parameters into neural field activations so that they can be processed by the architecture.

Figure 6 displays a graphical representation of the performance of a T-38 Talon pilot trying to hold the aircraft at 20000 ft constant altitude manually for 2 minutes and 55 seconds. The plot indicates that there are various deviations from the target altitude up to approximately 90 ft. Some of these deviations may originate from the aircraft dynamics and some from the pilot. Accordingly, we deduce that a human pilot's performance unified with the aircraft dynamics may result in up to 90 ft deviations at high altitudes. The same Test Pilot showed a better performance with a maximum deviation of 53.2 ft when the holding task was carried out at 8450 ft during the same flight. When the target altitude is 100 ft above ground, the same pilot made an error of maximum 7.5 ft. Therefore, we can deduce that as the aircraft is closer to the earth's surface (i.e. as the danger increases) during the holding task, the pilot naturally becomes more careful.

A similar analysis may be performed for lateral hold performance. Our analysis on flight test data records have shown that the same pilot have a performance of pattern holding on lateral navigation with a maximum error of 29.504 ft. Lateral performance is hold out of scope for current study.

In this study we tried to hold our 3 DoF aircraft model at level flight and our aim was to hold the deviations on or below the deviations observed in human pilot performance data. One important point is that the given deviations may be dependent on the pilot's experience. However, since the identity and the flight experience of the pilots were not available to the researchers, we cannot incorporate the variability due to different expertise levels in our study.

Another important consideration for pilot modelling is that, whatever the controlled attitude (i.e. pitch or lateral), the pilot uses an angular parameter to control the Cartesian behaviour of the aircraft. Thus, the pilot model should be able to make a transformation between coordinate systems and compute the required angular correction to re-enter the flight path or hold the flight pattern.

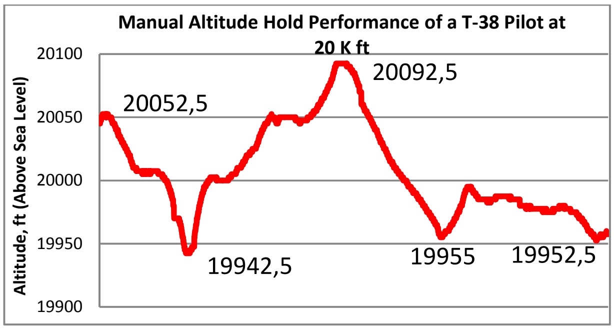

Figure 6. Manual altitude hold performance example from flight tests

Results & Discussion

The DFT based pilot described above performed some simulated flights completely autonomously and the results are qualitatively compared with actual flight test data obtained from T-38 flights. The behaviour of the human test pilot exhibits an oscillatory behaviour around the targeted flight pattern with plus or minus deviations. Some of these deviations are due to the dynamical behaviour of the T-38 aircraft, which is expected. Especially in high altitudes the pilot was not able to follow the target altitude loss strictly. A similar behaviour is obtained with the DFT based pilot model. Figure 7 shows the output obtained from a sample run.

Figure 7 suggests that the DFT pilot is able to control aircraft pitch attitude by limiting the aircraft altitude deviations. In the above example, the aircraft makes constant decrease from 10.000 ft with a constant loss of altitude with 138 ft/step size (about 5 seconds). When the pilot model is started, it directly creates an input to stop the decrease in altitude in an effort to protect the current flight path. As the plot indicates, the aircraft altitude oscillates around the targeted altitude under the control of the pilot model, which is trying to keep the altitude constant. Notice the model reaction times and amplitudes can be adjusted via using the dynamic fields' time constant (shown in equation 1), sensor layer tolerances and excitory or inhibitory field parameters.

Overall, our preliminary results suggest that the pitch attitude performance of our DFT based pilot model is comparable to the human pilot's performance. Human pilots do not make any trigonometric computations to acquire the cross track component of the distal deviation to obtain the required angle to hold the pitch attitude of the plane. The process of the computation happens naturally, embodied and embedded in a continuous way. The continuity in the inner and outer loops of pilot control in the proposed DFT architecture captures the dynamic and embodied nature of the human pilot's actions. Therefore, DFT seems to be a promising approach for modelling dynamic, embodied and embedded aspects of pilots' cognitive and behavioural performance.

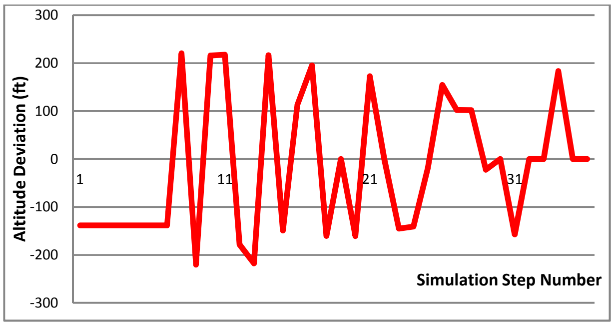

Figure 7.Pitch hold performance of the DFT pilot.

In future work, the aircraft model will be improved with 6 DoF dynamics to be able to discriminate between the behaviour of the aircraft and the behaviour of the pilot model. In the next step, the control of the attitude will be improved with lateral navigation, roll control and obstacle avoidance hierarchy.

Acknowledgment

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Appendix

A working set of parameters is given below. This set of parameters is used with two interacting fields to obtain dynamical control behaviour. Static gains are also used in the architecture to adjust motor behaviour but they are not considered here since the reader can easily adjust its own parameters to create the temporal behaviour of the pilot. This is similar to the neuromuscular delays and transfer functions used in the optimal pilot model.

Initial Mass: 5000 lbs, Constant Trust: 6000 lbfs, Initial X Position: 0, Initial X Position: 0, Initial Altitude: 10000 ft, Initial Airspeed: 298 Knots, Fuel Burn Rate: 5 lbs/min.

Pitch Decision Neural Field 1; Resting level: -1, Time scale: 100, Global inhibition: -0.001, Dimensionality: 1, Sizes: 90, Input noise gain: 0.1, Sigmoid Kernel Threshold: Threshold: 0, Beta: 100, Lateral kernels, Gaussian: Dimensionality: 1, Amplitude: 2, Sigmas:3,

Pitch Decision Neural Field 2; Resting level: -1, Time scale: 500, Global inhibition: -0.01, Dimensionality: 1, Sizes: 90, Input noise gain: 0.1, Sigmoid Kernel Threshold: Threshold is 0, Beta: 100,

Wind Mean (ft/s): 5, Standard deviation: 0,

Memory Trace as Intention Layer Sizes: 90; Time scale build up: 10, Time scale decay: 10^9.

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