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PILOTED SIMULATION EVALUATION OF A NEURAL NETWORK LIMIT AVOIDANCE SYSTEM FOR ROTORCRAFT

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Piloting a rotorcraft is typically a high gain task, and under adverse conditions the workload may increase to the extent that the pilot is not able to achieve all goals simultaneously. Increased exceedances of operating limits may occur as a result of this high workload. The goal of this research has been to implement in piloted simulations a system that reduces workload and helps pilots to avoid aircraft limits. The system uses neural networks to predict near-future limit exceedances, and alerts pilots to these impending exceedances through tactile cues on the control inceptors and visual cues on the head-up-display. The system was demonstrated in piloted simulations of the UH-60A and OH-58D and was found to reduce limit exceedances and pilot workload. In these experiments, tactile cues alone generally performed better than visual cues alone, but the combination of visual and tactile cues generally performed best. Pilot comments and handling qualities ratings of the system were highly favorable.

INTRODUCTION

Even under ideal conditions, rotorcraft pilots face a high workload. In conditions such as adverse weather or operation in an area of enemy threats, the pilot's workload may be increased to the extent that he cannot adequately monitor and exercise control to avoid exceedances of operating limits. Consequences of these limit exceedances include impaired flight safety and shortened equipment lifetimes. The current research has sought to implement a system that aids pilots in avoiding limit exceedances.

The current work has built on the findings of a number of prior research efforts. These included a study conducted by Jeremy Howitt at the Defence Research Agency (U.K.) that showed force feedback cueing to be beneficial for reducing limit exceedances.[1] This study used a "novel heave-axis automatic flight control system (AFCS) mode that blends between collective blade pitch command (Θ_0), torque command (Q_e) and rotorspeed command (Ω_r) as a function of collective lever position (δ_c)".[1] At high collective input positions, collective position commanded torque and a soft-stop (force feedback) on the collective stick indicated the continuous torque limit. The use of this cue was shown to reduce limit exceedance, reduce task time, and improve handling qualities.

Other research has shown that force feedback is superior to other types of cueing to alert a pilot to limit exceedances. The HelMEE II (Helicopter Maneuver Envelope Expansion) study conducted by the Army Aeroflightdynamics Directorate (AFDD) compared the benefits of collective stick force feedback, aural tones, voice warnings, and visual/head-up-display (HUD) information as limit cues, while performing an air-to-air task and a turning autorotation task. The statistical data and pilot comments from those experiments strongly supported the use of control force feedback, complemented by either a visual or aural confirmation of the limit exceedance. A key finding of the HelMEE II studies that led to the current work was that if measured values of the states related to limits were used to drive visual, aural, or tactile cues, the dynamic nature of these states and limits was such that warnings came too late to prevent exceedances. The results indicated a need to *predict* near-future limit exceedances and to use the predictions rather than the current observables to drive limit cues.

The authors chose to use polynomial neural networks (PNNs) to provide the indicated predictions of near-future limit exceedances. Under a Phase I SBIR contract, Barron Associates, Inc. (BAI) demonstrated the feasibility of using PNNs for this application.[2] Feasibility was shown principally by demonstrating that representative critical variables

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could be accurately modeled by PNNs using simulation or flight data. The quantities examined in the Phase I effort were main rotor torque, main rotor angular speed, normal load factor, lateral velocity, and main rotor blade bending moment (flapping axis).

In Phase II of this SBIR program, Barron Associates worked with Matthew Whalley of the AFDD to implement a neural network limit avoidance system for rotorcraft (nnLASR). The system uses PNNs to predict future rotorcraft operating parameters on the basis of pilot commands and system observables and provides the pilot with information regarding future limit exceedances based on these predictions. Information is primarily provided to the pilot through tactile feedback on the various inceptors, with a secondary cue on the HUD for confirmation. The effectiveness of the system for reducing main rotor torque exceedances during a bobup task was demonstrated in the HelMEE IV experiments.[3] These experiments were performed in the Vertical Motion Simulator (VMS) facility at NASA Ames using a UH-60A model. Subsequent fixed-based piloted simulation experiments of the OH-58D demonstrated cueing over a range of maneuvers using a slightly modified cueing approach. This modified cueing approach was successfully applied to multiple maneuvers and multiple limits for the UH-60A during the HelMEE V experiments (which also used the moving base VMS facility). These pilot-in-the-loop demonstrations represented major steps toward transitioning the nnLASR technology to production aircraft.

This paper discusses the general architecture of the cueing systems, the specific implementations for the UH-60A and OH-58D simulators, and the results of piloted simulation experiments of both helicopters.

PNNs FOR LIMIT PREDICTION

The polynomial neural network models used in this work were synthesized with the $GNOSIS^{TM}$ software package. $GNOSIS^{TM}$ is an advanced inductive modeling environment developed by Barron Associates to solve multivariate estimation and classification problems.

Considerations for Creating Synthesis Databases

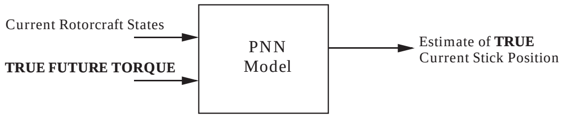
To create PNN models that perform well for situations not encountered during network synthesis, the databases used for model synthesis must be carefully constructed. Nonlinear models perform best when interrogated within the synthesis data range, so it is important that synthesis data encompass the range of flight conditions and maneuvers on which the model will be evaluated. Because of the high dimensional spaces involved, analytically determining regions of space populated by the synthesis data can be a difficult task. The authors have employed a multi-dimensional clustering analysis to screen evaluation data in some cases, but, because of the limitations of such approaches, it is important to use knowledge of flight regimes seen in synthesis to determine appropriate interrogation regimes.

