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Improving Air Traffic Control Through Advanced Machine Learning Algorithms: A Focus on Safety and Efficiency

V.Sangeetha[1] ,S.Kevin Andrews[2],E.Mercy Beulah[3],N.Jayashri[4]

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Abstract: Due to constrained airspace and airport capacity, excessive air traffic demand overwhelms air traffic control and results in traffic delays. The current air traffic management system is limited by the workload of the air traffic controllers (ATC). ATC is crucial for maintaining human health because airspace is a frequent site of fatal flight accidents. The parameters of the airline system can be predicted in order to control or avoid air traffic.In this paper, Hybrid algorithms such asstepwise linear regression, Coarse Gaussian SVM, Exponential GPR, Ensemble Boosted Trees and Optimizable Neural Networkproposed to predict and control the air traffic. The proposed hybrid algorithms are predicting the air traffic from air traffic dataset. Stepwise linear regression, Coarse Gaussian SVM, Exponential GPR and Ensemble Boosted Treesalgorithms give huge difference in prediction such as accuracy level and speed. To solve the above problem, air traffic data fed to the pre-trained for prediction of air traffic. The proposed algorithm Optimizable Neural Networkgives high accuracy prediction compared to other statistical algorithms. Optimizable Neural network algorithm gives high accuracy of about 89% compared to other algorithms.According to the analytical findings, the suggested method can increase both the compliance rate and the mean expected delay.

Keywords: *Air Traffic data; stepwise linear regression; Coarse Gaussian SVM; Exponential GPR; Ensemble Boosted Trees; Optimizable Neural Network*

1.INTRODUCTION

The continuous movement that takes place in the air is known as air traffic. It needs strict rules and regulations, as well as ongoing monitoring and control through various procedures. With the assistance of the governments of various nations and the airlines that make up those governments, the International Air Transport Association (IATA) and the International Civil Aviation Organization (ICAO) have established the rules and regulations for advancing the regular movement of aviation businesses and travel agencies through airspace. Ground-based controllers who direct aircraft in controlled airspaces and inform and assist pilots in uncontrolled airspaces are known as air traffic controllers (ATC). Their mission is to maintain the safety, efficiency, and order of air traffic. The controller may give mandatory instructions or recommendations that pilots may choose to ignore depending on the type of flight and the airspace class. The pilot is the aircraft's ultimate decision-maker, and in an emergency, he or she may deviate from ATC instructions to maintain flight safety. Radar keeps track of all flights and their movements globally. The radar waves encounter and bounce off of aircraft, helicopters, drones, and other objects as they travel through the air. To pinpoint the precise location of the objects, the distance from the wave emitter to the point of impact is measured. A real-time flight radar that can be viewed at any time is created by digitising the location information and sending it to a map. The use of a single wave emitter does not allow for the global registration of all flights. To produce a complete image, data from radar receivers all over the world are combined. Depending on the season and time of day, there are generally more than 16,000 flights in the sky on a Friday between 2:00 and 4:00 p.m. (UTC coordinated universal time), for example, in July or August. However, there will be about 13,000 flights in the sky on the same day and time in January or February. The size of the global air transportation network doubles, according to the International Civil Aviation Organization (ICAO), at least once every 15 years, and is predicted to do so once more by 2030. In order to meet the estimated need for nearly 40,000 new aircraft over the next 20 years, there will likely be 63,220 aircraft worldwide by 2037 after the old ones have been retired. They are in charge of safely, efficiently, and quickly directing aircraft traffic in the airspace and at airports. It gives pilots the guidance and knowledge required to prevent collisions in the airspace under their control,

[1]Research scholar, Department of Computer Science and Engineering,Dr.MGR Educational and Research Institute,Chennai, E.mail:sangeetha.mca@drmgrdu.ac.in
[2]Professor, Department of Computer Applications,Dr.MGR Educational and Research Institute,Chennai, E.mail:kevin.mca@drmgrdu.ac.in
[3]Assistant Professor,Department of Computer Science and Engineering,VeltechMultitech Dr.Rangarajan Dr.Sakunthala Engineering College,Chennai,E.mail:mercybeulah@veltechmultitech.org
[4]Associate Professor,Department of Computer Applications ,Dr.MGR Educational and Research Institute,Chennai, E.mail:jayashri.mca@drmgrdu.ac.in

most commonly between aircraft and objects in the manoeuvring area. Given the heavy air traffic, potential weather changes, and other unforeseen circumstances, their work is challenging. Candidates with strong spatial aptitude are chosen as the controllers. To gain a deeper understanding of the instruments, they receive extensive training in control tower simulators, approach control, area control, and radar, as well as with pilots and in-flight simulators. Air navigation is the process of flying an aircraft along a predetermined path from one geographic location to another while keeping track of its location along the way. The three fundamental navigational techniques are visual, dead reckoning, and instrument support. Observing the sky, the terrain, and the information the flight instruments provide are the foundation of air navigation.

