Estimating Aircraft Fuel Consumption using Radar Tracks Data

Fangzi Liu\textsuperscript{a}, Chao Wang\textsuperscript{b,*}, and Lei Wang\textsuperscript{c}

\textsuperscript{a}Civil Aviation College, Nanjing University of Aeronautics and Astronautics, Nanjing, 210016, China
\textsuperscript{b}College of Air Traffic Management, Civil Aviation University of China, Tianjin, 300300, China
\textsuperscript{c}Huabei Air Traffic Management Authority, Tianjing, 300450, China

Abstract

For accurately measuring the energy-saving contribution of air traffic management technology on air transportation, this paper proposed a calculation method of fuel consumption in the air traffic control area based on radar tracks. This paper firstly analyzed nine influencing factors, including aircraft type, flight state, true airspeed, and altitude, that could affect aircraft fuel consumption. Taking air traffic trajectory data as input, a fuel flow time series prediction model based on echo state network was built. The predicted approximate error of the model can reach 0.032\%, 1.79\%, and -1.11\% in level flight, climbing state, and descending state, respectively. Due to aircraft weight and missed calibrated airspeed data in radar tracks, a key influencing factors extraction method for fuel consumption based on sensitivity analysis has been further explored. Input parameters of the ESN fuel flow time series approximate model have been simplified reasonably. The Xiamen ATC area was taken as an example, and the total fuel consumption of 1021 flights on a specific day within the Xiamen control area was calculated to be 1044.84 tons. Research results in this paper will construct a technical foundation for measuring air traffic control system performance through implementation of the ASBU plan.

Key words: air traffic management; radar track; fuel consumption; Echo State Network; sensitivity analysis

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1. Introduction

Global air traffic activities have maintained a sustained and rapid growth. Air transportation has made traveling much more convenient for the public. Meanwhile, it has also exerted serious influences on global and regional environments, mainly manifested in CO2 emissions during flying in the air or taxiing on the ground. Statistics show that carbon emissions of civil air transportation have become one of the fastest growing emitters of greenhouse gases, accounting for around 2\% of total carbon emissions from human activities [1]. The total emission of greenhouse gases will follow a continuously increasing trend, along with further growth in air traffic volume. The International Civil Aviation Organization (ICAO) required its members in a statement about environmental protection to optimize air traffic management and reduce environmental impact. Many measures in the Aviation System Block Upgrade (ASBU) proposed by ICAO are designed to save fuel and reduce carbon of air traffic systems.

Real fuel consumption of the aircraft could be obtained from the QAR (Quick access recorder) data provided by airlines. However, QAR data used for fuel-saving and carbon-emission in air traffic management has the following deficiencies: 1) QAR data are a commercial secret of airline companies and are thus difficult to obtain; 2) trajectory data used for optimizing the performance of an air traffic system come from numerous airlines, and it is difficult to collect and process all this data. Therefore, the easily obtainable radar tracks have become a feasible way to analyze air traffic fuel-saving and carbon-reducing performance from a macroscopic view.

Many scholars have conducted research on fuel consumption measurement. In terms of flight performance, Collins et al. [2] proposed using energy balancing methods for modelling fuel consumption. Lathasree et al. [3] adopted fuel consumption information listed in the flight manual provided by the aircraft manufacturer to set up a fuel consumption
model through a neural network for predicting fuel consumption. Senzig et al. [4] utilized data provided by the aircraft manufacturer to develop a fuel consumption model based on TSFC (Thrust Specific Fuel Consumption) and calculate fuel consumption based on the design thrust and Mach number. Wei and Wang [5] calculated the flight time and fuel consumption of each phase by deducing a flight dynamics model of each phase. A disadvantage of this method was that it was difficult to obtain the required performance parameters. Regarding mathematical modeling, Turgut and Rosen [6] explored the influence of level flight in low flight altitude under the descending phase on fuel consumption; a genetic algorithm was employed to build an index model between fuel consumption and flight altitude. Baklacioglu [7] studied the relationship among fuel consumption, flight altitude, and TAS under the climbing phase and also utilized the genetic algorithm to solve unknown parameters in the model upon separately setting up expressions of fuel consumption, flight altitude, and true speed. Existing fuel consumption models that were widely applied in environmental analysis were all based on the LTO method [8] of ICAO or the BADA (Base of Aircraft Data) model [9]. The LTO method is mainly used for measuring take off and landing fuel consumption as well as emissions below 1500 feet, and it is not applied to the cruise phase [4]. The BADA fuel consumption model has good applicability in the cruise phase [10], but David [11] pointed out that it has low accuracy in measuring fuel consumption during take off and landing within the terminal area.