The authors have also found it important to use synthesis data that capture the varied dynamics of multiple pilots. In synthesizing networks to predict limit exceedances for a single type of maneuver, the authors found that networks created using data for a single pilot would perform well on unseen maneuvers for the same pilot but not for maneuvers performed by other pilots. This suggests that PNNs modeled the behavior of the specific pilot (or combined pilot-vehicle system) rather than just the aircraft dynamics. This specialization is undesirable for most cueing system applications.

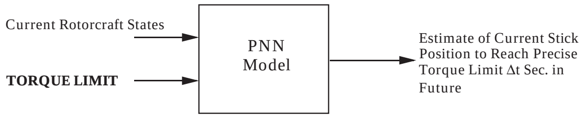
PNN Architectures

Two distinct PNN architectures have been used in nnLASR implementations. The first, hereafter referred to as the "inverse architecture", was used for main rotor torque cueing in the HelMEE IV experiments. Using the inverse modeling approach to torque cueing, a PNN was synthesized to estimate the current stick position using the current rotorcraft states and the true value of *future* torque as inputs. When the resulting PNN was implemented in the cueing system, the value of the torque limit was used in place of true future torque input. The intention was for the PNN to compute the current inceptor position that would cause torque to be precisely at its limit one prediction horizon in the future. Fig. 1 illustrates the inverse PNN configurations as used in model synthesis and in the cueing system implementation, respectively.

The inverse architecture is attractive because it explicitly computes a "soft-stop" location that can be applied to the collective stick. However, some problems do exist with this architecture; among these are the arbitrary pairing of current vehicle states with a future torque equal to the limit. This combination of inputs may not be realizable for the



Configuration Used for Synthesis (and Evaluation)



Configuration Used for Cueing

Fig. 1: Synthesis of Inverse Models vs. Use in Collective Stick Cueing System

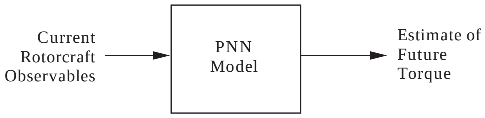


Fig. 2: Forward PNN Configuration Used for Synthesis and Cueing

physical system, and PNN behavior for unrealizable input sets may be unpredictable. Also, in multi-axis maneuvers, multiple inceptors may simultaneously influence a limit of interest. In these cases, there may not be a unique set of inceptor positions that causes the limit of interest to be reached, and the PNN cannot find a unique solution if such a solution does not exist. An additional difficulty exists in making off-line evaluations of inverse network performance. The "soft-stop" location estimated by the inverse network is not a parameter of the physical system so the truth value cannot be determined. Estimation error for the network in the cueing configuration therefore cannot be determined.

The authors believe an alternate cueing configuration, referred to here as the "forward" architecture, is more appropriate for multi-axis tasks, and this structure was used in piloted simulation experiments involving multi-axis maneuvering. In the forward architecture, the future value of the parameter of interest is estimated using current (and, in some cases, prior) observables. Fig. 2 shows this architecture. A drawback to this approach is that an additional step is required to compute an appropriate inceptor limit position based on the network output.

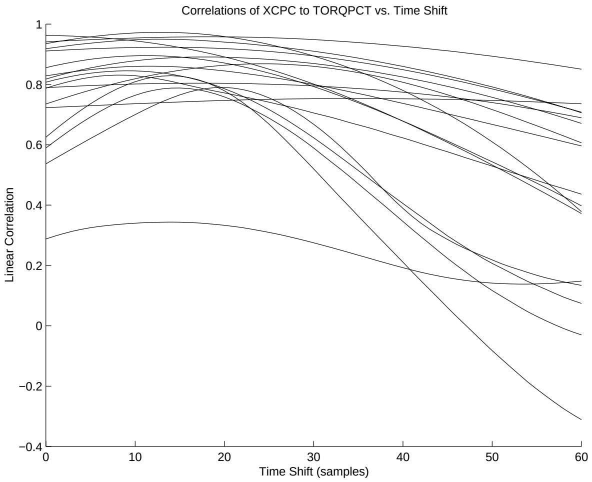


Fig. 3: Linear Correlations of Torque to Collective Inceptor

Prediction Horizon

The prediction horizon used for the PNNs is an important parameter that affects the performance of both the PNN and the cueing system with a pilot in the loop. In selecting prediction horizons, the authors have used several criteria with the goal of making a reasonable assessment of what horizon(s) will yield the best closed-loop cueing system performance. Ultimately, however, pilot-in-the-loop testing is required to determine conclusively the best prediction horizon(s).

One criterion considered in the selection of prediction horizons has been the linear correlation between the inceptor position and limits of interest. Prior to the HelMEE V experiments, linear correlations between current inceptor position and the limit variable n samples in the future were computed for all integer values of n from zero to 60, where each integer corresponds to a 23 ms increment. Fig. 3 shows the correlations between torque and collective position plotted against the time shift, n, with each curve representing a separate maneuver. (The maneuvers shown in this figure are non-bobup maneuvers recorded in the VMS facility during the HelMEE IV experiments.)

