Comparative analysis of AGBFM and IWOFM with Forecasting Models LSSVM-PSO, LSSVM-ACO and LSSVM-WOA

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Abstract: Performance analysis is utmost important with the purpose of propelling the development of both software and hardware systems. By conducting a comprehensive study, it is possible to identify bottlenecks in the system and architecture, obtain essential information for selecting frameworks and platforms, and ultimately result in improvements in performance. Performance analysis is major step towards performance optimizations. Various methods of optimization exist in order to achieve better performance of various machine learning algorithms. In this paper, performance of proposed forecasting models is compared with various existing models. The performance of proposed models Improved Whale Optimization Based Forecasting Model (IWOFM) and Adaptive Gradient Based Forecasting Model (AGBFM) is compared after the final iteration of the forecasting models with LSSVM-PSO, LSSVM-ACO and LSSVM-WOA using the similar dataset scenarios.

Introduction

Predicting network traffic has been a crucial issue in the telecom sector in recent years. The rapid rise in data services and mobile device consumption has made monitoring and optimizing network capacity extremely difficult (Teodorescu et al., 2023). Network operators may effectively manage resources, avoid congestion, and improve end-user service quality by using accurate prediction models. In the context of Long-Term Evolution (LTE), which supports contemporary mobile data communications, traffic forecasting has emerged as a crucial component of telecommunication network management and optimization (Panjavarnam et al., 2024). For efficient resource allocation and to guarantee customer quality of service, it is crucial to comprehend traffic patterns and features, such as seasonality, trends, and the ongoing increase in mobile cellular traffic. Traffic forecasting is useful because it may give operators insight into future network demand, enabling them to prepare for and adjust to changes in traffic patterns. Operators may make well-informed judgments about network development, capacity improvements, and resource allocation by examining historical data to find trends and seasonal fluctuations (Ferreira et al., 2023b). This proactive approach mitigates network congestion, minimizes service disruptions, and enhances the overall user experience.

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The proposed forecasting models (AGBFM and IWOFM) are compared with three other models namely LSSVM-ACO, LSSVM-PSO and LSSVM-WOA (Sucarrat, 2021). Despite the fact that meta-heuristic algorithms are highly effective in many application areas, it has been noted that LSSVM-ACO, LSSVM-PSO, and LSSVM-WOA perform worse than the suggested ones when it comes to traffic burst forecasting. This is due to thefact that the first proposed model, The suggested prediction model may be immediately integrated with the adaptive gradient-based optimizer (AGBO) through parameter optimization (gamma and sigma)(Chakrabarti & Chopra, 2023). The second proposed model, IWOA enhances the explorationability by using inertia weight factor whereas ACO and PSO cannot do optimizationand proper exploration using LSSVM(Suykens et al., 2002). Moreover, the search criteria of ACO and PSO include exploitation instead of inherent gradient-based optimization in AGBFM. Also, the usage of input data for tuning of parameters makes the proposed algorithms (AGBFM and IWOFM) adaptive and efficient. The extra searches make the ACO and PSO loosely coupled optimizers (Manakkadu& Dutta, 2024). In case of PSO the convergence did happen faster, butit did not achieve good fitting cost. Compared to ACO, the PSO achieved lower average fitting cost i.e. lower efficiencybut not better than AGBFM and IWOFM (Eberhart & Shi, 2002).The evaluation parameters, namely, MSE, accuracy, TPR, FPR, precision andF1-score are also calculated for all the existing and proposed forecasting models.

Research Methodology

The procedures used in this work's approach are depicted in Figure 1. Using historical data and an organized methodology, traffic forecasting makes predictions about future traffic trends. Gathering pertinent historical traffic data is the initial phase, after which it is pre-processed to guarantee its accuracy and consistency. After that, a model is chosen based on the data's properties. For example, the AGBFM model could be the best choice if the data shows significant seasonal trends (Hasan et al., 2024b). On the other hand, IWOFM could be more appropriate if the data has a complicated structure with several variables. After the model has been chosen, the historical data is used to train it, and its parameters are changed to best suit the data. Metrics like Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R2) are then used to assess the model, which provide insights into the model's performance. These indicators aid in determining which model is best suited for the job. The best model is chosen to predict future traffic patterns after examination. To guarantee quality and consistency, the predicted values are then post-processed. In order to make comprehension and decision-making easier, the results are finally represented. The most precise and trustworthy traffic predictions are produced thanks to this methodical process, which supports well-informed judgments about infrastructure design and traffic management.

