RESEARCH ON ESTIMATING METHOD OF FUEL AND EMISSIONS USING NEURAL NETWORKS IN LTO CYCLE FOR PRELIMINARY AIRCRAFT DESIGN

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Abstract

This paper introduces a method using Neural Networks to estimate the fuel use and emissions of the aircraft Landing and Take-Off (LTO) cycle. This method is expected to provide an environmental criterion for weighing between distinct configurations during the preliminary aircraft design stage. Both Back Propagation (BP) and Generalized Regression Neural Networks (GRNN) are respectively implemented to establish the model. Test results show that both nets have promising advantages for the estimation work.

1 Introduction

Worldwide more attention is being paid toward the environmental problems, among which greenhouse effect and acid rain are the most recent ones. Contribution of the aircraft emissions to total anthropogenic carbon dioxide (CO_2) emissions was considered to be about 2% in 1990, and the effect of emissions from aircraft at high altitude (especially nitrogen oxides (NO_x) and water vapor) is also of great concern[1-4]. Due to the significance of environmental problems and the contribution to it from aircraft, it is imperative to estimate the fuel use and emissions of the aircraft. Additionally, we hope to estimate these two factors during the preliminary aircraft design stage, as which may provide an "environmental criterion" for weighing between distinct preliminary aircraft designs.

In this paper we try to develop such a method as to estimate the fuel use and emissions of the aircraft. Neural Networks are implemented in this paper to develop this method. This paper is organized as follows: basic estimation model is described in section 2. In section 3 Neural Networks are briefly introduced, while training and test procedures are detailed in section 4. The simulation result of a civil aircraft using the trained net was presented and briefly discussed in Section 5, and Section 6 mainly includes conclusions of this paper and work that might warrant future attention.

2 Basic mathematical model

Generally, establishment of an estimation model using Neural Networks is divided into 3 steps. Output, or estimation target of the model is firstly settled, and variables that are closely correlated with the output is chosen as the input layer of the net. Based on a large training date set, the bias and weights within the net structure are then determined via certain training algorithms. At last accuracy of the net also needs to be tested.

As for the first step, when we try to build the input layer of the net for the fuel use and emissions estimation task during the preliminary design stage, the choosing of these input nodes are mainly restricted in 2 aspects:

1. All the variables in the input layer are closely correlated with the output.
2. All the variables can be acquired in the aircraft preliminary design stage.

In this paper an input layer with 5 portions is used. These portions include input of aircraft range (L), total thrust of aircraft engines (T), aircraft empty weight (G_0), take-off weight (G), and wing areas (S). Check the 2nd aspect we mentioned above, all these 5 inputs can be acquired from preliminary design configurations. As for the 1st aspect, however, we may conclude that the variables that are included in the input layer are surely correlated with the estimation output. And within the context of physical analysis, the 2nd portion, total thrust indicates the efficiency of the engines; the 2nd and 4th portion of the layer represent the thrust-weight ratio (T/G); the 4th and last portion indicate the wing load (G/S); while all the former 4 ones might necessarily indicate the fuel use of the aircraft.

However, note that we are not here making a universal conclusion on choosing the input layer nodes of the estimation model. In future work, if more efficient aircraft configuration data are available, these data can be added to, or substitute the above-mentioned 5 portions, as long as estimation accuracy of the net satisfies certain error tolerance requirements.

After estimation task of aircraft emissions is finished, however, it is not proper to "judge" the environmental performance of an aircraft simply based on the weight of the gas emitted from the engines. Take A380 as an example; A380 possibly consumes more fuel in the LTO cycle due to large take-off weight of the aircraft, and the emissions could be much larger than an old type aircraft like A320, even if engine efficiency or "environmental friendliness" of A380 is probably much better. Therefore in this paper we adopt the emission factor Q defined as:

$$Q=G_e/G_f$$

Where G_e is the total emission of the aircraft, and G_f is the fuel use of the aircraft, both defined in LTO cycle of the aircraft. Physically, this factor could be interpreted as emission that is induced by one kilogram of fuel use. Environmental performance of the aircraft could then be estimated on a more objective and unbiased basis by using this factor.