Fig. 3 shows a clear trend across maneuvers, with maximum linear correlation for the maneuvers occurring at an average offset of 16 samples. This suggests that a horizon of approximately 16 samples has some physical significance in the system and would be a good choice for a prediction horizon, excluding consideration of human factors. Linear correlations were investigated for all limits explored in the HelMEE V experiments, and similar trends were found for other pairs of inceptor inputs and limits.[*]

A second aspect considered in the selection of prediction horizons was the performance of PNNs for various horizons. Even when the linear correlations between inceptor position (or rate) and the variable being limited show a definitive maximum at some horizon, the performance of the nonlinear PNN is not guaranteed to be best at this horizon. PNN performance is an important component that influences overall system performance and should be considered when selecting a prediction horizon. PNN performance is not, however, the sole factor influencing overall system performance, and it has been found that the closed-loop system performance is sometimes improved by increasing the prediction horizon even at the expense of some sacrifice in PNN accuracy. This result emphasizes that off-line analysis alone is not sufficient to evaluate a cueing system, and that pilot-in-the-loop evaluation is a critical part of system development.

Mapping PNN Output into Cueing Force

Types of Cues Used

The UH-60A and OH-58D piloted simulation experiments both used a breakout and gradient cue for main rotor torque.[†] Fig. 4 shows the collective stick feedback force as a function of inceptor position with respect to the moving limit as implemented in UH-60A experiments. Note that the breakout was not a pure step force, but was a 26.7 lb./in. gradient. This necessitated a slight correction in the force calculation to ensure that the stick would overcome the friction force and return precisely to the limit position when the pilot relaxed his input against the upper gradient. The OH-58D experiments used a similar approach, though the exact form was modified for different hardware.

The cue used for the blade stall limit in the UH-60A experiments was a stick shaker at the blade stall limit. Using the stick shaker cue for blade stall allowed pilots to distinguish between the main rotor torque and blade stall cues when both were used.

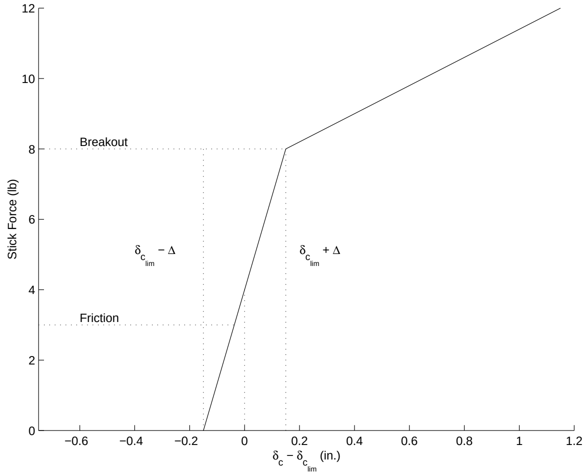


Fig. 4: Tactile Cueing Force for Main Rotor Torque as a Function of Collective Stick Position

For cueing of hub moment exceedances on the cyclic inceptor, increased stick damping rather than a stick force was used as a cue. The increased damping cue was selected because hub moment corresponds more closely to stick rate than to stick position, making it appropriate to cue the pilot to limit stick rate.

Computing Inceptor Limit Positions

As discussed above, PNNs using the inverse architecture directly estimate the moving limit position or damping that is sent to the force feel system. Forward architecture PNNs estimate a limit exceedance which must then be used to compute an appropriate limit position. In the case of main rotor torque this limit position is computed as

$$\delta_{c_{lim}} = \delta_c - K_Q(\tau_{Predicted} - \tau_{Limit}) \qquad (1)$$

where $\delta_{c_{lim}}$ is the collective stick limit position, and δ_c is the current collective stick position. The gradient K_Q represents the collective stick displacement corresponding to a unit change in torque. This approach is based on the assumption that torque can be modeled locally as a linear function of stick position and that the value of K_Q, which defines the slope of the linear relationship, can be found. The approach used to determine K_Q in the current work has been to use linear regression in off-line evaluation to estimate the desired slope. The initial estimate was then tuned based on pilot feedback in prelim-

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[*] Investigation of linear correlations also supported the use of a damping cue to limit inceptor rate rather than a force cue to limit position for hub moment cueing in UH-60A experiments. It was found that little or no linear correlation exists between cyclic inceptor position and hub moment for the UH-60A, but that a correlation does exist between cyclic inceptor rate and hub moment.

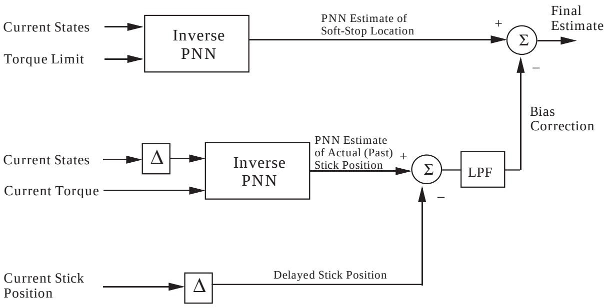
[†] The HelMEE IV experiments compared a breakout and gradient cue to a stick shaker and found the breakout and gradient to be superior. A stick shaker was also evaluated briefly in the OH-58D experiments and pilot comments again indicated a preference for the breakout and gradient.

inary system evaluation. A constant value of K_Q determined in this manner has been found adequate in the experiments conducted thus far, but for some highly nonlinear control systems a means of on-line adaptation might be required, or the K_Q value itself could be modeled via a PNN.