The above studies have disadvantages including complex input parameters and inaccurate measuring accuracy, which makes it difficult to apply them to fuel consumption measurements based on radar data. Additionally, quantitative assessment analyses on the selection of modeling parameters were unable to explain how to extract key parameters from multiple coupling factors affecting fuel consumption. In this paper, the Echo State Network (ESN) was adopted with sensitivity analysis to solve the above problems, realizing fuel consumption measurements based on radar data.

2. How to Value Fuel Consumption

2.1. Echo State Network

As a new recursive neural network, ESN has recently become a research hot spot due to its unique way of training as well as rapid simulation results of high precision. As early as 2004, Jaeger [12] put forward the concept of ESN, and its predicted results on time series were improved by 2400 times compared with the traditional neural network. Since then, the time series predicted research based on ESN has gained great attention and has been widely applied in various fields like communication, finance, and electrical load predicting [13-16]. Shi et al. [13] adopted Support Vector Echo-State Machines (SVESMs) to predict the chaotic time series, while Zhai et al. [14] predicted the finance time series based on ESN. The results indicated that ESN had better performance compared with other neural networks. The fuel flow series and parameter series affecting the fuel consumption are multivariate time series in nature. Applying a predicting method of time series to measuring research on fuel consumption features rationality and innovation.

Upon introducing ESN, the computing model of the reserve pool overcame problems of the training algorithm in the previous neural network model, such as slow convergence speed and local minimum. The core idea of ESN is the following: a random sparse network with a large-scale processing unit is used as a reserve pool so that input signals can be mapped from low-dimensional input space to high-dimensional space, where a linear regression method can be adopted to train partial connection weights of network, while other connection weights are generated randomly and remain unchanged during the network training process.

The typical structure of ESN is shown in Figure 1. It is mainly composed of an input layer, a state reserve pool, and an output layer. Each layer is connected by weights. Its internal neuron node state is the high-dimensional manifestation of the input signal, reflecting the linear features of the input signal in the high dimension.

![Figure 1. The structure of ESN](image)
ESN can be expressed as formulas (1) and (2):

\[ x(k + 1) = \text{sig}(W_x \cdot x(k) + W_{in} \cdot u(k) + b_s) \]  
(1)

\[ y(k) = W_{out}^T \cdot x(k) + b \]  
(2)

Where \( \text{sig} \) represents the activation function of sigmoid, \( x(k) \) represents the state variable of the reserve pool, \( u(k) \) represents the output variable. \( W_x \) which represents the sparse matrix connecting to the internal part, is generally set as 0.01 to 0.05, and the spectral radius is generally less than 1. \( W_{in} \) and \( W_{out} \) represent the input matrix and output matrix, respectively, while \( b_s \) and \( b \) are the amount of yawing. The internally-connected matrix, input matrix, and the amount of yawing are generated randomly and remained unchanged during training.

2.2. Multi-Parameter Aircraft Fuel Consumption Model based on ESN (Multi-Para-ESN)

Ten influencing factors including aircraft type, flight states (State), Mach number (M), CAS, ground speed (GS), true air speed (TAS), acceleration (A), flight altitude (H), temperature (T), and weight (W) were selected in this paper to build, train, and measure the fuel consumption model. This is shown in Figure 2:

The steps for measuring fuel consumption based on ESN are outlined below:

**Step 1** Set ESN parameters. The size of the reserve pool, spectral radius, sparse degree, and internally connected weight matrix were included. The internal coefficient matrix \( W_{in} \) and input matrix \( W_x \) were initialized.