3 Networks implemented in this paper

Neural Networks are implemented in this paper to develop the model for the estimation task. Basically the estimation model is a function regression from the chosen input to estimated target. Neural Networks are specifically chosen in this paper because of their ability to extract information from complexly-correlated inputs. It has been proved that a feed-forward Neural Network with one hidden layer is able to approximate any continuous functions to an arbitrary level of accuracy based on abundant training data and proper training process. Neural Networks also have inherent parallel properties that provide a robust and fault-tolerant structure. Besides, as mathematical operation within the net structure includes merely addition, subtraction and multiplication, information processing speed of the net is very rapid, which is also practical to the estimation task [5-6].

A basic feed-forward network, BP net has been used in this paper to develop the model. During the training process of BP net, input of training data is delivered to the net input layer, based on the net output error, internal structure of the net including weights on nodes of the layers are reestablished using certain training algorithms through iteration. The iteration will not stop until net output error falls into a certain pre-determined training error tolerance. As a basic feed-forward network and probably the most classic network, BP net sometimes is indicated as an "omnipotent net", and it can be used in a variety of fields, including function regression, data processing, system identification, adaptive control, etc.

However, structure of the BP net is relatively complex. In the training process of the net, variables like number of hidden layers, or nodes of every hidden layer influence the net accuracy and efficiency significantly. For most of the time it takes a "brutal force" to adjust these variables for determination of the net optimal structure [5-6].

Generalized Regress Neural Network (GRNN) is a classic network using radical basis functions to accomplish the regression task. The GRNN net has several distinguished advantages: structure of the net is very simple, containing only one hidden layer. Iterations are not included in the training algorithm, thus it costs much less time for the training stage. Practically, only spread of the function regression needs to be adjusted during the training process.

Table 1. Fuel and Emissions of the Aircraft

Aircraft	L (km)	T (kN)	G_0 (ton)	G (ton)	S (m^2)	Fuel (kg)	CO_2 (ton)	CH_4 (kg)	Acid (kg)	Toxic (kg)
F100	1380	88	23	42	94	740	2.340	0.20	6.50	14.20
BAC1-11	2320	93	21	34	93	680	2.150	6.80	5.70	129.40
F28(300)	2743	88	16	33	79	670	2.115	5.50	6.10	104.10
DC9(30)	3030	125	24	44	93	880	2.780	0.80	8.20	14.70
Tu154	3740	450	55	100	201	2190	6.920	8.30	16.40	192.71
B727(200)	4400	194	45	95	158	1410	4.455	0.30	14.10	12.10
B737(400)	5000	196	33	68	105	830	2.625	0.08	9.10	12.80
A320(200)	5700	224	42	77	122	810	2.560	0.04	11.90	5.70
B757(200)	5834	333	57	117	181	1300	4.110	0.10	23.00	11.40
A300(B4)	7085	467	90	168	260	1730	5.470	1.00	29.11	43.70
DC8(63)	7400	338	70	141	272	1860	5.890	5.80	16.90	117.40
A310(300)	8200	486	82	153	219	1550	4.900	0.40	24.40	23.00
B707(320C)	9262	338	66	151	283	1860	5.880	9.80	12.90	180.20
DC10(40)	9631	683	121	263	368	2360	7.460	2.10	43.60	78.50
B747(200B)	10500	974	173	378	511	3380	10.68	3.60	56.90	123.00
B767(300ER)	11065	505	81	181	283	1710	5.405	0.40	28.60	23.50
L1011(500)	11286	667	111	229	329	2540	8.025	7.30	32.50	177.40
B747(400)	13398	1032	183	397	511	3390	10.71	1.20	60.00	55.80

Data of the 5 input portions are gathered with Ref. [7] or by using open resources; fuel use and emissions weight data might be found in Ref. [8].

GRNN net has been widely used in a variety fields like function regression, system identification, and data processing, etc. [5-6].

4 Training and test of the Network

4.1 Training procedure

Training procedure of the Neural Networks for the estimation task in this paper might be summarized as follows:

1. Choosing of the net input layer nodes, namely the aforementioned 5 portions including aircraft range, total thrust, aircraft empty weight, take-off weight, and wing area (L, T, G_0, G, S), as has been mentioned in the 2nd Section.
2. Gathering and pre-processing of the net training data. All the aircraft data sets used in this paper are presented in Table 1. Totally we manage to gather 18 sets of the data, all belonging to the category of civil aircraft with gas turbine engines.
3. Selection of the test data set. In this paper DC9(30), A320(200), A310(200), and B747(200B) are chosen for the Network test. The 4 tested aircraft necessarily indicate short, medium short, medium long, and long range civil aircraft.
4. The remained 14 sets of the aircraft data are used for net training. Note that training data sets exceed 2/3 of the total date set. Both BP and GRNN net are respectively implemented to develop the estimation model of fuel use and emissions, with proper training algorithms.