Inceptor limit positions for the blade stall and hub moment cues were computed in similar fashion.

BIAS CORRECTION FOR ONLINE ADAPTATION

In the first UH-60A experiments with neural network limit avoidance cueing, it was found that flight conditions not seen in training could lead to a bias in the PNN estimate. A bias correction was applied which used recent prior PNN output errors to estimate the current output error. In the inverse configuration the output error of the PNN in the cueing configuration is not known even after a time delay, so the time delayed error of the PNN output in the synthesis configuration was used to approximate the error in the cueing configuration. Fig. 5 shows how the bias correction was applied to torque cueing with the inverse PNN architecture.



Δ represents a delay equal to the prediction horizon

Fig. 5: Bias Correction Applied to Inverse PNN Architecture

The bias correction applied to the inverse architecture was found to improve cueing system performance, but the inability to apply a bias correction based on true prior error was viewed as a drawback to the inverse PNN architecture. For the forward PNN architecture, a time delayed PNN error can be computed provided the limited parameter of interest is observable. Fig. 6 shows the application of the bias correction for torque cueing with the forward PNN architecture:

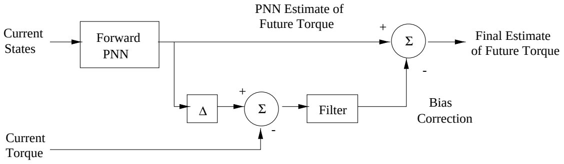


Fig. 6: Bias Correction Applied to a Forward PNN for Torque Prediction

This bias correction approach was used in the OH-58D experiments and those UH-60A experiments that employed the forward PNN architecture.

OH-58D PILOTED SIMULATION EXPERIMENTS

Piloted simulation experiments using a fixed based OH-58D simulator were conducted at Bell Helicopter Textron, Inc. In the first phase of the work, data were recorded for approximately 100 maneuvers of various types using two pilots. These data were used to synthesize PNNs that comprised the core of the tactile cueing software. The experiments were initially intended to consider cueing for two limits (main rotor torque and engine torque) and cueing software was developed for both limits. Due to unexpectedly shortened simulation time, however, it was not possible to evaluate the performance of the cueing system for engine torque. The discussion in this paper is thus limited to main rotor torque cueing experiments, which, though also shortened by technical difficulties with the BHTI simulation, provided sufficient results for preliminary evaluation.

PNN Synthesis

Because the authors believe the forward PNN architecture offers certain conceptual advantages, as discussed above, initial network synthesis was done using that architecture. Networks were created using prediction horizons of both 0.25 and 0.5 sec. (In off-line evaluation, networks using a prediction horizon of 0.25 sec. were found to perform significantly better than those using a 0.5 sec. horizon.) Figs. 7 and 8 show truth and model output for the 0.25 and 0.5 sec. prediction horizon networks, respectively.

Because of the authors' success using the inverse architecture in prior research, a PNN using the inverse architecture was also synthesized; it used a prediction horizon of 0.5 sec. This network was synthesized and evaluated with the same databases used for the forward architecture PNN. Performance of the inverse model was compared to that of the forward model in terms of the ability of each to predict accurately whether or not a limit exceedance would occur.[‡] It was found that the inverse model incorrectly predicted whether a limit exceedance would occur approximately three times more frequently than the forward network. As discussed previously, the authors believe that while the inverse architecture may be appropriate for single-axis tasks, the forward architecture is better suited to predicting in multi-axis tasks. The inferior performance of the inverse PNN in this context was therefore not unexpected.

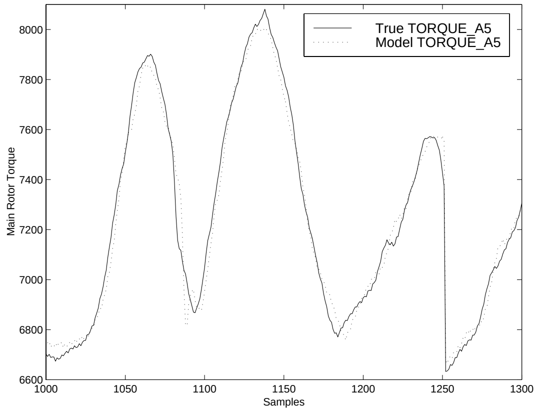


Fig. 7: OH-58D Main Rotor Torque PNN Output (0.25 sec. Prediction Horizon)

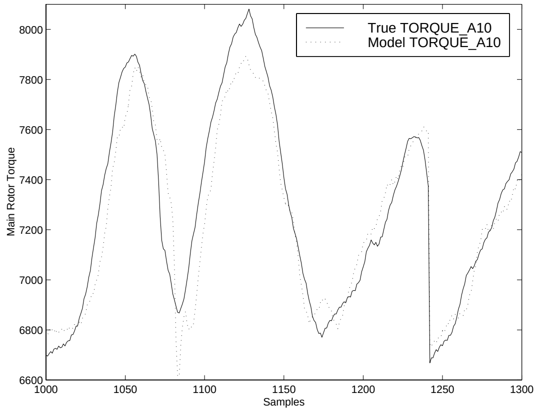


Fig. 8: OH-58D Main Rotor Torque PNN Output (0.50 sec. Prediction Horizon)

It was decided that forward architecture PNNs with prediction horizons of both 0.25 sec. and 0.5 sec. would be used for the piloted evaluation. The network with 0.5 sec. prediction horizon was retained for piloted evaluation despite its less promising performance in off-line evaluation because this prediction horizon worked well in prior research. As discussed previously, the critical measure of the cueing system is pilot-in-the-loop performance, and this can be significantly influenced by factors other than off-line network performance.