Radar and radio are used by air traffic controllers to track the whereabouts of aircraft in the designated airspace and to communicate with the pilots. ATC enforces traffic separation regulations, which guarantee each aircraft maintains a minimum amount of empty space around it at all times, to prevent collisions. All private, armed forces, and commercial aircraft operating in a country's airspace are given services by ATC. [Reference needed] ATC may issue directives, which pilots must follow, or advisories (referred to as flight information in some countries), which pilots may choose to ignore depending on the type of flight and the class of airspace. In an emergency, the pilot in command, who is ultimately responsible for the safe operation of the aircraft, may deviate from ATC instructions to the extent necessary to maintain that safety.Visual observation from the airport control tower is the main means of managing the immediate airport environment. On the grounds of the airport, there is a tall, windowed building called the tower. Aircraft and vehicles operating on the airport's taxiways and runways as well as aircraft in the air within a range of 5 to 10 nautical miles (9 to 18 km), depending on the airport's procedures, are separated from one another and moved efficiently by air traffic controllers. A controller's job requires the precise and effective application of rules and procedures, which must be flexible enough to be altered in response to various circumstances, frequently under time pressure. In a study that compared stress in the general population and in these kinds of systems, controllers were found to have significantly higher levels of stress. The characteristics of the job can at least partially account for this variation. At larger airports, controllers can also use surveillance displays to help manage air traffic. When airborne traffic is approaching or departing, controllers may use a radar system referred to as secondary surveillance radar. These displays include a map of the region, a list of the positions of different aircraft, and data tags that contain information from local procedures like the identification of the aircraft, speed, and altitude. To control traffic on the manoeuvring area during bad weather, tower controllers may also use Surface Movement Radar (SMR), Surface Movement Guidance and Control System (SMGCS), or Advanced Surface Movement Guidance and Control System (ASMGCS) (taxiways and runway). Three general operational disciplines make up the areas of responsibility for tower controllers: local control or air control, ground control, and flight data/clearance delivery. At extremely crowded airports, additional categories like apron control or ground movement planner may exist. The following gives a general idea of the delegation of responsibilities within the tower environment. While each tower may have specific airport-specific procedures, such as multiple teams of controllers ('crews') at large or complex airports with multiple runways, each tower may also have its own unique procedures. A system called remote and virtual tower (RVT) allows air traffic controllers to be stationed elsewhere than at the nearby airport tower while still being able to provide air traffic control services. The displays for the air traffic controllers could be live video, fake images created using information from surveillance sensors, or even both.

Problem statement

There are lot of predicting methods available in air traffic prediction from air traffic data.Stepwise linear regression, Coarse Gaussian SVM, Exponential GPR and Ensemble Boosted Treesalgorithms give huge difference in prediction such as less accuracy level, low speed and performs less. These algorithms have time complexity. The above problems are solved through hybrid algorithms.

Contributions

To predict and control the air traffic, predicting methods plays a vital role. To solve the above problem hybrid algorithms are proposed.

(i) To determine the air traffic through proposed methods hybrid algorithms such stepwise linear regression, Coarse Gaussian SVM, Exponential GPR, Ensemble Boosted Trees and Optimizable Neural Networkfrom air traffic dataset.
(ii) To detect the high accuracy prediction of air traffic dataset through proposed hybrid algorithms.
(iii) To control the air traffic and avoid flight accidents through proposed hybrid algorithms.