4.2 Test result of the Networks

Fig. 1-4 shows the results of the Network test. The mark "+" represents the estimated results of the Network, while "o" indicates the real data as presented in Table 1. Detailed estimation errors might be found in Table 2-3.

Basically, we have the following test results:

1. For aircraft fuel use, GRNN net is more accurate than the BP net, especially for

estimating medium short and long range aircraft, respectively represented by A320 and B747.

2. For aircraft emissions, GRNN performs better in estimating CO_2 emissions weight, while BP net excels at CH_4, acid and toxic gas estimation work.
3. Generally, the GRNN net is recommended for aircraft fuel use estimation. However, for emissions, due to a less accuracy of BP net in CO_2 estimating, and as CO_2 takes the major part of the emissions weight, it is suggested to use GRNN net to estimate CO_2 emissions, while estimation of the latter 3 types of emitted gas might be accomplished with BP net.

5 Simulation result

In this paper we introduce a simulation result on the fuel and emissions estimation of a civil aircraft. Basic input portions of this aircraft include: aircraft range 2225km, total thrust 100kN, aircraft empty weight 25ton, aircraft take-off weight 37ton, and aircraft wing area 80m^2.

Fuel use and CO_2 emissions are estimated using GRNN net, while CH_4, acid and toxic gas emissions of the aircraft are acquired with BP net. Detailed results are presented in Table 4. Basic information of two other civil aircraft, BAC1-11 and B737(400) are also included in the table. Emission factor Q has been defined in the 2nd section, this factor of the simulated aircraft and both BAC1-11 and B737 is calculated.

Table 2. Estimation Errors of BP Net

	DC9(30)	A320(200)	A310(300)	B747(200B)
Fuel	19.88%	12.61%	2.70%	0.29%
Emissions	21.69%	46.85%	7.24%	0.28%

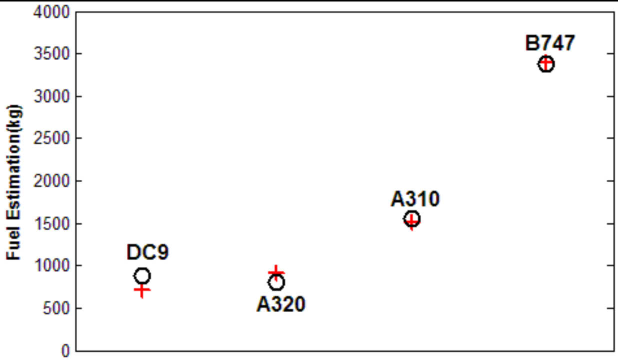

Fig.1. Test of BP Fuel Net

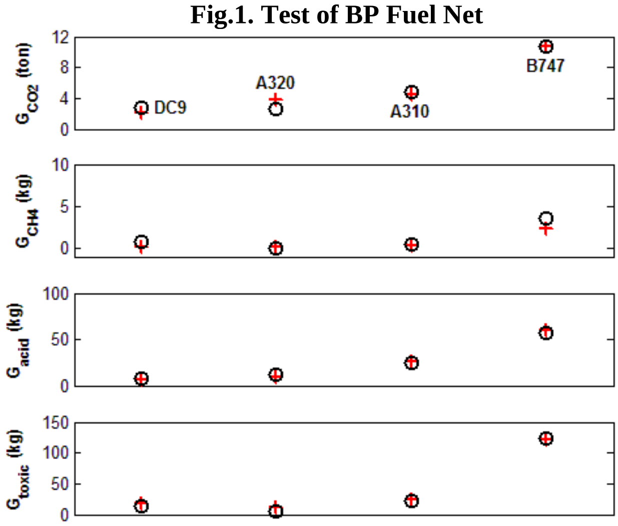

Fig.3. Test of BP Emissions Net

Table 3. Estimation Errors of GRNN Net

	DC9(30)	A320(200)	A310(300)	B747(200B)
Fuel	23.22%	2.47%	11.61%	0.30%
Emissions	19.19%	2.69%	12.05%	0.34%