Test Configurations and Tasks

Pilots were given the opportunity to fly the system with numerous configurations and for a variety of tasks in a brief preliminary evaluation. Based on feedback from this preliminary evaluation, the team decided to limit the experiment to three maneuver types (bobup, bob-down, and slalom), a single heavy weight (5,500 lb.), main rotor torque cueing only, and the following cueing system configurations:

1. Force breakout cue using 0.25 sec. prediction horizon PNN with bias correction (see Fig. 4)
2. Force breakout cue on current torque (see Fig. 4)
3. Shaker cue on current torque
4. No cue

Piloted Evaluation

The first pilot to evaluate the system was Mr. Jim Lindsey, who flew the system using configurations 1, 2, and 4 listed above. When a cue was used, Mr. Lindsey was unaware of which cueing configuration was in use. Mr. Lindsey reported that the soft stop with prediction was the preferred configuration. He found the stop to be better defined with the prediction, and reported a slight pilot-induced oscillation (PIO) when prediction was omitted. He also found that the cue noticeably reduced pilot workload and allowed him to check the cockpit gauges less frequently.

Subsequent to the evaluation by Mr. Lindsey, the authors analyzed the data from the bobup maneuvers; summary statistics are shown in Table 1. While sufficient data could not be collected to make detailed conclusions, the indications confirmed the results of the NASA/Army VMS experiments, i.e., the cue with prediction allowed the pilot to perform the maneuver more quickly and with smaller torque

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[‡] A comparison between the performance of the two networks in terms of a more standard metric such as normalized RMS error is not possible because, as discussed above, the true output value for the inverse network in the cueing configuration is not known.

exceedances as measured by both maximum and integrated torque exceedances.

Table 1: Performance on Bobup Maneuvers during First Day of OH-58D Experiments (Pilot: Mr. Lindsey)

Cueing Configuration	(Avg.) Maneuver Time (Sec.)	(Avg.) Max. Torque Exceedance	(Avg.) Integ. Torque Exceedance
No Cue	9.1	2.2%	6536
Cue on Current Torque	11.0	1.6	3139
Cue on Predicted Torque	8.9	1.5%	1757

The second pilot to evaluate the system was Mr. Steven Kihara.[§] Though time constraints prevented data recording of maneuvers flown by Mr. Kihara, he was able to compare three approaches and provide subjective comments. He reported that the cueing system with prediction provided sufficient advance warning to prevent over-torques during aggressive collective inputs. He preferred the soft stop configuration to a stick shaker, and believed that the soft stop would work well in a real environment.

Results of OH-58D Experiments

The OH-58D simulation experiments successfully demonstrated tactile cueing for multiple maneuvers. They also demonstrated the use of the forward PNN architecture in a predictive limit avoidance cueing system and demonstrated the use of such a system for a second type of helicopter.

UH-60A PILOTED SIMULATION EXPERIMENTS AT NASA AMES

The HelMEE V experiments were conducted by Mr. Whalley with support from Barron Associates. These experiments continued the HelMEE series of UH-60A piloted simulation studies in the VMS facility and provided an in depth study of cues for multiple limits evaluated for a variety of maneuvers. Cueing was provided for the main rotor torque limit, the blade stall limit, and the hub moment or mast bending limit. To the authors' knowledge, these were the first experiments to provide tactile cueing for multiple limits, and the first to provide cues on both the collective and cyclic inceptors. Also, the cues were demonstrated over a broader range of flight conditions than in previous experiments.

Facility Description

The HelMEE V investigation was conducted using the six-degree-of-freedom Vertical Motion Simulator (VMS) at the NASA Ames Research Center. The VMS is unique among flight simulators in its large range of motion. This large motion capability provides cues to the pilot that are important to the study of handling qualities. The specific simulator configuration used for the experiments included a single pilot cockpit with standard helicopter controls and a three window computer generated imagery display. The instrument panel was configured to represent a UH-60A. The heads-up-display (HUD) included: a torque meter; a radar altitude thermometer; a horizon bar; a heading tape; a side-slip ball; and digital readouts of torque, load factor, airspeed, and radar altitude.

Comparison of PNNs to Alternative Prediction Approaches

An important question raised in previous experiments was whether nonlinear models perform better than linear models for predicting limit exceedances. Though no comparison was made between the performance of linear and nonlinear models during piloted evaluations, it was possible to post-process data gathered during the experiments to allow a statistical comparison of the prediction accuracy of nonlinear and linear models. That is, data recorded during piloted experiments were used to make an *off-line* comparison of the performance of alternative prediction techniques. The authors sought to perform the comparison in a manner that would favor neither the linear nor the nonlinear model. The linear models used for the comparison were thus constructed using the same input set as the nonlinear models to which they were compared, and the coefficients of the linear models were optimized using the same database used to create the nonlinear models. The current value of the parameter of interest was also compared as a possible predictor. The current value may be a good predictor for a signal that typically varies little over the time span of one prediction horizon. All predictors were compared with and without bias correction.

