# Modelling of Atmospheric Parameters Using Artificial Neural Networks

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***Abstract*— In this article, atmospheric parameters are modelled by using artificial neural networks and the obtained models are compared with atmospheric lookup tables in terms of accuracy, speedup and memory usage. First, input and output data were generated for the five different atmosphere layers divided by altitude ranges using the U.S. Standard Atmosphere 1976 atmosphere model. Then, the artificial neural networks trained with these data were added to the simulation and measurements were taken. The results show that the use of artificial neural network modelled by using atmospheric data instead of atmospheric lookup table is more efficient and encourages new studies.**

***Keywords—artificial neural networks, atmospheric table, accuracy, performance, simulation***

## I. Introduction

With the help of emerging computing technologies, engineering simulations become more complex and the expectations of the stakeholders start to increase.

Testing of the systems in the simulation environment ensures successful production process. Therefore, there is a need for realistic simulations and a large number of tests. Increasing the realism of simulations requires a source of time and processing power, but in projects with strict time constraints, it is not possible to employ sufficient simulation and the benefits of simulation technologies are not sufficiently utilized. There is always a need to run simulations faster to overcome this problem.

Lookup tables are used to make simulations run faster. However, values not found in lookup tables are obtained by using interpolation method and used in simulations. In this case, the absence of the values near the desired value in lookup table causes the developer to compromise the accuracy of the simulation. However, the cost of memory usage increases when the lookup tables are enlarged to get more accurate results. In addition, moving, backing up, updating, and similar jobs are becoming a problem for large lookup tables.

To overcome these problems, it is possible to use machine learning techniques instead of data tables. With the methods that non-linear functions can be taught, successful results can be achieved just as in interpolation methods.

Machine learning is an artificial intelligence field that enables the learning of complex problems that are difficult to model by computer systems by using statistical techniques instead of programming them. Artificial Neural Networks (ANNs) are one of the most well-known and widely used methods of machine learning and developed by inspiring from biological neural networks. Although it is more commonly used for classification and clustering problems, it can be used successfully in regression problems [1].

ANN consists of layers containing neurons having activation functions and inner product operations in these layers. According to the basic operating principle of the ANN, neurons in each layer multiply the incoming input signals by a weight vector and add a bias vector to the sum of these weights. The net sum is passed through the activation function and the output is sent to the next layer. The learning stage aims to find the optimal set of weights and biases that produce the desired input/output mapping.

The problems mentioned above are frequently encountered in simulations and ANNs are used as a solution. For example, it is necessary to know the atmospheric temperature, pressure and density at wide altitude ranges where a vehicle can operate for a flight in the atmosphere. In general, these atmospheric parameters are reached by using atmospheric tables that vary according to different altitudes. These tables are derived from the atmosphere model representing the average conditions or conditions peculiar to a particular time and place. Instead of obtaining these atmospheric parameters from the data table, it is possible to model them with ANNs and to use them in simulations [2].

In this paper, we present a study in which five different ANNs are exploited for different atmospheric layers. Each atmosphere layer (troposphere, stratosphere, mesosphere and upper layers) was modelled and temperature, pressure, and density outputs were obtained for altitude inputs. Compared to the data obtained from lookup tables, it is seen that ANNs can predict atmospheric parameters with high precision. In addition, ANNs were found to be more efficient in terms of memory utilization and speedup. ANNs worked 20.6 times faster than traditional interpolation methods and memory usage decreased by 2256 times.

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This paper is organized as follows. Section 2 summarizes the previous work. Section 3 provides information on the training data and the ANN method used during the modelling of atmospheric parameters. Section 4 shows the ANN structures designed for different atmospheric layers. In Section 5, the results obtained from ANNs are compared with the results obtained from the lookup tables in terms of accuracy, speed and memory usage. Finally, Section 6 presents the conclusions.

## II. Related Work

In 2009, Cunying and Xiong [3] modelled the middle atmosphere using ANN. They designed a three-layer feed-forward network based on the back-propagation algorithm and used latitude, longitude, altitude as the network input and obtained the temperature data. They compared the temperature values obtained from the empirical NRLMSISE-00 model with the ANN outputs in terms of accuracy and they showed that the values are close to each other.

In 2013, Ray et al. [4] developed an ANN model to predict the atmospheric pressure. They used temperature, humidity, air pressure and vapour pressure as input for training the model and they showed the improvement of the performance in the prediction accuracy.