**Step 2** Select the sample set for training. As per modelling requirements in this paper, corresponding networks should be trained according to different flight states. Input parameters of network training were extracted from QAR data to conduct de-noise processing on TAS and decrease the influence of noise on stability on network training.

**Step 3** Form the network state. Update the initial network state and saved related parameters of the current state.

**Step 4** Train the ESN. The network randomly generates input weights and internally-connecting weights. The ESN outputs the training sample according to the parameters inputted. The internal weight matrix \( W_x \) is adjusted by comparing network inputting parameters and given outputted parameters, thus obtaining the outputted weight matrix \( W_{out} \). The calculating method is shown in formula (3):

\[ W_{x(n)} = \frac{1}{\lambda_{max}} W_{x(n-1)} \]  
(3)

Where \( W_{x(n)} \) is the internal weighting matrix obtained in the \( (n-1)^{th} \) training, \( W_{x(n)} \) is the internal weighting matrix obtained in the \( n \)th training, and \( \lambda_{max} \) is the maximum flag value of the internal weighting matrix.
Step 5 Predict the network. The method consistent with the training sample is used for standardized processing of the testing sample. Input testing parameters into ESN under different flight states. According to the predicted results outputted from formulas (1) and (2), calculated results are compared with the real fuel consumption to verify the accuracy of the model predicted.

2.3. Verification of the Fuel Consumption Model based on QAR Data

QAR data were employed to extract real data of fuel consumption for comparison with network predicted data, so as to verify the accuracy of the multi-parameter fuel consumption model of ESN. B738 and A320 were selected as testing types, and ten flights’ QAR data of each type were used as training data. In addition, data of 22 flights of each type were selected as the testing data set.

The size of the reserve pool N, spectral radius, and sparse connecting degree of the reserve pool were set as 100, 0.8, and min[10/N, 1], respectively in the ESN. Then, training parameters were inputted into the network to complete the training. After that, testing parameters were inputted. Measured results of fuel consumption are presented in Figure 3 to Figure 5, respectively giving the measured results of fuel consumption under climbing state, level flight, and descending state:

Measured results of fuel consumption under the climbing state are presented in Figure 3:

We can observe that the measured curve of fuel consumption of the multi-para-ESN closely follows the real curve of fuel consumption. This can reflect the concave change of fuel consumption caused by the state conversion of motor, indicating a better measuring effect.

Measured results of fuel consumption under level flight state are presented in Figure 4:
ESN-measured results under level flight can be fitted to the real data of fuel consumption, accurately reflecting variation trends of fuel consumption.

Measured results of fuel consumption under the descending state are presented in Figure 5:

Figure 4. Calculation results of fuel consumption in level flight state

Figure 5. Calculation results of fuel consumption in descending state
As there are many aircraft maneuvers in the descending state with complex fuel consumption, it is difficult to accurately measure the fuel consumption. The multi-para-ESN fuel consumption model can effectively reflect the variation trend of fuel consumption and improve the measuring accuracy. Specific errors are presented in Table 1.

MRE and AE are used as indicators for judging the accuracy of the model. MRE mainly reflects the deviation between the calculated fuel consumption and the actual consumption, while AE analyzes the deviation between the calculated fuel consumption and the actual consumption from an overall viewpoint. The calculating method is shown in formulas (4) and (5):

\[
MRE = \frac{1}{n} \sum_{i=1}^{n} \left| F_{\text{echo}}(i) - F_{\text{rel}}(i) \right|
\]

\[
AE = \frac{1}{n} \sum_{i=1}^{n} (F_{\text{echo}}(i) - F_{\text{rel}}(i))
\]

Where \( F_{\text{echo}} \) represents the fuel consumption measured by ESN, \( F_{\text{rel}} \) represents the real fuel consumption, and \( n \) represents the overall amount of tracks in the research.