[§] A third pilot flew the simulator after Mr. Lindsey and before Mr. Kihara but had significant complaints about the OH-58D simulation and did not evaluate the cueing system.

The prediction models used in this research were created for the purpose of providing interpolation within the range of conditions seen in synthesis. The intent of the authors is for models to be synthesized using data encompassing the range of conditions for which they will be evaluated. Because the data available to synthesize the networks were limited in the number and scope of maneuvers represented, it was important in assessing network performance to insure that the PNNs were interrogated in regions represented in their synthesis databases. Two approaches were used to analyze the input data ranges. One approach considered the ranges of individual input parameters (the evaluation range allowed was typically $\mu \pm 2\sigma$), while the second involved a simple multidimensional clustering analysis.[4] Both approaches were used to restrict input ranges considered in the PNN performance analysis.

In considering the comparison of model performance presented here it is important to recall that this is an *off-line* comparison. The authors believe that the statistical performance of predictors in off-line evaluation is an important factor influencing cueing system performance, but it is not the only factor influencing pilot-in-the-loop performance, and off-line evaluation is not intended to eliminate the need for piloted comparisons.

Main Rotor Torque

Main rotor torque prediction PNNs were synthesized with prediction horizons of 11 and 22 samples, corresponding to the prediction horizons successfully used in prior OH-58D and UH-60A work. In preliminary evaluation, pilots preferred the network with the longer prediction horizon because of the greater lead time it provided, despite the superior off-line performance of network with the 11-sample prediction horizon. The 22-sample prediction horizon was thus adopted for the final piloted evaluation.

Table 2 shows the performance of the three predictors considered (the PNN, linear model, and current torque). The performance of each predictor is shown with and without bias correction.[¶] The results shown in the table are based on 203 recorded maneuvers. RMS errors were computed separately for each maneuver and averaged to yield the results shown. Also shown in the table are the bias-correction coefficients that (of the three sets evaluated) yielded the best performance for each predictor.

Table 2: Comparison of Three Approaches for Predicting UH-60A Main Rotor Torque (units: % of nominal limit)

Predictor	Average RMS Error	Best Bias Coefficients
PNN	1.6378	-
PNN + Bias	1.4077	0.1, 0.9
Linear Model	3.0148	-
Linear + Bias	1.7140	0.2, 0.8
Current Torque	2.6781	-
Current + Bias	3.1418	0.02, 0.98

In the absence of bias correction, the performance of the nonlinear model is far superior to that of the other predictors. With bias correction, the gap between the linear and nonlinear models is narrowed significantly, but the nonlinear model still significantly outperforms the linear model.

Blade Stall

Equivalent Retreating Indicated Tip Speed (ERITS) is a numerical parameter used by Sikorsky to indicate main rotor stall. The value of the ERITS parameter is related to the size of the reverse flow region and to blade loading. Table 3 compares the performance of a PNN model, a linear model, and the true current value of ERITS as predictors of future ERITS. Again the linear model used in the comparison employed the same inputs as the PNN and was optimized with the same database used for PNN synthesis.

Table 3: Comparison of Three Approaches to Predicting UH-60A ERITS

Predictor	Average RMS Error	Best Bias Coefficients
PNN	17.55	-
PNN + Bias	16.42	0.02, 0.98
Linear Model	21.84	-
Linear + Bias	20.80	0.2, 0.8
Current ERITS	17.51	-
Current + Bias	18.96	0.02, 0.98

It is unclear whether the true value of ERITS can

[¶] Three different sets of bias filter coefficients were used: $\theta_1 = 0.2$, $\theta_2 = 0.8$; $\theta_1 = 0.1$, $\theta_2 = 0.9$; and $\theta_1 = 0.02$, $\theta_2 = 0.98$. Results reported are in all cases those for the set of coefficients which yielded the best performance. No further tuning was attempted to optimize performance for any of the bias-corrected predictors.

be practically observed for a production rotorcraft. In synthesizing the PNNs, the authors treated this parameter as unobservable and did not allow it as a network input. If ERITS is unobservable, then only the linear and nonlinear models (without bias correction) are realizable as predictors (the bias correction requires the current value of ERITS) and of these the nonlinear model performs significantly better. If ERITS can be observed, then all of the predictors in Table 3 are realizable as predictors, and the PNN with bias correction provides the best performance. Also, if ERITS is observable both the linear and nonlinear models could be synthesized using current ERITS as an input and this would improve model performance.

Longitudinal Hub Moment

The longitudinal hub-moment PNN used in the final experiments was synthesized using a data set containing only a single type of maneuver, and all maneuvers in the database were flown by a single non-rated engineering pilot. When this network was initially evaluated in piloted simulation, its performance was deemed adequate, but it was not found to offer significant improvement over previous linear models. Subsequent models, synthesized when more data became available, yielded improved off-line performance but were not incorporated into the on-line system. Analysis performed after the experiments indicated that linear models would have performed as well as or better than the nonlinear model used in piloted evaluations. The authors believe, however, that with data from a greater range of maneuvers available for synthesis, nonlinear modeling techniques would likely show significant benefits for the hub moment parameter.