In 2015, Pérez and Bevilacqua [5] presented an approach based on ANNs for reducing the error in the atmosphere density estimated by empirical models. They used the density estimated from the accelerometers as targets for the training. The test results indicated that ANN produces density estimates with less error than empirical models.

Although there are many studies in the literature, this work advances the subject area towards the direction of obtaining a compact model of the atmosphere, obtaining a computationally feasible and efficient model of atmosphere, making it easy for flight training specialists and meteorologists.

## III. Atmospheric Modelling Using ANN

The atmosphere is a layer around the globe that contains various gases. The reason for the fact that the gases forming the atmosphere surrounds the Earth is the force of gravity acting on gas molecules. In general, while the air pressure and density decreases with altitude; the air temperature decreases, remains constant or increases [6]. Because the overall shape of the temperature-height profile is stable and recognizable, the temperature behaviour provides a useful measurement to distinguish between atmospheric layers. In this way, Earth's atmosphere can be divided into four main layers as shown in Table I [7].

The U.S. Standard Atmosphere 1976 is an atmosphere model that shows how the values of the Earth's atmosphere such as temperature, pressure, and density change according to altitude [8].

In this study U.S. Standard Atmosphere 1976 atmosphere model is used to determine atmospheric parameters (pressure, temperature and density). Five different atmospheric lookup tables (troposphere layer, stratosphere layer, mesosphere layer, upper atmosphere layers and all atmosphere layers) are prepared to train and test five different ANNs.

There is no specific rule in the determination of parameters such as learning rate, neuron number, number of layers in ANNs. Although there is no specific standard for the determination of these values, there may be a different approach for each problem. In our case, the number of neurons was changed by controlling the value of coefficient of determination coefficient of determination ($R^2$). Initially, the ANN was trained by using a small number of neurons and layers. However, in tests where the value of $R^2$ were close to zero, number of neurons was increased in a controlled manner and the ANN was re-trained to meet the precision expectations.

TABLE I. ATMOSPHERE LAYERS

| Layer Name | Altitude Range |
|---|---|
| Troposphere Layer | 0 to 11 km (36.000 ft) |
| Stratosphere Layer | 11 to 51 km (167.000 ft) |
| Mesosphere Layer | 51 to 71 km (232.000 ft) |
| Upper Layers | above 71 km (above 232.000 ft) |

## IV. Training

The training and testing of the ANNs were done in MATLAB [9].

In the study, it was seen that the increase in the number of layers negatively affected the speed and memory efficiency. Therefore, different network structures have been designed by considering only one hidden layer.

Figures 1 – 3 show that these ANN structures designed for different atmosphere layers. For each hidden layer, the activation function *tansig* and the learning algorithm *Levenberg-Marquardt* were used. Input-output information of the ANN structures is shown in Table II. The properties of the computer where the ANNs are tested be found in Table III.

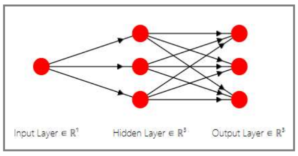

Fig. 1. ANN structure trained for troposphere layer

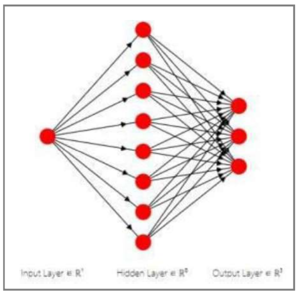

Fig. 2. ANN structure trained for mesosphere and stratosphere layers

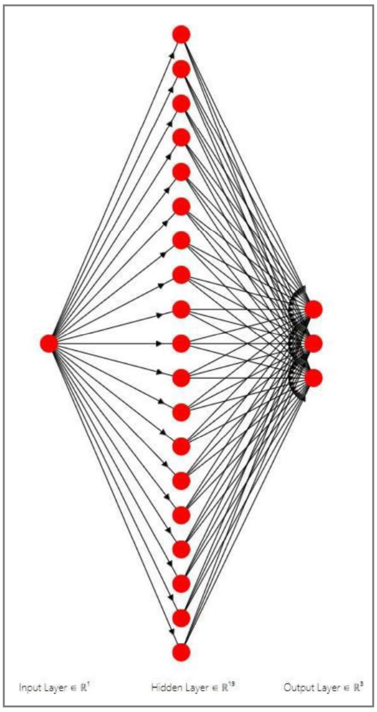

Fig. 3. ANN structure trained for upper and all atmosphere layers

TABLE II. INPUT AND OUTPUT OF ANNS

| Input | Output |
|---|---|
| Altitude [m] | Temperature – [Kelvin]<br>Pressure – [Pa]<br>Density – [kg / m3] |