1. LITERATURE SURVEY

Due to constrained airspace and airport capacity, excessive air traffic demand overwhelms air traffic control and results in traffic delays. Utilizing traffic management initiatives (TMIs), such as ground delay, miles-in-trail, and speed adjustment, air traffic flow management (ATFM) is used to control this demand. A time-assignment TMI for an in-flight aircraft called Calculated Time over (CTO) is currently undergoing extensive development, and CTO operational trials have also been carried out in Japan[1].Urban air mobility (UAM) is the term used to describe on-demand air transportation services provided within urban areas. We investigate air traffic control (ATC) for a fleet of UAM vehicles while upholding system safety requirements like traffic separation[2]. A model that effectively uses performance-based navigation (PBN) requirements to allocate the standard terminal arrival route during continuous descent approach (CDA). This method aids in lowering time separation minima, resulting in up to a 50% reduction in traffic delays during peak hours[3].Through a human-in-the-loop experiment with a simplified air traffic control environment in which a novel triggering mechanism uses the calibre of the controller's decisions to determine when support is needed, the study's objective is to gain empirical understanding of these difficulties[4].Air traffic control (ATC) is profitable for AI applications as it becomes more automated and autonomous. In this paper, studies that use AI techniques to enhance ATM capability are systematically reviewed[5].The focus of air traffic flow management (ATFM) is typically on making the best use of the available airspace and airport capacities while upholding the necessary distance between aircraft for safety. An ATFM framework that uses a probabilistic approach based on chance constraints to examine the stochastic nature of the Air Transportation System (ATS)[6].Although several simulation tools have been created to help air traffic controllers make decisions, these tools do not effectively incorporate the cognitive process of air traffic controllers. The statistical physics method is used to study the equilibrium property of the air traffic system by adding the safety distance parameter to the cellular automata (CA) model[7].In the terminal control area, the departure routes are balanced, and the best control inputs are also acquired for the departing flights. To enhance the operational impact of air traffic flow, a new optimization model and solution method are introduced. Finally, various scenarios, including deterministic and stochastic cases, are provided to show how the system model performs[8].An automatic hierarchical clustering algorithm based on Eigen gaps is proposed in order to circumvent the need for human intervention in hierarchical clustering in order to determine the number of track clusters in the terminal area. This algorithm is derived from Automatic Dependent Surveillance-Broadcast technology[9]. The involvement of human controllers, who serve as the last line of defence in the control chain, makes it even more difficult to optimize procedures and protocols in air traffic management (ATM). In this article, we suggest using computational intelligence techniques like agent-based modelling and simulation (ABMS) and evolutionary computing (EC) to design a distributed simulation-based architecture to optimize control plans and procedures in the context of ATM[10].In order to create a traffic environment for the estimation of airspace capacity, predicted trajectories are used in the decision-making process, and simulation of aircraft motion is a crucial component. This article discusses the estimation of airspace capacity in relation to the suggested system and an optimization-based autonomous air traffic control (ATC) system[11].Initiatives for UAS Traffic Flow Management (UTFM) are required as the demand for Unmanned Aircraft Systems (UAS) operations rises in order to reduce congestion and to guarantee safety and efficiency[12].The traditional radar system has been unable to keep up with the demands of flight supervision due to the exponential growth in the number of flights. The possibility of creating a more intelligent air traffic flow management (ATFM) architecture is made possible by the advanced automatic dependent surveillance-broadcast (ADS-B) technique, which enables the tracking and monitoring of aerial vehicles in real-time and with accuracy[13-14].Uncertainties in the air transportation system (ATS) can cause sudden imbalances in demand and capacity, changes in flight schedules, and other unexpected anomalies. Current air traffic flow management (ATFM) models typically concentrate on minimizing the flight delays under deterministic constraints, rarely taking into account both demand and capacity uncertainties in their algorithms[15].

Inference from literature survey

Prediction of air traffic has different methods such as continuous descent approach (CDA), automatic dependent surveillance-broadcast (ADS-B) technique, artificial intelligence (AI),agent-based modelling and simulation (ABMS) and evolutionary computing (EC).CAD gives inaccuracy and unstable to predict the air traffic.ABMS only work with independent variables. AI has limited usability during prediction of air traffic. ADS-B and ECgives less accuracy. To solve the above problems hybrid algorithms are proposed. The proposed hybrid algorithms give high accuracy prediction, good performance, high speed, and less time.

2. METHODOLOGY

In this paper, **Figure 1** shows the block diagram of hybrid algorithms for air traffic control. The air traffic data trained through hybrid algorithms such as stepwise linear regression, Coarse Gaussian SVM, Exponential GPR, Ensemble Boosted Trees and Optimizable Neural Network to predict and control the air traffic.