The accuracy of fuel consumption measurements under each flight is presented in Table 1:

<table>
<thead>
<tr>
<th>States</th>
<th>AE</th>
<th>MRE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climb</td>
<td>0.580%</td>
<td>7.77%</td>
</tr>
<tr>
<td>Level flight</td>
<td>0.032%</td>
<td>4.58%</td>
</tr>
<tr>
<td>Descend</td>
<td>-1.110%</td>
<td>25.99%</td>
</tr>
</tbody>
</table>

The ESN-based multi-parameter fuel consumption model has good measuring accuracy, and the fuel consumption measuring error can reach 0.032% under level flight. With small errors in measurement, the overall model has a high calculating accuracy. Likewise, the measuring effect under the climbing state with good performance can reach 0.58%, and the fuel consumption AE under the descending state can reach -1.11%. MRE displayed poor performance. This indicates that the calculating accuracy of the total fuel consumption in the descending state was high as a whole, but it also reflected a certain deviation between the measured fuel consumption and the real fuel consumption. This was caused by the fluctuation of fuel consumption data while using the minimum thrust, even though the model had good reactivity on the fluctuation of fuel consumption in the descending state.

3. Less Parametric Fuel Consumption Model based on Sensitivity Analysis

The analysis of parameter sensitivity can quantitatively evaluate the influence of changes in the parameter input on the output results, which is mainly divided into partial sensitivity analysis and global sensitivity analysis. Partial sensitivity analysis is employed to examine the influence of changes in the signal parameter on model output [17], while the global sensitivity analysis also considers the influence of all parameters to observe the interaction of changes in different parameters on model output. Inspired by the local sensitivity analysis method, the influence of each factor on fuel consumption can be quantified through the analysis of the sensitivity. No quantified data were proposed when selecting modelling parameters in previous research. The method put forward in this paper can solve the coupling parameters of complex systems on measure problem of influencing degree of output variables. This method can also be used to extract key factors affecting fuel consumption of the aircraft to simplify the model, making it more applicable in the measurement of fuel consumption based on radar data.

3.1. Methods of Sensitivity Analysis

The widely applied partial sensitivity analysis is a corrected Morris screening method that has been extensively applied in all disciplines, such as the ecological field and precipitation model analysis [18-19].

The fixed step length variation is adopted in the corrected Morris screening method of independent variables to calculate the variation degree of the dependent variable. The calculating method for judging factors of sensitivity [19] is shown in formula (6):

\[
MRE = \frac{1}{n} \sum_{i=1}^{n} \left| F_{\text{echo}}(i) - F_{\text{rel}}(i) \right|
\]

\[
AE = \frac{1}{n} \sum_{i=1}^{n} (F_{\text{echo}}(i) - F_{\text{rel}}(i))
\]
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\[ S = \frac{1}{n} \sum_{i=0}^{n} \frac{(y_{i+1} - y_i)}{P_{i+1} - P_i} \]  

(6)

Where \( S \) is the sensitivity discriminating factor, \( y_i \) is the \( i \)th operation output value of the model, \( y_{i+1} \) is the \((i+1)\)th operation output value of the model, \( y_0 \) is the initial value of the calculating result, \( P_i \) is the percentage of the \( i \)th model computational parameter value against initial parameter changes, \( P_{i+1} \) is the percentage of the \((i+1)\)th model computational parameter value against initial parameter changes, and \( n \) is the operating time of the model.