TABLE III. TEST ENVIRONMENT

| | |
|---|---|
| **Processor** | Intel(R) Core(TM) i7-4700MQ CPU @ 2.40 GHz |
| **RAM** | 8,00 GB |
| **System type** | 64 – bit Operating System |

## V. RESULTS AND OBSERVATIONS

In this study, ANNs were used to estimate atmospheric parameters. Various ANN models were tried and the findings are given below.

ANNs were trained for 500 and 1000 iterations and their performances were calculated. Accuracy percentages of ANNs trained for 500 iterations were lower than the accuracy percentages of ANNs trained with 1000 iterations. In order to obtain an accurate solution, it was decided that 1000 iterations were sufficient.

The U.S. Standard Atmosphere 1976 atmosphere model is illustrated in Fig. 4 and in Figs. 5 - 7, we depict the result obtained from ANN model having 1-19-3 configuration. The training of the ANN lasted 1000 iterations.

As shown in Fig. 4 [10], while the pressure and density values obtained from the U.S. Standard Atmosphere 1976 atmosphere model decreases with the increase in the altitude, the temperature value decreases in the troposphere and mesosphere layers and increases in the stratosphere and upper atmosphere. For this reason, while the temperature graph in Fig. 5 fluctuates, the pressure and density graphs in Figs. 6 - 7 show an almost linear decrease in the low altitude.

Table IV shows the performance results of different ANNs trained for different atmospheric layers. Temperature, pressure and density values are obtained from the trained ANNs and the target outputs are obtained from U.S. Standard Atmosphere 1976 atmosphere model. Comparison is based on the $R^2$ values. For each output, it was observed that $R^2$ values were close to 1, for this reason the outputs obtained by interpolation and the outputs obtained by using ANNs were close to each other in terms of accuracy.

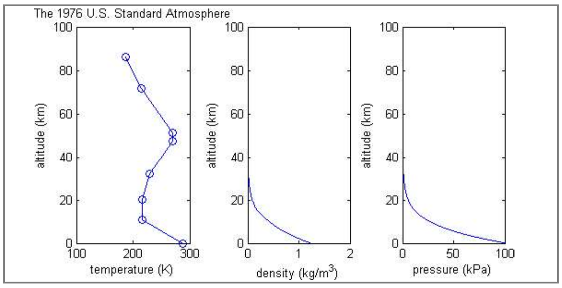


Fig. 4. U.S. Standard Atmosphere 1976 Atmosphere Model

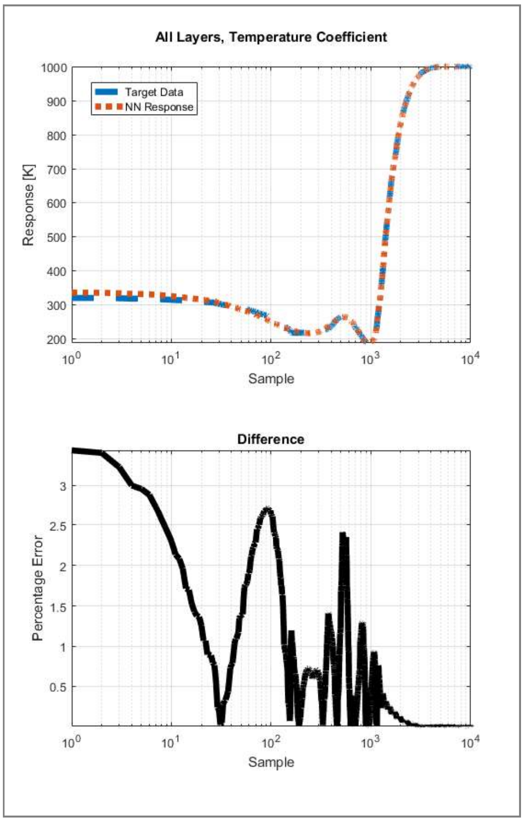


Fig. 5. ANN response and the error plot for the temperature coefficient.