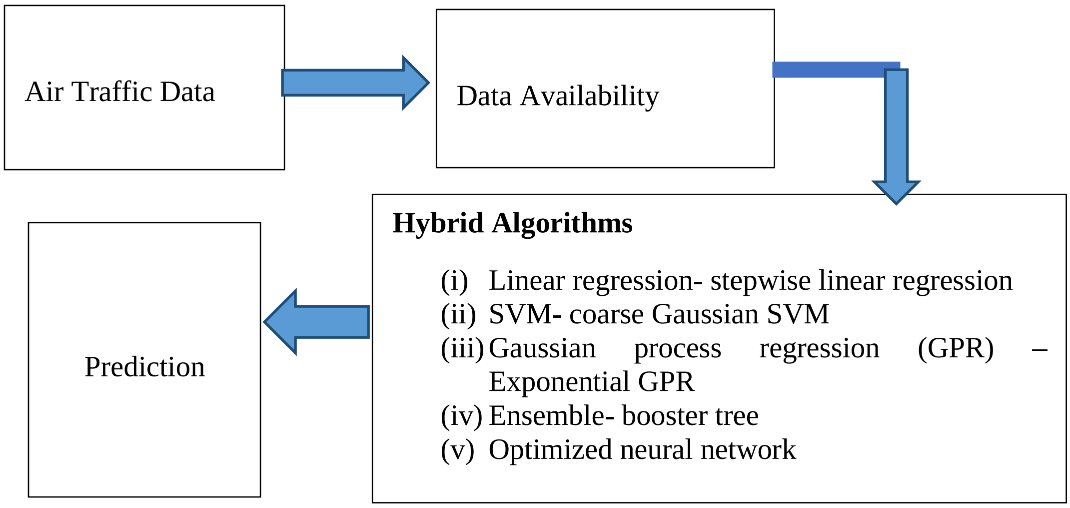


Fig 1 Block diagram of hybrid algorithms for air traffic control

2.1. Linear regression- stepwise linear regression

Stepwise regression is the iterative process of building a regression model step by step while choosing independent variables to be included in the final model. After each iteration, the potential explanatory variables are successively added or removed, and the statistical significance is tested. Even in models with hundreds of variables, stepwise regression is possible thanks to the availability of statistical software packages. Stepwise regression is a technique that iteratively assesses each independent variable's statistical significance in a linear regression model. The forward selection method begins with nothing and gradually introduces each new variable while conducting statistical significance tests. The backward elimination method starts with a full model that is loaded with a variety of variables, then it eliminates one variable to gauge its significance in relation to the overall outcomes. Stepwise regression is a method for fitting data into a model to get the desired result, but it has drawbacks as well. Currently, the fields of economics and investing make extensive use of regression analysis, both linear and multivariate. Finding historical patterns that may repeat themselves in the future is frequently the goal. For instance, a straightforward linear regression may examine price-to-earnings ratios and stock returns over a long period of time to determine whether stocks with low P/E ratios (the independent variable) provide higher returns (dependent variable). The issue with this strategy is that market conditions frequently change, and connections that have held true in the past may not do so in the present or the future. Many people have criticised the stepwise regression process, and some have even called for its complete discontinuation. The method has a number of flaws, according to statisticians, including inaccurate results, a bias in the process itself, and the need for a lot of computing power to create complex regression models iteratively. Iteration, which is the method of reaching results or making decisions by going through numerous rounds or cycles of analysis, is used to accomplish this with computers. The benefit of conducting tests automatically is that it saves time and reduces errors with the aid of statistical software packages.

2.2. SVM- coarse Gaussian SVM

The supervised learning algorithm known as SVM can be used to solve problems involving classification and regression, including support vector classification (SVC) and support vector regression (SVR). Because it takes too long to process, it is only used for smaller datasets. Finding a hyperplane that best divides the features into distinct domains is the foundation of SVM. Gaussian SVM in coarse. Hard. Low. Establishes rough class distinctions with a kernel scale of sqrt (P)*4, where P is the number of predictors. Because Gaussian kernels are universal kernels, using them with the right regularisation ensures that the predictor is globally optimal and that the classifier's estimation and approximation errors are kept to a minimum. Both classification and regression can be done using supervised learning methods that use Gaussian processes. Gaussian processes are an effective algorithm for both classification and regression. Their ability to accurately estimate their own uncertainty is their greatest practical benefit. Statistical modelling can benefit from the properties of Gaussian processes, which are inherited from the normal distribution. A machine learning classification algorithm is the Gaussian Processes Classifier. A sophisticated non-parametric machine learning algorithm for classification and regression can be built using Gaussian Processes, a generalisation of the Gaussian probability distribution.

2.3. Gaussian process regression (GPR) – Exponential GPR

In the field of machine learning, Gaussian process regression (GPR) is a non-parametric, Bayesian approach to regression that is causing a stir. GPR has a number of advantages, including the ability to measure prediction uncertainty and performing well on small datasets. The Bayesian approach infers a probability distribution over all potential values, in contrast to many popular supervised machine learning algorithms that learn exact values for each parameter in a function. Since Gaussian process regression (GPR) is nonparametric (i.e., not constrained by a functional form), it computes the probability distribution of parameters for all valid functions that can fit the data rather than just one particular function. On the function space, we specify a prior, compute the posterior using the training data, and compute the predictive posterior distribution on our points of interest, all as in the previous example. A Gaussian process is more precisely comparable to an infinite-dimensional multivariate Gaussian distribution, where any grouping of the dataset's labels is jointly distributed. By choosing the mean and covariance functions, we can incorporate prior information about the space of functions into this GP prior.Because of the flexibility of their representations and built-in measures of prediction uncertainty, Gaussian processes regression models are frequently used in machine learning applications.

2.4. Ensemble- booster tree

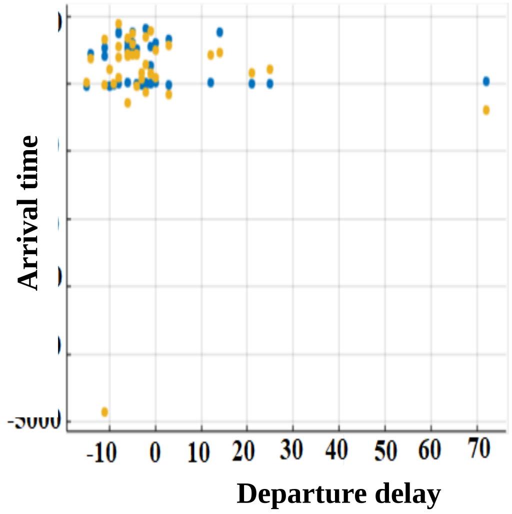
In order to reduce training errors, boosting is an ensemble learning technique that combines a number of weak learners into a strong learner. A random sample of data is chosen, fitted with a model, and then trained sequentially in boosting, where each model tries to make up for the shortcomings of the one that came before it. The weak rules from each classifier are combined during each iteration to create a single, powerful prediction rule. The "wisdom of crowds" theory, which contends that a larger group of people's decisions are typically better than those of a single expert, is supported by ensemble learning. Similar to this, ensemble learning describes a collection (or ensemble) of base learners, or models, who collaborate to produce a more accurate final prediction. Due to high variance or high bias, a single model, also known as a base or weak learner, may not perform well on its own. But when weak learners are combined, they can become strong learners because the reduced bias or variance that results from their combination improves model performance. Decision trees are frequently used to illustrate ensemble methods because they can be overfitting (high variance and low bias) when they haven't been pruned and under fitting (low variance and high bias) when they are very small, such as decision stumps, which are decision trees with only one level. Ensemble methods are used to prevent this behaviour from occurring so that the model can generalise to new datasets. Keep in mind that when an algorithm over fits or under fits to its training dataset, it cannot generalise well to new datasets. Despite the fact that decision trees have the potential to exhibit high bias or variance, it is important to note that other modelling techniques also use ensemble learning to identify the bias-variance trade-off's "sweet spot."

