

Onboard real time modeling of aircraft engines with Hammerstein-Wiener representation

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Abstract: An identification-based approach for aircraft engine modeling using the nonlinear Hammerstein-Wiener representation was proposed. Hammerstein-Wiener modeling for both limited flight envelope and extended flight envelope was investigated. Simulation shows that the resulting model can be valid over 10% variation of rotational speed of the engine, compared with those linear models that are only valid over 3%—5% change of rotational speed. It is further demonstrated that the proposed method can be utilized over large envelope up to 20% variation of rotational speed of the engine. The fundamental idea is to use nonlinear models to extend the feasible/valid region rather than those linear models. This may consequently simplify the switching logic in the onboard digital control units. This is often overlooked in aircraft engine control community, but has been emphasized in the research.

Key words: aircraft engines; engine modeling; onboard real time modeling;
system identification; Hammerstein-Wiener representation

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It has been increasingly recognized that onboard real time modeling can play an important role for aircraft engine performance improvement, e. g. as many important engine variables such as turbine temperature, surge margin, net thrust can not be measured directly (or can only be measured with a very complex, therefore unreliable instrumentation system), an onboard engine modeling can be integrated into control system to provide real time information about these variables, hence forth enabling virtue measurements, helping to increase the safety and life cycle, reducing the specific fuel consumption etc. As another example, onboard models can be used to generate “future” control signals enabling model reference control techniques^[1]. In essence, the significance of using onboard models can be best exemplified by the

fact that it has sparked two of the most important research directions in aircraft engine control systems, namely, model-based design (MBD) and engine health management (EHM). MBD and EHM have called upon serious investigations in recent years, particularly with the new generation of full authority digital engine control (FADEC) systems, which provide even powerful computational capabilities and flexible hardware interfaces.

Indeed, real time modeling has become an important area of research since 1990s with the initiation of “performance seeking control (PSC)” research program in US^[2]. The PSC system integrates a simplified state space model into the engine control system of a F-15 aircraft to optimize the engine operation. This, from the personal viewpoint, represents a major milestone

in aircraft engine optimal technology not only because of the demonstrated flight-tested feasibility (Ref. [3-5]) but also its catalytic role on shifting the experience yet trial-and-error-based design to model-based design in the aircraft engine industry. As a consequence, real time modeling has since become one of the vital aspects in developing high performance aircraft engine control systems.

For aircraft engine modeling, three of the most important criteria to consider are: (1) achievable accuracy; (2) flexibility; (3) real time performance. However, there are compromises among the three indices. In principle, the most accurate to simulate engine performance is the aerothermal component-level engine model^[6-11]. This type of models can take heat soakage, time delay, turbine cooling etc. into account, hence requiring extensive computing power and relatively long computation time. This makes them extremely accurate (even within 1% full scale for pressures, temperatures and speeds^[12]) but not suitable for onboard real time uses. Real time modeling can only be developed by accepting lower accuracy than that of component-level engine models. They are achieved through two fundamental techniques: (1) linearization; (2) identification. The former results in the well-known gain scheduling control, with the most recent development called linear parameter varying control^[13-15]; the latter takes advantage of system identification theories and usually identifies neural networks models over the flight envelope^[16-17]. While gain scheduling control has long been a standard practice^[18] (particularly for civil aircraft engine controls), its performance can deteriorate seriously during controller switching^[19], and this leads to the development of linear parameter varying control to obtain “smooth” transition of controller switching. This approach has been extensively investigated in Snecma^[20-25] and the following challenges have been identified: (1) the linear parameter varying modeling of aircraft engine is difficult to obtain; (2) control design is relatively difficult to

perform due to the non-convexity of linear matrix inequalities (LMIs); (3) the order of resulting controllers is relatively high. Therefore linear parameter varying modeling needs further investigation for the benefit of onboard real time modelings.

The above difficulties associated with the linearization technique to real time modeling are reflected by the recent trend in utilizing system identification approaches. One of the most often is used, which is the neural networks model that constitutes off-line training and on-line adaptation process to improve accuracy and real time performance. However, to the best of the authors' knowledge, there have not been flight-tested results so far. The significance of neural networks, is that it motivates the utilization of other identification methods for onboard real time modeling and the investigation of control-oriented MBDs.

Given the above account, this paper advocates another identification-based onboard real time modeling technique—Hammerstein-Wiener (H-W) representation. The H-W model has long been used in process industries, biological processes and communication systems etc. due to its reported capability to modeling a large amount of nonlinear systems (Ref. [26-28] for example), and it is therefore an irresistible impetus to adopt the H-W representation for aircraft engine modeling. However, a detailed, yet careful analysis has to be carried out to justify the feasibility of modeling of aircraft engines using H-W representation. This will be analysed in section 1; section 2 studies the model identification/validation over a limited flight envelope while identification over an extended flight envelope is attempted in section 3. Finally section 4 concludes the paper.