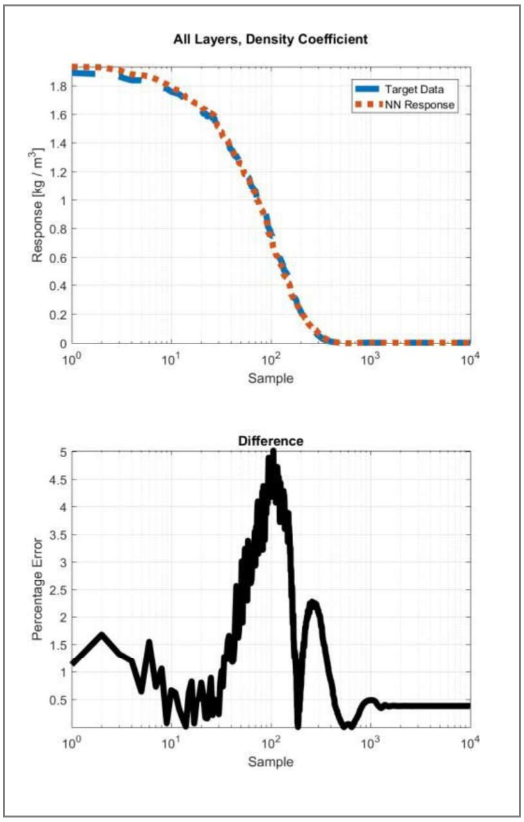


Fig. 6. ANN response and the error plot for the density coefficient.

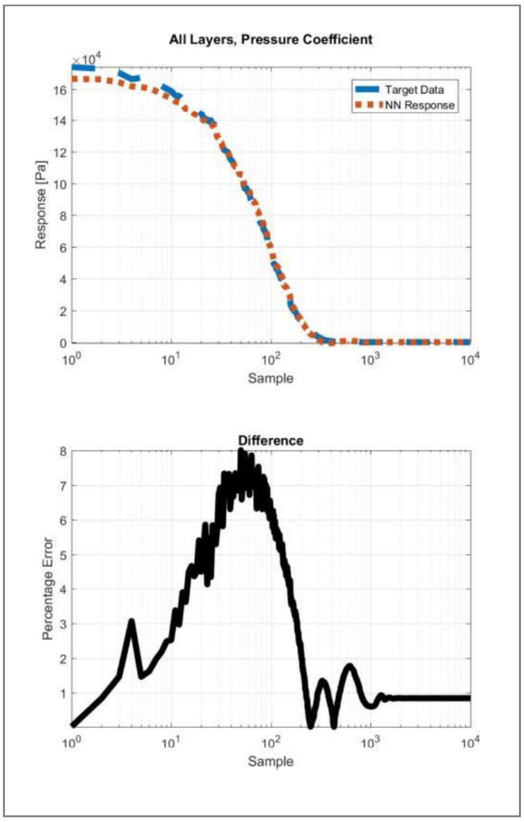


Fig. 7. ANN response and the error plot for the pressure coefficient.

TABLE IV. $R^2$ VALUES FOR ATMOSPHERIC PARAMETERS OF FIVE ATMOSPHERE LAYERS USING FIVE ANNS

| | Atmospheric Parameter | $R^2$ |
|---|---|---|
| **Troposphere Layer** | Temperature | $9.999999\times10^{-1}$ |
| | Pressure | $9.999491\times10^{-1}$ |
| | Density | $9.999372\times10^{-1}$ |
| **Stratosphere Layer** | Temperature | $9.999709\times10^{-1}$ |
| | Pressure | $9.999857\times10^{-1}$ |
| | Density | $9.999927\times10^{-1}$ |
| **Mesosphere Layer** | Temperature | $9.999982\times10^{-1}$ |
| | Pressure | $9.999850\times10^{-1}$ |
| | Density | $9.999811\times10^{-1}$ |
| **Upper Atmosphere Layers** | Temperature | $9.999331\times10^{-1}$ |
| | Pressure | $9.999753\times10^{-1}$ |
| | Density | $9.999884\times10^{-1}$ |
| **All Atmosphere Layers** | Temperature | $9.999722\times10^{-1}$ |
| | Pressure | $9.988095\times10^{-1}$ |
| | Density | $9.991347\times10^{-1}$ |

Fig. 8 shows the results of the ANN structures trained for all atmospheric layers with different number of adjustable parameters. The tests were with single hidden layer and randomly assigned number of neurons in between 1 and 15. The neuronal activation functions were *tansig* and the learning algorithm was Levenberg-Marquardt. The number of epochs was chosen as 1000 to reach an acceptable result. Mean Squared Error (MSE) values were calculated for a total of 30 test results and it was seen that the costs obtained for each test were generally close to each other, but as the number of adjustable parameters increases, there was a small decrease in the cost.