2.5. Optimized neural network

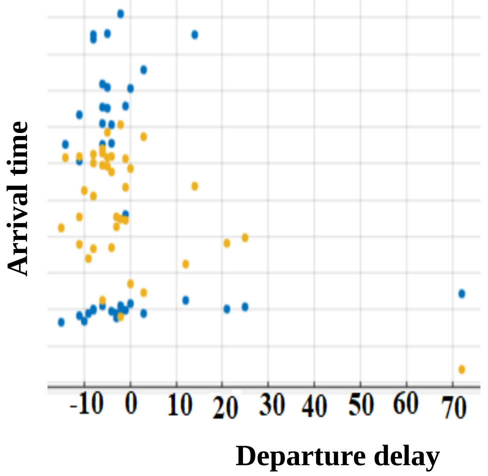
A neural network is a collection of algorithms that aims to identify underlying relationships in a set of data using a method that imitates how the human brain functions. In this context, neural networks are systems of neurons that can be either organic or synthetic in origin. Simply put, a basic neural network is one that only has two or three layers.Optimizers are programmes or techniques that modify the neural network's properties, such as its weights and learning rate, in order to minimise losses. By minimising the function, optimizers can solve optimization issues. The goal of optimization algorithms is to minimise losses and deliver the most precise results. The simplest but most popular optimization algorithm is gradient descent. Algorithms for linear regression and classification make extensive use of it. The gradient descent algorithm is also used for backpropagation in neural networks. Gradient Descent has a variant called Stochastic Gradient Descent. It tries to perform more frequent parameter updates for the model. The model parameters in this are changed after the loss on each training example is computed. Therefore, instead of updating the model parameters once as in Gradient Descent if the dataset has 1000 rows, SGD will do so 1000 times. The best optimizer is Adam. Adam is the optimizer to use if one wants to train the neural network more quickly and effectively. Use optimizers with a dynamic learning rate for sparse data. Adam (Adaptive Moment Estimation) deals with first- and second-order momentums. The idea behind the Adam is that instead of rolling quickly just so we can clear the minimum, we should slightly slow down to allow for a more thorough search. Adam also keeps an exponentially decaying average of past gradients M in addition to storing an exponentially decaying average of past squared gradients like AdaDelta.In order to enable the use of other techniques to solve the problem, this work suggests the use of artificial neural networks to approximate the objective function in optimization problems. An optimization issue can be solved by using a non-linear regression to approximate the objective function. The accuracy of the Adam optimizer, which improved CNN's classification and segmentation capabilities, was 99.2%.