1 Introduction to H-W system and feasibility analysis

1.1 Introduction to Hammerstein-Wiener system

The H-W system is represented by a cascade connection of a static nonlinearity

(NL1), a dynamic linear system (LS) that is followed by another static nonlinearity block (NL2), refer to Fig. 1, where $u(t)$ denotes input, $y(t)$ is output, with $v(t)$ and $x(t)$ as intermediate variable. The cascade connection NL1 and LS is called the Hammerstein system while the cascade connection of LS and NL2 is called the Wiener system. Therefore the H-W system includes both Hammerstein system and Wiener system as special cases. Although these models are the simplest types of block-oriented nonlinear systems, they appear in many engineering applications. The identification of both Hammerstein system and Wiener system has been investigated intensively, to a lesser extent for identification of H-W system^[29-30]. But many iterative algorithms have been proposed to identify the H-W system and estimators exist in commercial software such as Matlab, where the nonlinearity class can be piecewise linear, one layer sigmoid network, wavelet network, saturation, dead zone, one-dimensional polynomial, even with user-defined nonlinearities.

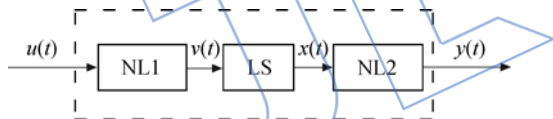


Fig. 1 H-W system

Therefore the H-W system can be a black-box structure providing flexible parameterization of nonlinear models. This makes the H-W model find applications in modeling electro-mechanical systems and radio frequency components, audio and speed processing, chemical processes etc. The block representation and transparent relationship to linear systems are more attractive than those nonlinear models such as neural networks and Volterra models, which are relatively heavy-duty and computationally demanding. However, even with these desirable properties, the application of H-W representation to the modeling of aircraft engines has to suffer a careful study which is turned to in the next subsection.

1.2 Feasibility analysis

It is seen that the H-W system is represented by two static nonlinear blocks “sliced” by a linear subsystem. To model the aircraft engines, first identify $u(t)$ and $y(t)$ in Fig. 1 as the fuel flow ratio W_f and engine rotational speed N , respectively. That is, the engine rotational speed is controlled by fuel flow ratio. First start with components analysis, it is well-known that at certain (steady state) operation condition, both the compressors and turbines work at certain position along the working lines, whose typical characteristic map is shown in Fig. 2 for compressors and similarly for turbines. Now increasing the fuel flow to the combustor will cause an increase in the gas temperature that is proportional to the amount of fuel being injected. This linearity would conform with N , should W_f be small, e. g. within 1% of fuel flow change. However once the deviation of W_f is large, significant nonlinearity emerges as both the compressors and turbines will work at different positions upon their characteristic maps. In fact, this nonlinearity can be represented by a series of piecewise linear functions and this justifies the widespread usage of linear gain scheduling and linear parameter varying (LPV) controls. As a consequence, viewing the aircraft engine as an integrated system (changing dynamics with scheduling variables of height H and flight velocity Ma , or inlet temperature T_1 , inlet pressure p_1), the Wiener system can be capable of representing the aircraft engine modeling, at least over relatively larger flight envelope than a linear model could be.

From the control system point of view, one of the key functions is limit protection, e. g. preventing the engine from surge, from flaming, from reaching mechanical limits etc. Also, the actuators have limits such as saturation. This nonlinearity can be represented by the Hammerstein system.

That is, NL1 can usually be chosen to be saturation nonlinearities, while NL2 is designated to be piecewise linear functions. Therefore,

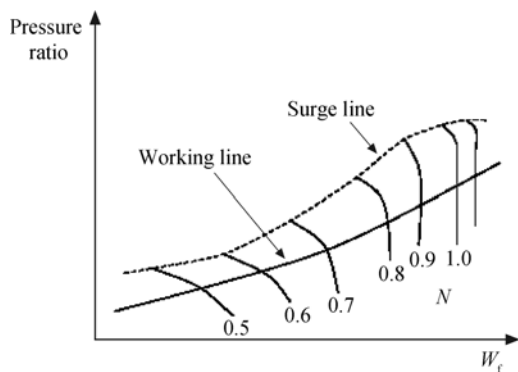


Fig. 2 Overall compressor characteristics over the operational speed range (adopted from Ref. [31])

using the H-W system can indeed represent the aircraft engine modeling, at least over an extended flight envelope. Such an attempt will be made in the next section.