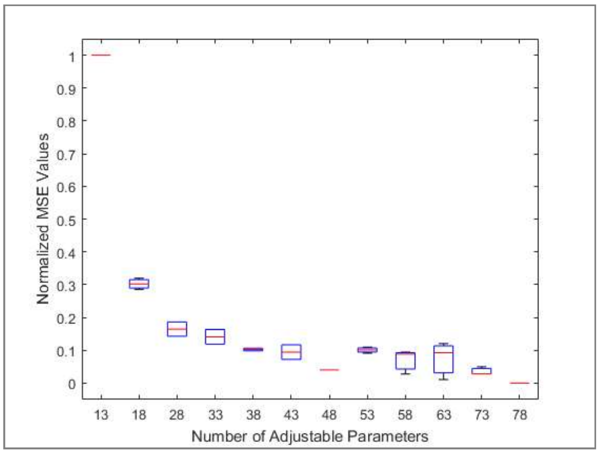


Fig. 8. Cost - number of parameters relationship for different ANN structures.

The result seen in Fig. 8 indicates that we do not need not necessarily large sized neural network structures and the problem is solvable with ANNs introducing affordable complexity.

Table V shows the average run times obtained using interpolation and ANNs for different atmospheric layers, speedup and the size of lookup table used during validation. As the size of the lookup table increases, the speedup increases as shown in the table. Because the average execution time of ANNs increases depending on the number of hidden layers, while the average execution time of the interpolation method increases depending on the lookup table size. In our case, since the number of hidden layers used in different ANNs is the same, the execution times are close to each other. However, since the size of the lookup table used for the different atmospheric layers changes, the execution times of the interpolation method are different.

Figs. 9 - 13 illustrate the execution time obtained using ANNs and interpolation method according to the test results for five different atmosphere layers. According to the results of the experiments, it is seen that the execution times measured by using ANNs are shorter than the execution times measured by using interpolation. The speedup obtained by proportioning the execution times is at most 20.6 times.

TABLE V. AVERAGE TIME, SPEEDUP AND TEST DATA SIZE COMPARISONS OF FIVE ATMOSPHERE LAYERS

| | | Average Time (sec) | Speedup ($T_{interp}$ / $T_{ann}$) | Lookup Table Size |
|---|---|---|---|---|
| **Troposphere Layer** | ***Interpolation*** | 1.556846 $\times 10^{-1}$ | 4.808446 $\times 10^{0}$ | 1601 × 4 |
| | ***Artificial Neural Network*** | 3.237731 $\times 10^{-2}$ | | |
| **Stratosphere Layer** | ***Interpolation*** | 1.642095 $\times 10^{-1}$ | 5.866015 $\times 10^{0}$ | 3900 × 4 |
| | ***Artificial Neural Network*** | 2.799337 $\times 10^{-2}$ | | |
| **Mesosphere Layer** | ***Interpolation*** | 1.692344 $\times 10^{-1}$ | 6.093964 $\times 10^{0}$ | 3600 × 4 |
| | ***Artificial Neural Network*** | 2.777082 $\times 10^{-2}$ | | |
| **Upper Atmosphere Layers** | ***Interpolation*** | 6.866299 $\times 10^{-1}$ | 1.965651 $\times 10^{1}$ | 91400 × 4 |
| | ***Artificial Neural Network*** | 3.493143 $\times 10^{-2}$ | | |
| **Il Atmosphere Layers** | ***Interpolation*** | 7.266357 $\times 10^{-1}$ | 2.060606 $\times 10^{1}$ | 100501 × 4 |
| | ***Artificial Neural Network*** | 3.526320 $x10^{-2}$ | | |