Results of Piloted Evaluation of the Cueing System

Piloted evaluation of the cueing system involved three standard maneuvers (a bobup, an acceleration/deceleration, and a maximum performance turn) and a more complex search and rescue mission task. Only a brief familiarization period was required before pilots were able to effectively use the cueing system. Benefits from cueing were realized for all maneuvers, and improvements were seen with regard to exceedances of each limit considered.

The blade stall limit was encountered primarily in the maximum performance turn task and the search and rescue mission. In both cases the HUD cue alone reduced limit exceedances, the force cue alone further reduced exceedances, and the combined HUD and force cues yielded the greatest performance improvements.

The longitudinal hub moment limit was encountered primarily in the acceleration/deceleration maneuver and in the search and rescue mission. The HUD and tactile cues alone yielded nearly the same level of improvement, though the HUD-only cue was slightly better. Here, the combined HUD and tactile cue yielded worse performance than either cue alone. The results indicate that cueing for the hub moment limit is beneficial, but further research will be required to conclusively determine the best type of cue to be used.

Main rotor exceedances were tracked for all three tasks and the search and rescue mission. HUD-only cueing yielded little reduction in rotor torque exceedances for the maximum performance turn, and actually caused increased exceedances for the acceleration/deceleration maneuver and bobup. HUD-only cueing performed marginally better than force cueing for the search and rescue mission. Force cueing alone was beneficial in all cases, but the combined HUD and force cue yielded the greatest performance improvements.

Quantitative improvements in the form of reduced limit exceedances are a convincing demonstration of the effectiveness of cueing for limit avoidance. If such a system is to be successful in fleet rotorcraft, however, gaining pilot acceptance will also be critical. The following sections present handling qualities ratings and comments from pilots who evaluated the cueing system.

Handling Qualities Ratings

Figs. 9-11 show handling qualities ratings for the various cueing configurations for bobup, acceleration/deceleration, and maximum performance turn maneuvers, respectively (the center dot indicates the average rating and the vertical bar indicates a 95% confidence interval). For all three maneuvers, pilots gave better handling qualities ratings to the force cue than to the HUD cue alone, though the combined HUD and force cue received the best handling qualities rating for all maneuvers.

Representative pilot comments for each maneuver/cueing configuration follow.

Pilot Comments: Bobup Maneuver

1. Baseline configuration (no cueing)

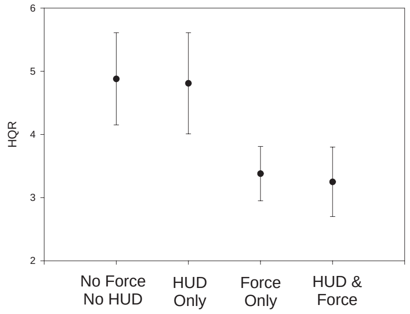

Fig. 9: Handling Qualities Ratings for Bobup Maneuver

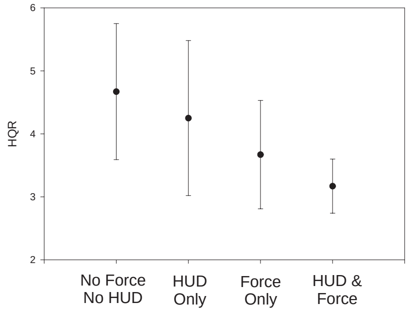

Fig. 10: Handling Qualities Ratings for Acceleration/Deceleration Maneuver

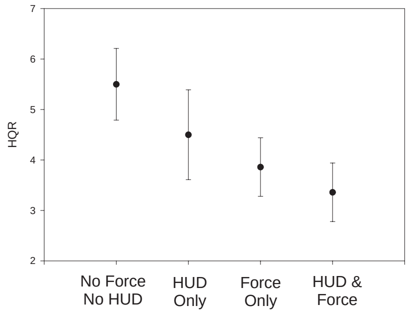

Fig. 11: Handling Qualities Ratings for Maximum Performance Turn

- Only awareness was by looking at the torque gauge. Difficult to get the exceedance factor (Pilot A).
- Can't incorporate the gauge into a continuous control task (Pilot C).
- Having to look back in the cockpit is more difficult (Pilot E).
- There is some mental workload now associated with watching the gauge. Harder than with force cueing (Pilot F).

2. HUD Cues Only

   - Noticed that you needed to split attention between the cones and the torque...Without the force cue you had to pay attention to what the torque tape was doing (Pilot A).
   - Could incorporate the HUD cues but could not be as aggressive (Pilot A).
   - Cannot use the whole envelope. Just not aware where the upper torque limit is (Pilot A).
   - Good sense of exceedances as long as you are looking at it (Pilot B).
   - Not able to confidently use the available torque (Pilot C).
   - Not as much awareness of exceedances (Pilot D).
   - No confusion on needed response (Pilot D).

3. Tactile Cues Only

   - Vague awareness of exceedances. Having it visually available gives you a better idea (Pilot A).
   - No confusion in required control input (Pilot A).
   - No need to refer to the panel (Pilot B).
   - Much more comfortable. More opportunity to concentrate on longitudinal performance. (Pilot B).
   - No confusion over required control input. Feedback is directly to the controlling appendage (Pilot C).
   - Can't see any way this could interfere with operation in cockpit (Pilot C).

- Was confident in using the system (Pilot D).
- Able to confidently use the system (Pilot F).
- Confident in the use of all the envelope (Pilot H).