2 Model identification over limited flight envelope

It is well-known that aircraft engine controls are gain-scheduled and normally six or more controllers are usually scheduled between idle and full power^[32-34]. Approximately 5% of the rotational speed of scheduling variable is covered by every controller. To demonstrate the capability of the H-W model, 10% variation of the rotational speed will be covered. If this can be done, it will show that a nonlinear model can extend the feasible region comparing with that a linear model, hence simplifying the scheduling logic. This is often overlooked in the literature and this note will thus contribute to this line of research.

2.1 Data preparation

Engine performance data should be prepared before the identification and validation processes. For model identification, while the model structure and model order can be determined through an iterated process, one thing that is often overlooked is the excitation function (or the time history of input data) that is used to generate the outputs. In fact, a good excitation function should cover the positive as well as the negative side of the nominal value of an input

variable. Ideally, there should be at least two crossovers in the excitation function^[35]. In terms of this remark, the data are generated as shown in Fig. 3. The model used is a component-level engine model that has been built recently for a generic two-spool, turbo-fan engine^[36].

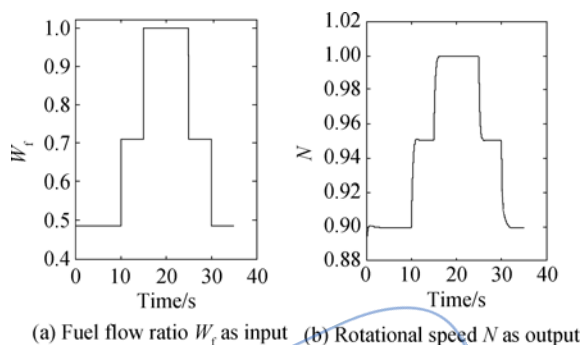


Fig. 3 Data prepared for identification and validation using the component-level model in Ref. [36] (the data are obtained at sea level and static condition)

2.2 Model identification and validation

The acceleration data from 5—20s for model identification and deceleration data from 20—35s for model validation will be used. Now observe the input/output data as shown in Fig. 3, then either NL1 or NL2 subsystem can be designated as saturation nonlinearity; the other one is chosen to be piecewise linear functions considering the gain-scheduling nature of an aircraft engine model; the linear subsystem is usually chosen to be a three-order linear model with unity delay. Given these considerations, the key to the H-W model of aircraft engine is to determine the saturation position (NL1 or NL2) and the order/number of the corresponding piecewise linear functions. The result for different options is shown in Fig. 4, where model 1—model 4 have the same saturation nonlinearity [0.485, 1.0] for NL1, with NL2 being piecewise linear functions with an order of 1, 8, 9, 20, respectively; model 5 has a piecewise linear function of order of 5 for NL1, with a saturation nonlinearity [0.9, 1.0] for NL2. It is seen that the model 2 (NL1: saturation nonlinearity [0.485, 1.0]; NL2: piecewise linear function of order of 8) has

an over 90% of fit with a loss function only 5.2684×10^{-5} . Therefore, it is remarkable that a single H-W model can cope with 10% variation of the rotational speed, significantly extending the feasible region of the model and consequently simplifying the switching logic comparing with those linear models that may only be valid within 3%–5% of rotational speed variation. A detailed discussion is turned to in the next subsection.

2.3 Identification results

Fig. 4 also reveals that saturation nonlinearity for NL2 as in model 5 is not feasible. This is comprehensive considering the aircraft engine control system is essentially fuel-based and as a consequence, for H-W model, NL1 can always be designated to be a saturation function while NL2 takes piecewise linear functions, reflecting the gain-scheduling nature of the aircraft engine dynamics. This design philosophy is validated by extensive simulations and a sample of results with NL1 being saturation nonlinearity $[0.485, 1.0]$ while varying orders of piecewise linear function for NL2 is shown in Table 1. It is seen that there is no linear correlation between the fitting degree/loss function and the order of the