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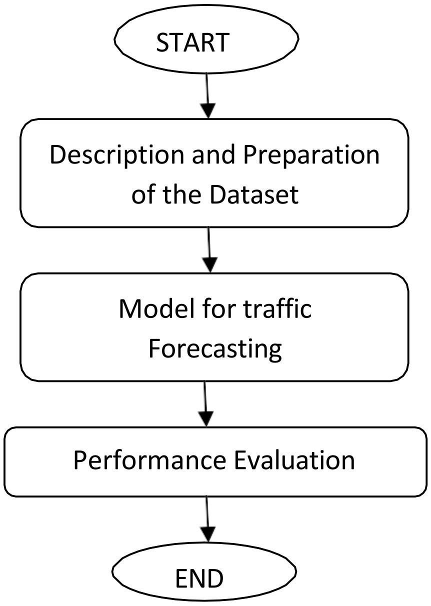


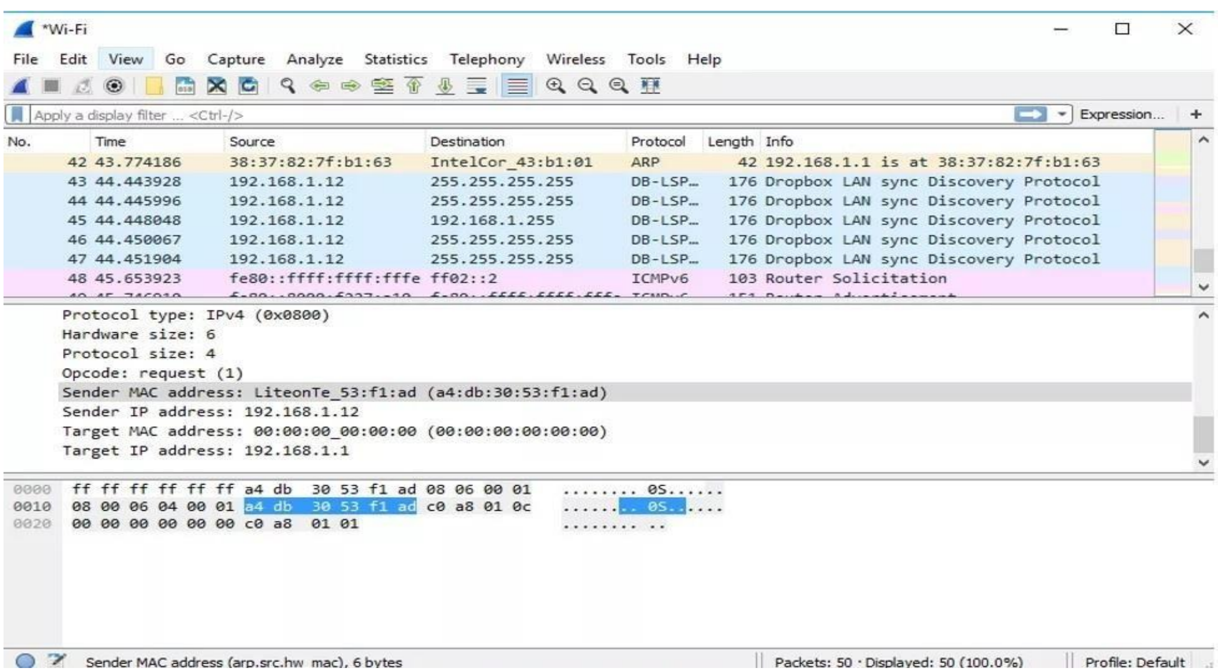
Figure 1. An illustration of the research approach flow

3.1. Dataset Description and Preparation

The data which is used for network traffic forecasting is taken using two different scenarios: Scenario I: Network traffic is flooded into several virtual computers to create raw data. Several commands might be executed at the host computer's command prompt to create network traffic. To overload the network with traffic, the "ping command" and "apache server" 50 instructions are repeatedly executed in this case. The host computer uses Wire shark to record these data bursts. Live network data is concurrently captured by the Wire shark capture engine from many network interfaces. The subset of captured traffic is shown in figure 2.