3. RESULTS AND DISCUSSION

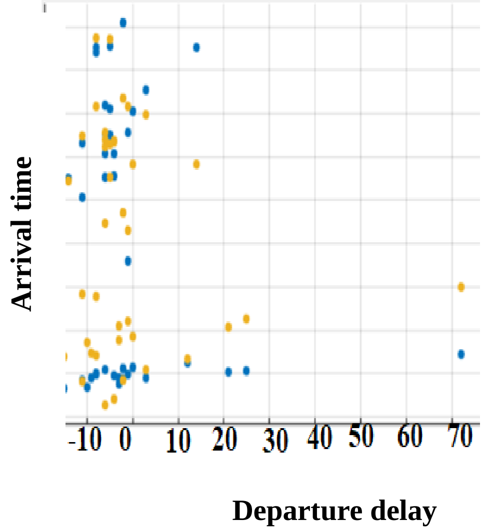
In this paper, air traffic is predict through hybrid algorithms such as stepwise linear regression, Coarse Gaussian SVM, Exponential GPR, Ensemble Boosted Trees and Optimizable Neural Network. The air traffic dataset has different types of attributes for hybrid algorithms such as arrival time, wheels off, elapsed time, distance, airtime, departure delay, and departure time. Departure time is the time at which a public transportation service is scheduled to leave from a specific point of origin. Domestic travellers are advised by the Transportation Security Administration and airlines to get to the airport at least 90 minutes before their flight, and even earlier during busy or unusual travel times.Departure delay, as it relates to travel insurance, is when your mode of transportation, such as a flight, ferry, or cruise ship, is delayed past the scheduled departure time due to no fault of your own. There is no set time limit for how long a flight can be delayed because the length of a delay can vary depending on the cause. For instance, once bees miraculously delayed a flight for up to four hours until a beekeeper was called to fix the problem.When the aircraft reaches the gate is the arrival time. A STA is the preferred time for an aircraft to pass over a specific location (landing or metering fix). It considers the configuration of the airspace and other traffic. The time between when an aircraft leaves a supporting surface and when it makes contact with that surface at the next point of landing is referred to as air time. The amount of time that has passed between the start and finish of an event is measured as its elapsed time. The amount of time that has passed between noon and two o'clock, or two hours, when an event begins at noon and ends at two o'clock, is known as the elapsed time. Since you already know how far you are from your destination, all you need to do to calculate your estimated flight time is divide the distance by your ground speed. Distance is the sum of an object's movements, regardless of direction. Distance can be defined as the amount of space an object has covered, regardless of its starting or ending point. Similar to this method, a radar altimeter times the reflection of brief radio wave pulses to determine how far away an aircraft is from the ground. Short-haul routes are typically defined as being less than 600–800 nmi (1,100–1,500 km), long-haul routes as being more than 2,200–2,600 nmi (4,100–4,800 km), and medium-haul routes as being in the middle. The landing gear of an aircraft is its wheels. The air is used by aeroplanes to provide thrust. There is no power to the wheels. The treadmill's top speed before the plane can no longer take off is constrained by the drag from the wheels. The plane's fuselage has two main wheels, one on each side. Then, close to the plane's front, there is one more wheel. The brakes on wheels function similarly to those on automobiles.**Figure 2** shows the response plot of hybrid algorithms and minimum MSE plot of optimizable neural network algorithm



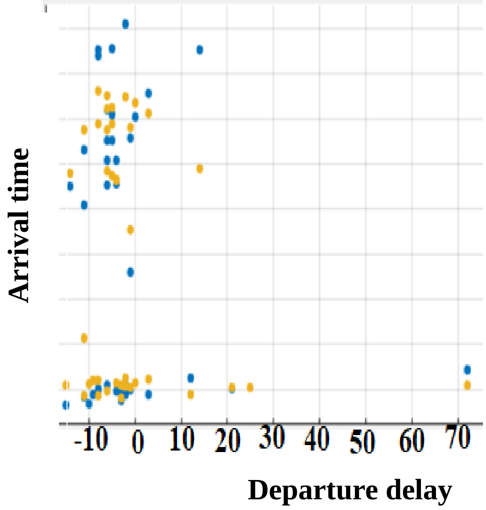
(a) Response plot for Stepwise Linear Regression



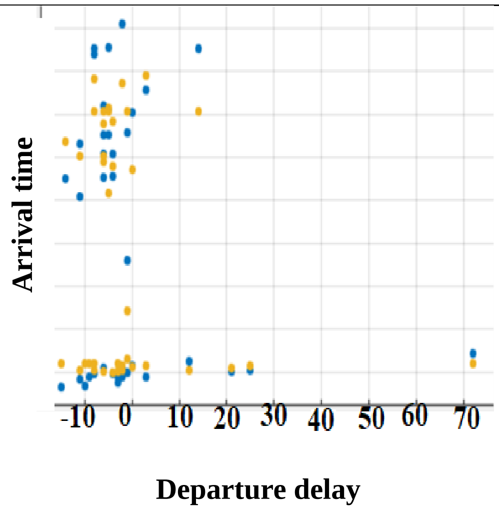
(b) Response plot for Coarse Gaussian SVM



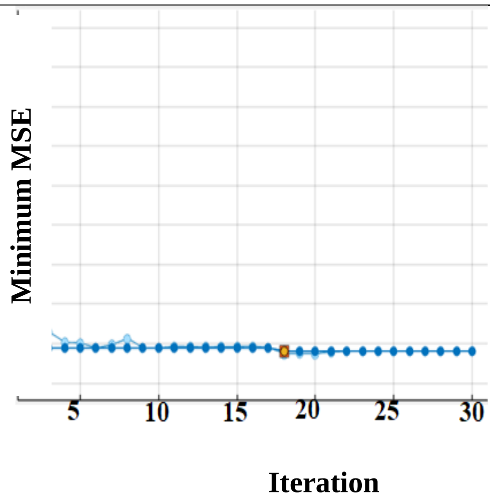
(c) **Response plot of Exponential GPR**