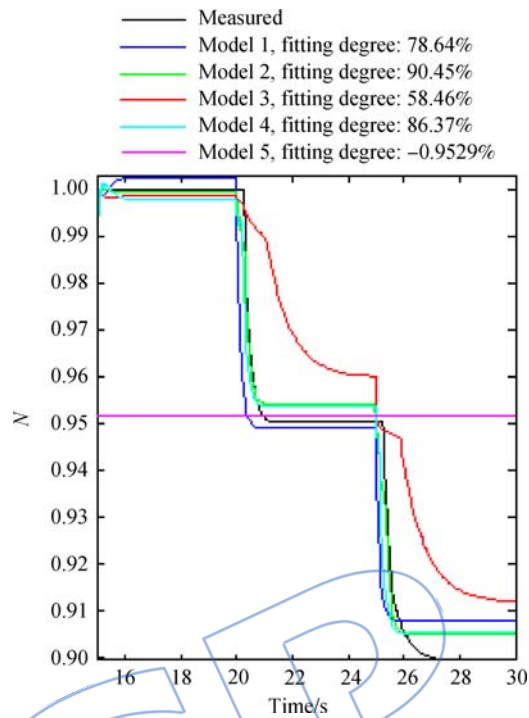


Fig. 4 Time response comparison for difference combinations

chosen piecewise linear function for NL2. Therefore the best strategy to determine the order is through trial-and-error. Here arises an interesting question: is it possible to deduce certain characteristics of the aircraft engine as reflected by the optimal order that provides best fit?

Table 1 Varying order of piecewise linear function for N over a limited flight envelope

Order	Fitting degree/%	Loss function/ 10^{-5}	Order	Fitting degree/%	Loss function/ 10^{-5}	Order	Fitting degree/%	Loss function/ 10^{-5}
1	78.64	7.2804	8	90.45	5.2684	15	81.25	6.9019
2	80.24	6.4856	9	58.46	4.4887	16	86.48	5.9525
3	80.43	6.2733	10	82.15	5.8726	17	84.86	5.606
4	81.67	6.3592	11	87.05	5.9196	18	87.94	5.9297
5	83.94	6.8837	12	82.1	5.844	19	84.89	6.3485
6	84.36	7.5602	13	84.34	5.8273	20	86.37	5.5305
7	84.75	6.5954	14	83.99	5.782			

3 Model identification over extended flight envelope

To further testify the capability of the H-W

representation for aircraft engine modeling, identification over an extended flight envelope is carried out. This time, 20% rotational speed variation of N from 0.8 to 1.0 (80% to 100%

take off max) is considered. The acceleration data for model identification and the deceleration data for model validation are still used again. A sample of results with NL1 being saturation nonlinearity[0.2, 1.0] while varying orders of piecewise linear function for NL2 is shown in Table 2. Comparing with Table 1 for 10% rotational speed variation of N from 0.9 to 1.0 (90% to 100% take off max), the optimal fitting degree drops from 90.45% to 85.58%, while the average fitting degree decreases significantly (most of the fitting degree in Table 1 are above 80%). Several fittings such as those with order of 9, 11, 13 and 15 can capture the engine dynamics and hence can be an acceptable model

for the engine, however although not shown here their transients indeed start deterioration comparing with the model for 10% rotational speed variation of N . Therefore the extension of the H-W representation to a large flight envelope, is promising but should meanwhile be explained carefully and be validated through more extensive simulations and possibly extreme events “training” than the brief study presented here.

Remark: three-layer radial-basis feedforward (RBF) neural networks is recognized to be a “universal approximator”, so it will also be interesting to compare H-W model with those of neural network-based models, e. g. in terms of accuracy and real time performance.

Table 2 Varying order of piecewise linear function for N over extended flight envelope

Order	Fitting degree/%	Loss function/ 10^{-5}	Order	Fitting degree/%	Loss function/ 10^{-5}	Order	Fitting degree/%	Loss function/ 10^{-5}
1	65.64	6.5862	8	41.07	4.8003	15	84.94	5.9988
2	-11.13	21.605	9	83.36	2.9222	16	44.63	0.07610
3	-25.43	17.432	10	58.97	0.2787	17	63.70	6.7889
4	32.83	15.001	11	85.44	7.9356	18	34.80	0.0946
5	69.15	13.267	12	25.46	0.1306	19	60.12	5.7418
6	80.51	11.428	12	85.58	8.8027	20	37.55	0.0169
7	82.50	11.646	14	34.90	0.09138			

4 Conclusion

H-W representation of aircraft engines has been studied in this note. It has been shown that nonlinear model can significantly extend the feasible/valid region over the flight envelope comparing with those linear models. Nonlinear models can thus have the potential to simplify the aircraft engine control logic carried onboard. For MBD and EHM, using nonlinear models to replace linear ones necessitates the study of nonlinear control techniques. This may bring some difficulty to aircraft engine control system design but its potentiality should be further evaluated. Proposed view is shaped by one of previous studies^[19] demonstrating the promising results of nonlinear control designs. The nonlinear techniques

are initiated to reduce the switching logics in FADEC. Utilization of nonlinear design toolsets for such a purpose is in fact very important but somehow has been overlooked by the aircraft engine control community. It is hoped that this note, however brief, can call upon this line of research.

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