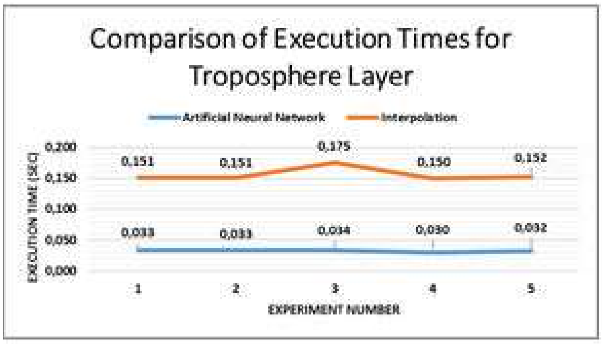


Fig. 9. Execution times of interpolation and ANN trained for troposphere layer

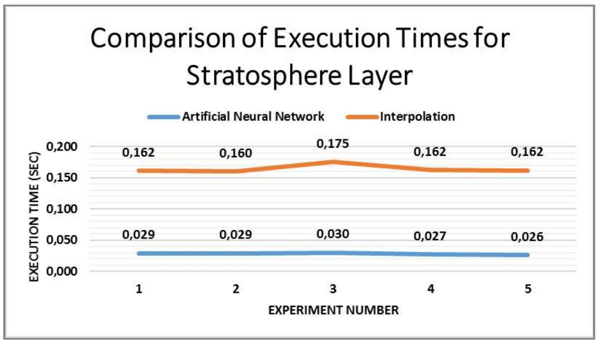


Fig. 10. Execution times of interpolation and ANN trained for stratosphere layer

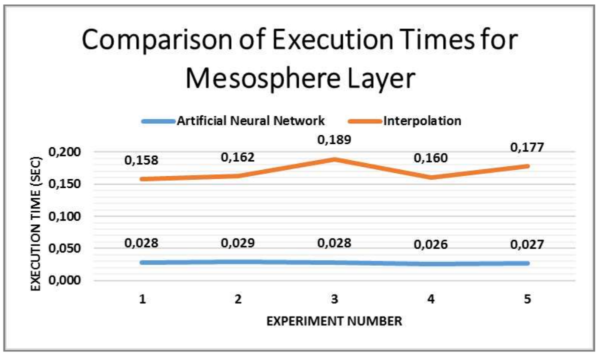


Fig. 11. Execution times of interpolation and ANN trained for mesosphere layer

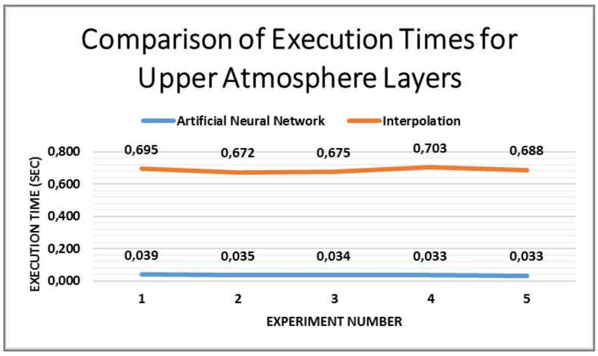


Fig. 12. Execution times of interpolation and ANN trained for upper atmosphere layers

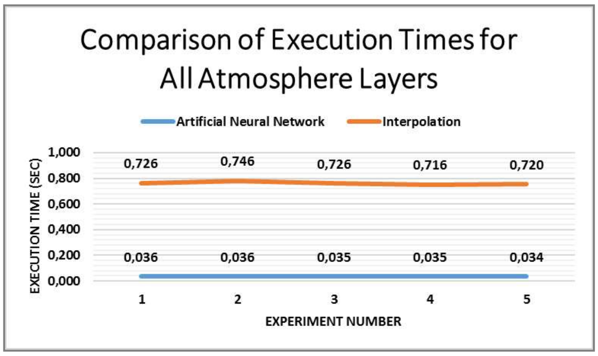


Fig. 13. Execution times of interpolation and ANN trained for all atmosphere layers

TABLE VI. MEMORY SIZE USED FOR INTERPOLATION

| | Size | Bytes | Class |
|---|---|---|---|
| **Troposphere Layer** | $1601 \times 4$ | 51232 | double |
| **Stratosphere Layer** | $3900 \times 4$ | 124800 | double |
| **Mesosphere Layer** | $3600 \times 4$ | 115200 | double |
| **Upper Atmosphere Layers** | $91400 \times 4$ | 2924800 | double |
| **All Atmosphere Layers** | $100501 \times 4$ | 3216032 | double |
| **Total Memory Size = 6432064 bytes** | | | |