3.2. Sensitivity Analysis on Influencing Factors of Fuel Consumption

Based on the revised Morris screening method, formula (6) was employed to calculate the sensitivity \( S \) of fuel consumption. Sensitive results calculated under different flight states are presented in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Climb</th>
<th>Level Flight</th>
<th>Descend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mach (M)</td>
<td>0.212</td>
<td>-1.658</td>
<td>-1.083</td>
</tr>
<tr>
<td>CAS</td>
<td>-0.550</td>
<td>0.701</td>
<td>0.323</td>
</tr>
<tr>
<td>T</td>
<td>-0.004</td>
<td>-0.01</td>
<td>0.0001</td>
</tr>
<tr>
<td>H</td>
<td>-0.212</td>
<td>-0.194</td>
<td>-0.162</td>
</tr>
<tr>
<td>W</td>
<td>0.694</td>
<td>0.273</td>
<td>0.623</td>
</tr>
<tr>
<td>TAS</td>
<td>0.307</td>
<td>1.868</td>
<td>1.418</td>
</tr>
<tr>
<td>GS</td>
<td>0.305</td>
<td>0.023</td>
<td>0.020</td>
</tr>
<tr>
<td>A</td>
<td>0.245</td>
<td>-0.000028</td>
<td>-0.266</td>
</tr>
</tbody>
</table>

Sensitivity is classified by referring to literature [17], namely: \( |S_i| \geq 1 \) are highly sensitive parameters, \( 0.2 \leq |S_i| < 1 \) are sensitive parameters, \( 0.05 \leq |S_i| < 0.2 \) are medium sensitive parameters, and \( 0 \leq |S_i| < 0.05 \) are insensitive parameters (\( i \) represents the \( i \)th state variable of the model). According to the calculated results, sensitivity under the climbing state can be obtained as follows, in order:

\[ W > \text{CAS} > \text{TAS} > \text{GS} > \text{A} > \text{M} > \text{H} > \text{T} \]

All are sensitive parameters, except total temperature.

The fuel consumption sensitivity under level flight can be obtained, in order:

\[ \text{TAS} > \text{M} > \text{CAS} > \text{W} > \text{H} > \text{GS} > \text{T} > \text{A} \]

As accelerated speed has small changes under level flight without obvious influence, it can thus be ignored.

Sensitivity under the descending state is, in order:

\[ \text{TAS} > \text{M} > \text{W} > \text{CAS} > \text{A} > \text{H} > \text{GS} > \text{T} \]

Sensitivities of total temperatures were found to be negligible under three states. Speed related parameters, such as Mach number (M), TAS, and CAS, are sensitive parameters that possess higher sensitivity compared with GS. Flight altitude and weight are also sensitive parameters. Temperature has the lowest sensitivity, and accelerated speed is not the main parameter with low sensitivity under level flight. Parameters can be directly or indirectly obtained in the existing radar data. The TAS and flight altitude selected to reconstruct the model can balance analyzing results of sensitivity and data accessibility. In the following, the TAS and flight altitude were adopted to reconstruct a less parametric ESN (less-para-ESN) fuel consumption model.

3.3. Less-Para-ESN Fuel Consumption Model Reconstruction and Verification

The overall constructed idea of the model was consistent with that in section II.B. The training data, testing data, and ESN parameter setting used were also consistent with those used in section II.C. A computational example of fuel consumption is
shown in Figure 6 to Figure 8. At the same time, the BADA model was also selected to be another evaluation standard for comparing the calculating accuracy of the BADA model and less-para-ESN fuel consumption model. Calculated results of fuel consumption under the climbing state are presented in Figure 6:

![Figure 6. Calculation results of less-para-ESN in climbing state](image)

As fuel consumption under the climbing state was stable as a whole, the simplified overall status is stable. The less-para-ESN model can be well fitted to the real data of fuel consumption. As the amount of input parameters was significantly decreased, the fuel consumption model failed to react to the fluctuation in small scope. Likewise, simplified input parameters contributed to stable calculations of fuel consumption, and good fitting was obtained when the real fuel consumption was stable. The less-para-ESN fuel consumption model was close to the calculated results of BADA fuel consumption, which could be well fitted in the stable variation phase of fuel consumption, but in a general fitting effect in fluctuation fuel consumption.

Calculated results of fuel consumption under level flight state are presented in Figure 7:
Calculated results of less-para-ESN fuel consumption were very close to real fuel consumption under level flight. Compared with the BADA fuel consumption model, the ESN fuel consumption model possessed a better fitting effect. Moreover, calculated results of ESN fuel consumption had less fluctuation when using the same data. Compared with the slightly decreasing fitting effect of the multi-para-ESN fuel consumption model, the accuracy of calculation is given in Table 3.