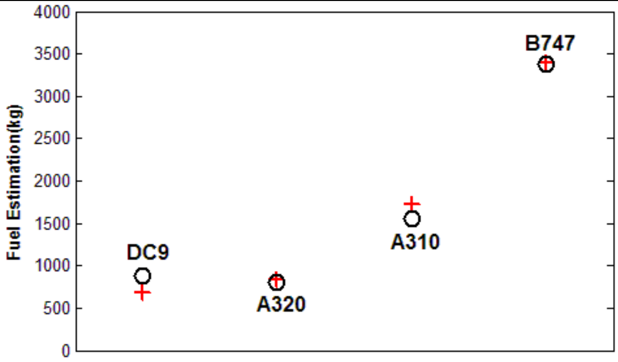

Fig.2. Test of GRNN Fuel Net

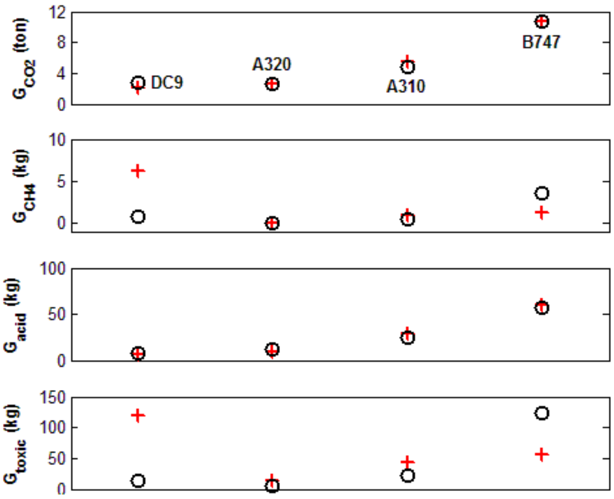

Fig.4. Test of GRNN Emissions Net

Table 4. Net Simulation Results

	BAC1-11	Simulated aircraft	B737(400)
G_f(kg)	680	680.7	830
G_{CO2}(ton)	2.15	2.1519	2.625
G_{CH4}(kg)	6.8	0.11	0.08
G_{acid}(kg)	5.7	6.70	9.10
G_{toxic}(kg)	129.4	14.00	12.80
G_e(kg)	2291.9	2172.7	2647.0
Q	3.3704	3.1919	3.1892

The aircraft BAC1-11 (or BAC 111) probably is unfamiliar to most people. This aircraft was designed and mainly produced by British Aircraft Cooperation (BAC); it was put into civil transportation mission for over 20 years around 1960s-1980s. This aircraft has a similar short range of the simulated aircraft. As for B737, however, it has been used worldwide even in nowadays. This aircraft falls into the medium short range aircraft category, which in the net test procedure was indicated by A320.

As presented in Table 4, using the criterion of emission factor Q, the simulated aircraft has a similar "environmental friendliness" as with B737, and both these two aircraft perform much better compared with BAC1-11, especially on the item of toxic gas emissions.

However, compare fuel use and CO_2 emissions of the simulated aircraft with BAC1-11 data, we may find that the estimated result literally varies very little from BAC1-11. As BAC1-11 was included in the training data set, so whether this similarity was caused by the local convergence of the net training, or the estimated data could be acceptably believable, this issue might still warrant future attention.

6 Conclusions and future work

In this paper, a method using Neural Networks to estimate fuel use and aircraft emissions during the preliminary aircraft design stage was developed. This method is expected to provide an environmental criterion to weigh between distinct aircraft configurations. Both BP and GRNN Networks were implemented to develop the estimation model, test results show that each net has respective advantages. A simulation result was also presented in this paper. Under the framework of emissions factor adopted in this paper, this aircraft performs better compared with an old-type short range BAC1-11. Basic performance of the simulated aircraft is very much similar to B737(400).

However, as has been mentioned in Section 5, the most recent problem in the net training process lies in the local convergence towards the training data set. Greater brutal force might be needed to build up a better structure of the net so as to overcome this problem, if possible. In addition, the environmental criterion in this paper has been developed mainly for the Landing and Take-Off cycle of the aircraft, performance of the aircraft ascending, cruise, and descending stage might also be included in future work.

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