(d) **Response plot of Ensemble Boosted Trees**



(e) **Response plot of Optimizable Neural Network**



(f) **Minimum MSE plot of Optimizable Neural Network**

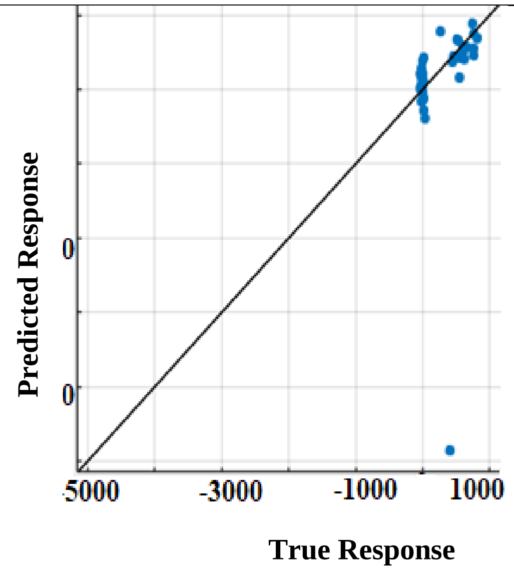
Fig 2shows the response plot of Hybrid algorithms and Minimum MSE plot for optimizable neural network

Stepwise linear regression is computationally efficient but performance is poor compared to other algorithms and biased in parameter estimation. Coarse Gaussian SVM algorithm overcome the performance of stepwise linear regression. But, the final model's variable weights and individual impacts make it challenging to comprehend and interpret. It's challenging to apply our business logic because we can't make minor adjustments to the final model because it's difficult to see. Exponential GPR use the whole information to perform and loss efficiency in high dimension space during prediction. Ensemble boosted tree also difficult to understand and expensive. It has high prediction time. Optimizable neural network overcomes these problems and gives high accuracy to predict the air traffic. In figure 2, a response plot drawn between departure delay and arrival time for hybrid algorithms. X-axis contain departure delay and Y-axis contain arrival time. Minimum MSE plot shows the iteration of Optimizable neural network. How closely a regression line resembles a set of data points is determined by the Mean Squared Error. It is a risk function that corresponds to the squared error loss's expected value. The average, more specifically the mean, of errors squared from data related to a function is used to calculate mean square error.**Table 1** shows the training parameters of hybrid algorithms. **Figure 3** shows theValidation predicted Vs actual plot of Hybrid algorithms.

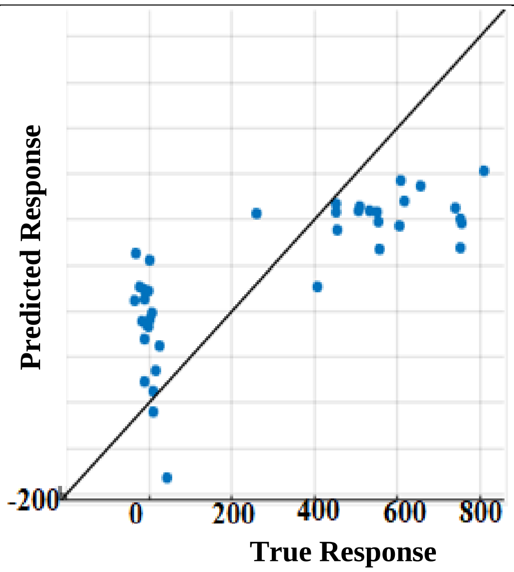
Tab 1 Training parameters of hybrid algorithms

Parameters/ Algorithms	Stepwise linear regression	Coarse Gaussian SVM	Exponential GPR	Ensemble Boosted Trees	Optimizable Neural Network
RMSE	868.48	210.13	135.73	126.41	104.52
R-Squared	-6.69	0.55	0.81	0.84	0.89
MSE	7.5425e+05	44155	18424	15980	10925
MAE	295.44	183.58	101.9	75.097	64.509
Prediction speed	~2800 obs/sec	~3200 obs/sec	~3700 obs/sec	~4800 obs/sec	~1100 obs/sec
Training Time	4.6724 sec	3.1067 sec	2.8345 sec	50.754 sec	2.9827 sec