Calculated results of fuel consumption under the descending state are presented in Figure 8:

The less-para-ESN fuel consumption model reacted poorly regarding the fluctuating fuel consumption series, whose fitting ability of fuel consumption under the descending state dropped greatly compared with the BADA fuel consumption model. BADA tends to reflect the fuel flow using the minimum thrust during continuous descending, while the less-para-ESN fuel consumption model is more inclined to the average value obtained in the whole descending process. Thus, its fluctuation in fuel consumption that exceeds the average value and minimum thrust fuel consumption that is lower than the average value can offset each other, causing the total fuel consumption to approach the actual fuel consumption in the whole descending state.
Table 3 shows error comparisons when using the same testing data in the multi-para-ESN, less-para-ESN, and BADA fuel consumption model.

<table>
<thead>
<tr>
<th>States</th>
<th>Error</th>
<th>Less-para-ESN</th>
<th>Multi-para-ESN</th>
<th>BADA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climb</td>
<td>MRE</td>
<td>13.06%</td>
<td>7.770%</td>
<td>11.82%</td>
</tr>
<tr>
<td></td>
<td>AE</td>
<td>1.79%</td>
<td>0.580%</td>
<td>9.46%</td>
</tr>
<tr>
<td>Level flight</td>
<td>MRE</td>
<td>7.10%</td>
<td>4.580%</td>
<td>12.90%</td>
</tr>
<tr>
<td></td>
<td>AE</td>
<td>-0.88%</td>
<td>0.032%</td>
<td>-11.82%</td>
</tr>
<tr>
<td>Descend</td>
<td>MRE</td>
<td>39.81%</td>
<td>25.990%</td>
<td>44.44%</td>
</tr>
<tr>
<td></td>
<td>AE</td>
<td>2.06%</td>
<td>-1.110%</td>
<td>-39.96%</td>
</tr>
</tbody>
</table>

In the table, the less-para-ESN fuel consumption model is lifted compared with the multi-para-ESN fuel consumption model MRE and AE. Due to the significant decrease in input parameters, increasing errors, and reasonable results, the less-para-ESN model maintains good calculation accuracy in the level flight and climbing state, with a 3% increase in MRE and 1% increase in AE. However, MRE increases by around 14% in the descending state without an obvious increase in the AE value. Compared with the calculated results of BADA, BADA errors were higher than those of less-para-ESN, except the MRE of less-para-ESN was slightly larger than that of BADA in the climbing state.

Upon the above analysis, it can be obtained that the measuring accuracy of the less-para-ESN fuel consumption model was declined compared with multi-para-ESN. Thus, merely selecting the flight altitude and TAS to build the ESN fuel consumption model was feasible and satisfied the accuracy requirement. It can be used for calculating the fuel consumption of aircrafts based on radar tracks.

4. Algorithm Simulation and Experiment A Use Case: Xiamen ATC Area Fuel Consumption Analysis

The radar track data of B738 types in the Xiamen ATC area were selected as illustrative examples to compare the less-para-ESN fuel consumption model with BADA calculated results. The following three points were regarded as criteria for the correctness of calculations: firstly, calculated results of the BADA fuel consumption model were close to those of the ESN fuel consumption model. Secondly, the magnitude of the fuel flow was close to the QAR data. Thirdly, the change rule of fuel consumption had identical presentation as the fuel consumption data of QAR. It can certify as corrective fuel assumption and acceptable if the above conditions are satisfied. Four radar trajectories were selected for illustrative analysis. Specific results of trajectories coded Traj-1 to Traj-4 are presented in Figure 9:
Calculated results of fuel consumption of four trajectories are presented in Table 4:

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>Less-para-ESN</th>
<th>BADA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traj-1</td>
<td>1878.66</td>
<td>1929.87</td>
</tr>
<tr>
<td>Traj-2</td>
<td>1601.19</td>
<td>1878.23</td>
</tr>
<tr>
<td>Traj-3</td>
<td>812.15</td>
<td>617.31</td>
</tr>
<tr>
<td>Traj-4</td>
<td>1057.23</td>
<td>966.77</td>
</tr>
</tbody>
</table>