4. Tactile and HUD Cues

    - Able to perceive the collective cue. Didn't notice the visual cues for the limits (Pilot A).
    - Able to confidently use the envelope without exceedances (Pilot A).
    - Good awareness of the tactile cueing. Fair awareness of the symbology (Pilot B).
    - Cue was easy to perceive and incorporate into the control strategy (Pilot C).
    - Having information from both the HUD and the tactile cue allowed focus entirely outside the aircraft (Pilot G).
    - All the info you need is there. Can't think of any way to improve it (Pilot G).

Pilot Comments: Acceleration/Deceleration

1. Baseline Configuration (no cueing)

    - Not aware of exceedances. Perhaps a glance at the gauge might tell you about torque (Pilot A).
    - No idea of where the hub moment is (Pilot A).
    - Completely unaware of hub moment exceedances (Pilot C).
    - Not confidently able to utilize all the available envelope (Pilot C).
    - Greatly reduced ability to meet performance standards, particularly hub moment (Pilot D).
    - Having to stare at torque gauge is a problem (Pilot F).

2. HUD Cues Only

    - Moment cue is kind of an on/off cue. No proximity info (Pilot F).
    - Flash of hub symbol was not enough to cue ... aware of it but it wasn't enough to keep within the limit (Pilot G).
    - Hub cue is a bit ambiguous; the flicker of the symbol does not contain enough info (Pilot G).

3. Tactile Cues Only

    - Cyclic cue was somewhat vague, might be confused with force trim (Pilot A).
    - Going from no cues to cues really is a significant thing for everybody to look at. It really emphasizes how much the tactile cueing helps (Pilot D).
    - Getting both the torque and hub limit cueing (Pilot D).
    - Not feeling the cyclic cueing (Pilot E).
    - No idea what I'm doing to cause hub moment exceedances (Pilot F).
    - Torque cue is easy to perceive. Could occasionally feel the cyclic cue but it is subtle (Pilot F).
    - No confusion in response to the cue (Pilot G).

4. Tactile and HUD Cues

    - The perception of the collective cue is predominant as compared to the hub moment cue (Pilot A).
    - Able to incorporate the collective cue but not in the cyclic. Not increasing aggressiveness to encounter the cue (Pilot F).
    - Hub force cueing is very light (Pilot G).
    - Reduced aggressiveness in response to feeling the cue. Still not really incorporated into control strategy though (Pilot G).

Pilot Comments: Maximum Performance Turn

1. Baseline Configuration (no cueing)

    - Able to acquire the torque value somewhat but not the stall (Pilot A).
    - Limiting factor was not knowing where the stall limit was so had to be conservative to avoid it (Pilot A).
    - Stall cueing is missed the most (Pilot B).
    - Performance was consistently bad (Pilot D).
    - Not able to confidently use the envelope (Pilot D).

- Aggressiveness limited by lack of information (Pilot G).
- No confidence whatsoever (Pilot H).

2. HUD Cues Only
    - Could incorporate limit cues by backing off on the stick in response to the HUD cues (Pilot A).
    - Would have been better with the force cues (Pilot A).
    - Hard to find the edge of the envelope (Pilot A).
    - Not satisfactory without improvement, but pretty straightforward (Pilot B).
    - Confidence level has dropped in ability to use the envelope (Pilot D).
    - Increased physical and mental workload (Pilot D).
    - Able to incorporate the limit cues into control strategy (Pilot G).
3. Tactile Cues Only
    - Very aware of limit exceedances. More precise in use of controls. Using the cues in control strategy by nibbling on the stall cue (Pilot B).
    - Very aware of limits (Pilot C).
    - Able to use the envelope confidently (Pilot C).
    - Able to incorporate the limit cues. Worked very well (Pilot D).
    - Workload has gone down from the HUD only configuration (Pilot F).
4. Tactile and HUD Cues
    - Good indication of exceedance magnitude with the HUD plus stick (Pilot A).
    - Easy to perceive the cues (Pilot A).
    - Immediately aware of the limit exceedances (Pilot C).
    - Air vehicle performance is now the limiting factor (Pilot C).
    - Awareness of exceedances is very obvious. Ability to perceive exceedances is high (Pilot D).
    - Very confident that I can fly close to the envelope (Pilot F).
    - Having the HUD adds to the info on torque if not feeling anything (Pilot F).

CONCLUSIONS

The effectiveness of predictive cueing for limit avoidance using neural networks was demonstrated in multiple piloted simulation experiments. Pilot-in-the-loop experiments of the UH-60A initially demonstrated cueing of a single limit (main rotor torque) for a single-axis bobup task using a PNN with an “inverse” architecture. Subsequent experiments with the OH-58D demonstrated cueing for a single limit (main rotor torque) for multiple maneuvers using a “forward” architecture PNN. A second set of UH-60A experiments demonstrated cueing of multiple limits during a variety of maneuvers.

Quantitative analysis of maneuver performance demonstrated that the cueing system effectively allowed pilots to achieve maximum maneuver performance with minimal limit exceedances. Handling qualities evaluations by pilots also showed the cueing system to be beneficial, and pilot comments were generally positive. Pilots felt more confident in their ability to achieve maximum aircraft performance because of increased awareness of the operational limits. Pilots also reported reduced workload as a result of the limit avoidance cueing.

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