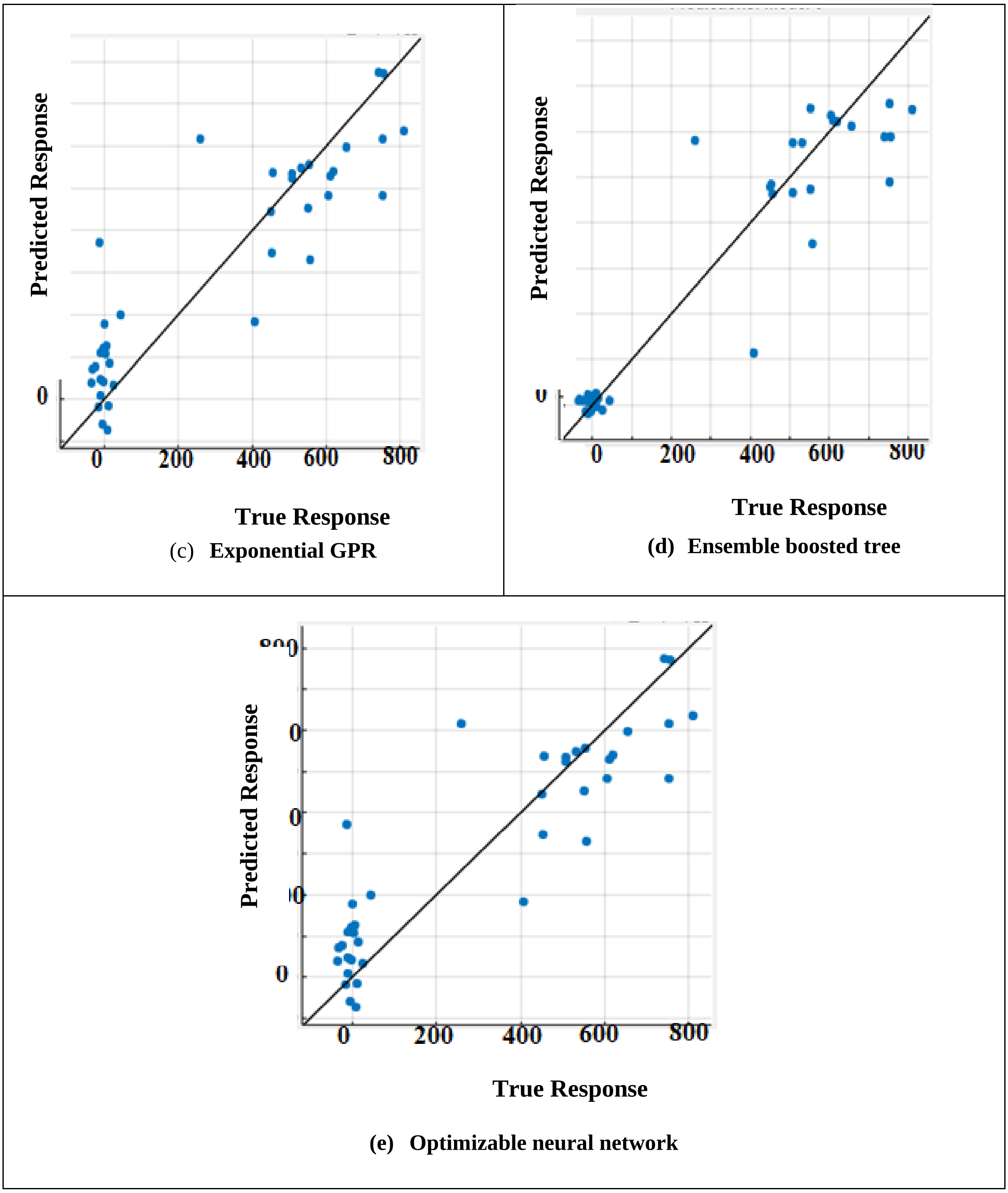
The square root of the mean of the square of all the errors is known as the root mean squared error (RMSE). RMSE is frequently employed and is regarded as a superior all-purpose error metric for numerical predictions. One of a regression model's two primary performance indicators is RMSE. It calculates the typical difference between values that a model predicts and actual values. It gives an estimate of the model's predictive power for the desired value (accuracy). High RMSE value gives less accuracy and Low RMSE value gives high accuracy. Stepwise linear regression has high RMSE value (868.48) and it gives less accuracy. Optimizable Neural network has low RMSE value (104.52) and it gives high accuracy level. The amount of error in statistical models is gauged by the mean squared error, or MSE. Between the observed and predicted values, it evaluates the average squared difference. The MSE is equal to zero when a model is error-free. The mean of the absolute errors, or MAE, is just what its name implies. The difference between the predicted value and the actual value, expressed as an absolute number, is the absolute error. The MAE reveals the average size of the forecast error that we can anticipate. The MAE is calculated by adding up the absolute differences between each observation's calculated and actual values across the entire array, and then dividing the result by the array's total number of observations. High MSE and MAE values give low accuracy. Low MSE and MAE values give high accuracy. Stepwise linear regression has high MSE (7.5425e+05) and MAE values (295.44). Optimizable Neural network has low MSE value (10925) and MAE value (64.509).Optimizable Neural network gives high accuracy level (89%) compared to other algorithms.



(a) Stepwise linear regression



(b) Coarse Gaussian SVM



(c) **Exponential GPR**

(d) Ensemble boosted tree

(e) Optimizable neural network

Fig 3 shows Validation predicted Vs actual plot of Hybrid algorithms

The Y-axis of the scatter plot shows the predicted values, and the X-axis shows the actual values. An effect of the model is displayed and contrasted with the null model in a predicted against actual plot. The points should have narrow confidence bands and be relatively close to the fitted line for a good fit.

4. CONCLUSION

In this paper the proposed hybrid algorithmssuch asstepwise linear regression, Coarse Gaussian SVM, Exponential GPR, Ensemble Boosted Trees and Optimizable Neural Network predicts air traffic from air traffic dataset. Compare to other algorithms optimizable neural network algorithm produces enhanced output for air traffic dataset.Optimizable Neural Network give satisfactory performance, response, regression, and clear plots of air traffic dataset compared to other methods. Optimizable Neural Network gives high accuracy about 89%, less time and speed for air traffic dataset. This prediction used to control the air traffic and avoid the flight accidents in air space.

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