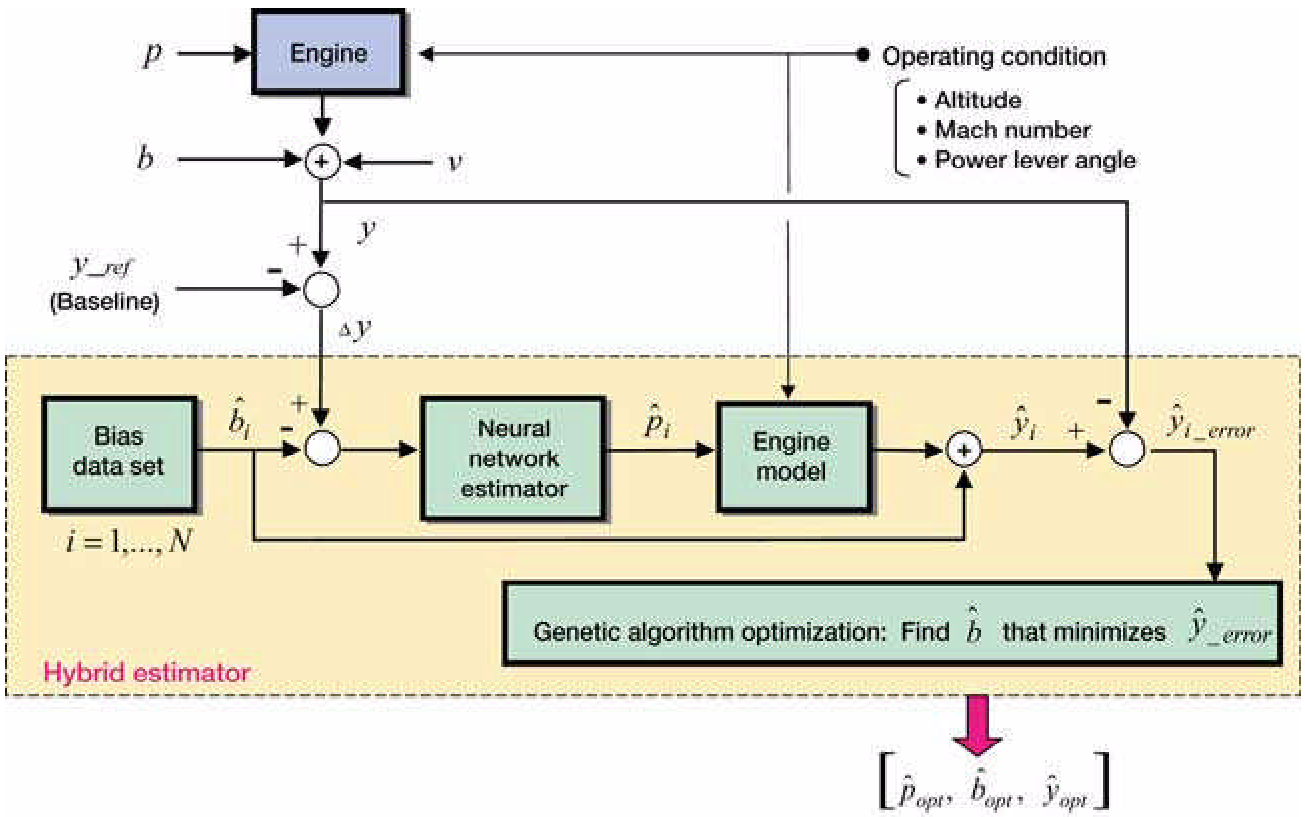
Hybrid Neural-Network--Genetic Algorithm Technique for Aircraft Engine Performance Diagnostics Developed and Demonstrated

As part of the NASA Aviation Safety Program, a unique model-based diagnostics method that employs neural networks and genetic algorithms for aircraft engine performance diagnostics has been developed and demonstrated at the NASA Glenn Research Center against a nonlinear gas turbine engine model. Neural networks are applied to estimate the internal health condition of the engine, and genetic algorithms are used for sensor fault detection, isolation, and quantification. This hybrid architecture combines the excellent nonlinear estimation capabilities of neural networks with the capability to rank the likelihood of various faults given a specific sensor suite signature. The method requires a significantly smaller data training set than a neural network approach alone does, and it performs the combined engine health monitoring objectives of performance diagnostics and sensor fault detection and isolation in the presence of nominal and degraded engine health conditions.