TABLE VII. MEMORY SIZE USED FOR ANN

| | | Size | Bytes | Class |
|---|---|---|---|---|
| **Troposphere Layer** | ***Input weight matrix*** | $3 \times 1$ | 24 | double |
| | ***Layer weight matrix*** | $3 \times 3$ | 72 | double |
| | ***Biases*** | $6 \times 1$ | 48 | double |
| | ***Normalization parameters*** | $1 \times 2 + 3 \times 2$ | 64 | double |
| | ***Name of transfer function*** | $1 \times 6$ | 12 | char |
| | ***Name of training function*** | $1 \times 7$ | 14 | char |
| **Stratosphere Layer** | ***Input weight matrix*** | $8 \times 1$ | 64 | double |
| | ***Layer weight matrix*** | $3 \times 8$ | 192 | double |
| | ***Biases*** | $11 \times 1$ | 88 | double |
| | ***Normalization parameters*** | $1 \times 2 + 3 \times 2$ | 64 | double |
| | ***Name of transfer function*** | $1 \times 6$ | 12 | char |
| | ***Name of training function*** | $1 \times 7$ | 14 | char |
| **Mesosphere Layer** | ***Input weight matrix*** | $8 \times 1$ | 64 | double |
| | ***Layer weight matrix*** | $3 \times 8$ | 192 | double |
| | ***Biases*** | $11 \times 1$ | 88 | double |
| | ***Normalization parameters*** | $1 \times 2 + 3 \times 2$ | 64 | double |
| | ***Name of transfer function*** | $1 \times 6$ | 12 | char |
| | ***Name of training function*** | $1 \times 7$ | 14 | char |
| **Upper Atmosphere Layers** | ***Input weight matrix*** | $19 \times 1$ | 152 | double |
| | ***Layer weight matrix*** | $3 \times 19$ | 456 | double |
| | ***Biases*** | $22 \times 1$ | 176 | double |
| | ***Normalization parameters*** | $1 \times 2 + 3 \times 2$ | 64 | double |
| | ***Name of transfer function*** | $1 \times 6$ | 12 | char |
| | ***Name of training function*** | $1 \times 7$ | 14 | char |
| **All Atmosphere Layers** | ***Input weight matrix*** | $19 \times 1$ | 152 | double |
| | ***Layer weight matrix*** | $3 \times 19$ | 456 | double |
| | ***Biases*** | $22 \times 1$ | 176 | double |
| | ***Normalization parameters*** | $1 \times 2 + 3 \times 2$ | 64 | double |
| | ***Name of transfer function*** | $1 \times 6$ | 12 | char |
| | ***Name of training function*** | $1 \times 7$ | 14 | char |
| **Total Memory Size = 2850 bytes** | | | | |

Tables VI and VII show the memory sizes required for interpolation and ANNs, respectively. In Table VI, the total memory size required for the temperature, pressure and density values measured in different atmosphere layers is calculated as 6.13 MB. These parameters were kept in *mat* files and MATLAB's *whos* method was used to find the size of each file. Table VII shows the amount of memory to store the minimum information required for ANNs to be used without re-training. Weight and bias information for each ANN, minimum and maximum values of input and target data to be used in normalization, training and transfer functions used during training can be recorded and ANN can be tested directly. In our case study, the minimum amount of memory required to store the information of all ANNs was calculated as 0.0027 MB. Compared to the memory sizes required for both methods, ANNs work 2256 times more efficiently.

## VI. CONCLUSIONS

In this study, it is aimed to develop a model based on feedforward ANNs instead of atmospheric lookup tables. According to the findings, the following conclusions can be drawn:

• When the accuracy of the outputs obtained from the ANNs was compared with the accuracy of the outputs obtained by interpolation from the lookup tables, $R^2$ value was found to be close to 1 for all three outputs.

• In terms of the execution times, a 20.6-fold speedup was achieved when using an ANN, using which all atmosphere layers were modelled instead of the lookup table.

• In terms of memory utilization, the size of the memory used by the ANN was 2256 times less than the size used by the lookup table.

According to these results, it was observed that the use of ANNs was promising. The limitation of this study is that this study has been carried out only for a single atmosphere model. The comparison of the results by applying this study for other atmosphere models would lead to a more useful generalization.

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