It can be seen that calculated results of BADA were close to those of ESN, and the values calculated were consistent with the real magnitudes of fuel consumption recorded in QAR. The change rule of fuel consumption calculated was the same as the QAR data presentation: fuel consumption was low under the climbing state, fuel consumption was less under the descending state along with less flight altitude variation, and the conversion of fuel consumption under different flight states could be displayed clearly. The fuel consumption of the departing Traj-1 was close to that of the departing Traj-2, while the fuel consumption of the arriving Traj-3 was close to that of the arriving Traj-4. The algorithm of aircraft fuel consumption based on radar tracks could be judged as accurate and effective, according to the evaluation standard of accuracy of fuel consumption above.

This verified the applicability of the aircraft fuel consumption algorithm based on radar tracks in a signal trajectory. Radar data from 1st Aug 2016 in the Xiamen ATC area were utilized for fuel consumption analysis. The ATC area, air route, and traffic flow are shown in Figure 10:

![Air route structure and traffic flow in Xiamen ATC area](image)

The blue tracks are the crossing aircraft, the red are the departures, the green are the arrivals, and the black boundary is a boundary of the restricted zone. According to statistics, there were a total of 1021 flights in the ATC area, of which there were 229 departing flights, 201 arriving flights, and 591 cross flights. The B738 type and A320 type accounted for 76.59%, while the rest of the types were supplemented by BADA according to the types matching results. The calculated fuel consumption is presented in Table 5:

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>DEP-traj</th>
<th>ARR-traj</th>
<th>THR-traj</th>
<th>ALL-traj</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num of Trajectories</td>
<td>229</td>
<td>201</td>
<td>591</td>
<td>1021</td>
</tr>
<tr>
<td>Fuel Consumption(ton)</td>
<td>557.92</td>
<td>177.99</td>
<td>1044.84</td>
<td>1782.06</td>
</tr>
</tbody>
</table>

Through calculation of the fuel consumption model based on radar tracks, the total consumption of the 229 departing flights, 201 arrival flights, and 591 over flights were 557.92 tons, 177.99 tons, and 1044.84 tons, respectively.

5. Conclusions

ESN was used in this paper to measure aircraft fuel consumption. Nine parameters, including Mach number, were utilized to build the multi-para-ESN fuel consumption model. Measuring results indicated that the model demonstrated good accuracy in each flight state, and the error in the level flight could reach 0.032%. After that, a quantitative evaluation was carried out on the influencing degree of each parameter by using sensitivity analysis, combining with the research purpose of calculating fuel consumption with radar data to prove the rationality of employing TAS and flight altitude, construct the less-para-ESN model, and verify the accuracy of the model. Errors of the less-para-ESN models were 1.79%, -0.88%, and 2.06% in the climbing state, level flight, and descending state, respectively. Radar tracks from 1st Aug. 2016 in the Xiamen ATC area were utilized for application analysis, and the total fuel consumption of 1021 trajectories was calculated to be 1044.84 tons. It illustrated that the less-para-ESN fuel consumption model proposed in this paper would have high practical value.
Less-para-ESN models for more types will be further enriched by applying radar tracks calculating fuel consumption to air traffic fuel efficiency assessments in order to analyze the single trajectory and overall fuel efficiency in the airspace as well as to accurately measure the energy-saving contributions of new technology in air transportation.

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References


Chao Wang received his Ph.D. degree in 2013 in Transportation Planning and Management from Nanjing University of Aeronautics and Astronautics. He is currently a professor at Civil Aviation University of China. His main research areas include air traffic management, air traffic simulation/analytics, and machine learning.

Lei Wang received her bachelor's degree in 2014 from Inner Mongolia University. She is currently a Master’s degree candidate at Civil Aviation University of China. Her main research area is energy conservation for air traffic management systems.