Aircraft engine performance is diagnosed by estimating a set of internal engine health parameters from available sensor measurements. The following relationship between the engine health parameters and the sensed parameters can be used to express the general approach:

$$y = f(p, \text{operating condition}) + w$$

where y is a vector representing the sensed parameters (gas path temperatures and pressures, spool speeds, fuel flow, and variable geometry), p is a vector of engine health parameters (component efficiencies and flow capacities), $f(\cdot)$ is a nonlinear function of p and the engine operating condition, and w is a vector representing measurement inaccuracies. System nonlinearities and potential sensor measurement inaccuracies make this estimation problem very challenging.



Hybrid engine health estimation architecture.

Long description: Block diagram of the hybrid neural network genetic algorithm architecture for aircraft engine performance diagnostics. The engine in this diagram has measurable output data that are a function of the amount of engine degradation and the current engine operating conditions, such as altitude, Mach number, and power lever angle. The measured, or sensed, engine output data are corrupted by sensor noise and sensor bias. These sensed data are passed into the hybrid estimator block. The hybrid estimator processes them, and produces output data of engine health parameter estimates, uncorrupted engine sensor value estimates, and engine sensor bias estimates. The hybrid estimator block consists of the following subblocks: a bias data set, a neural network estimator, an engine model, and a genetic algorithm that coordinates the estimation process. The genetic algorithm drives the search to choose candidate sensor bias vectors from the bias data set. The selected bias vectors are subtracted from the sensed engine parameter vector, and the difference is sent into the neural network estimator to estimate engine health parameters. These estimated engine health parameters are provided as input to the engine model that produces the estimated engine output data. The genetic algorithm compares engine model output data to measured engine output data to assess the fitness of the candidate solution. At the conclusion of the search process, the highest fitness solutions are output from the hybrid estimator.

The hybrid engine health estimation architecture, as shown in the figure, is composed of a bias data set, a neural network estimator, an engine model, and the genetic algorithm optimization technique. Engine output data are based on the current operating condition and engine health parameters. These sensed parameters are corrupted by a white noise vector *v* and a bias vector *b*. To make the problem manageable, we assumed that at most one sensor could be biased at a time. The bias data set, which is composed of a large number of bias vectors, is defined a priori and is used by the genetic algorithms in the search for a bias vector $\hat{b}_i$ that matches well with an actual bias contained in the measurement vector. The neural network estimator is trained offline with noise-corrupted, but bias-free, sensor measurements to estimate engine health parameters $\hat{p}_i$. The neural network will perform sufficiently well in estimating health parameters as long as the sensor measurements do not contain any bias. For a given set of estimated health parameters and sensor bias, the engine model is executed and its output data are evaluated against the physical sensor measurements. The bias data set, the neural network estimator, and the engine model are coordinated by the genetic algorithms in the search for an optimal solution. After the search process, the searched bias vectors are ranked according to their corresponding fitness value, which is a value indicating the agreement between the measured and predicted engine output parameters. A ranked list of several plausible fault candidates can help to avoid false alarms or missed detections.

The table shows an example of the technique's estimation performance applied to a military twin-spool turbofan engine simulation, which was used to represent both the engine and the engine model shown in the figure. Here, 12 sensed engine values were used to estimate the 9 engine health parameters listed in the table. In this case, a 9.5s bias was modeled in the sensed fuel flow value. Without bias detection, the estimation errors of some engine health parameters are higher than 20 percent, and one is as high as 120 percent. With bias detection, the estimator is able to correctly identify and quantify the bias in the fuel flow. This results in greatly improved health parameter estimation accuracy with all estimation errors at 15 percent or less.

HEALTH PARAMETER ESTIMATION WITH AND WITHOUT BIAS DETECTION
[9.5σ bias in fuel flow.]

Health parameter	**Actual condition, percent**	**With bias detection**		**Without bias detection**	
		Estimated condition, percent	**Error, percent**	**Estimated condition, percent**	**Error, percent**
Fan efficiency	-2.900	-2.788	-3.876	-2.950	1.722
Fan flow	-1.800	-1.811	0.596	-1.819	1.076
Booster flow	0	0		------- -0.134	
High-pressure compressor efficiency	-2.300	-2.172	-5.578	-2.305	0.234
High-pressure compressor flow	-1.900	-2.027	6.658	-1.497	-21.213
High-pressure turbine efficiency	-1.400	-1.614	15.254	-1.715	22.516
High-pressure turbine flow	1.000	0.875	-12.484	2.201	120.045
Low-pressure turbine efficiency	-2.000	-2.197	9.857	-2.303	15.146
Low-pressure turbine flow	2.100	2.083	-0.819	2.393	13.942

Bibliography

Simon, Donald L.: A Hybrid Neural Network-Genetic Algorithm Technique for Aircraft Engine Performance Diagnostics. AIAA-2001-3763 (NASA/TM-2001-211088, 2001.

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