Figure 2. The Wireshark engine is operating to capture network traffic

When capturing of data gets completed for a certain time interval, it is saved in .csv form. In the present study, firstly, normal data is captured without any traffic burst and plotted in a graph and then VMs (virtual machines) are flooded with data packets by running commands on prompt very frequently and these packets are captured. The normal and exponential bursts seen in



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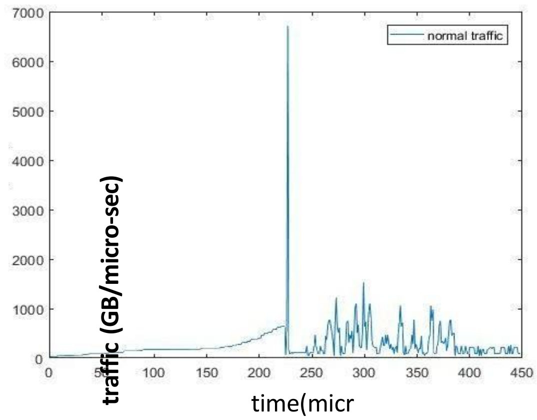
captured traffic is shown in figure 3 and 4 respectively.



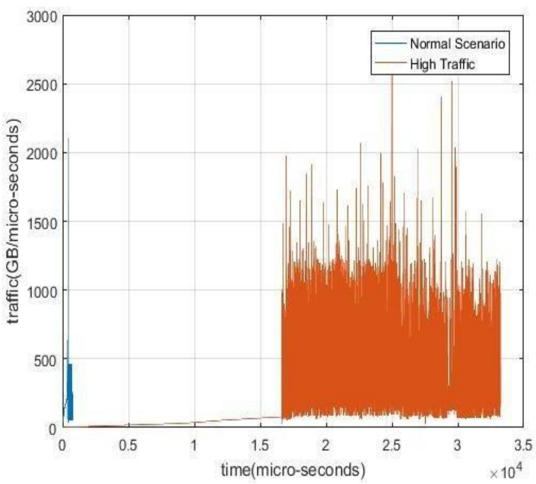


Figure3.Normal network traffic bursts data captured through Wireshark

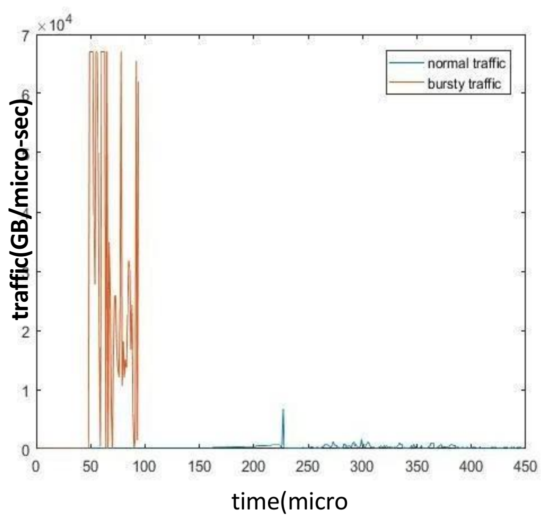


Figure 4. Exponential (bursty) network traffic laid over normal traffic data captured through Wire shark

Scenario II: In this case, the data used to evaluate the present study is taken from CRAWDAD (Community Resource for Archiving Wireless Data) iitkdg/app traffic datasets of a Smartphone app collected using tcpdump. The computer program Tcpdump is a command-line interface-based data-network packet analyzer. Through a network that the system is linked to, it enables the user to view TCP/IP and other packets that are transmitted and received. The desired traffic for evaluation came from Google Hangout of smartphone app. An application called google hangout [12] traffic (GB/micro-sec) time(micro-seconds) traffic (GB/micro-sec) time(micro-seconds) 52 facilitates its users to do chats, carry out VoIP calls and video calls. Google hangout is not a completely peer-to-peer service platform, although it has features of a peer-topeer application as it permits two users to interconnect in real-time using a session server which is selected dynamically. In the form of .pcap files, data was collected with only the Google Hangouts app running in the foreground and only required system functions running in the background. A portion of data from the CRAWDAD community's Google Hangouts smartphone app is shown in table 3.1.

Figure 5. Exponential (burst) network traffic overlaid over normal traffic data

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3.2. Models for Traffic Forecasting

In 5G base stations, traffic forecasting is essential for effective resource allocation, network management, and quality of service assurance. Traditional statistical models like ARIMA are among the models that have been put up and evaluated for this purpose (Rizkya et al., 2019), gradient-based machine learning models, such as AGBFM (Amara-Ouali et al., 2022), and techniques like IWOFM. This section provides a theoretical framework for traffic forecasting with these models, highlighting their advantages and potential uses (Ruan et al., 2016).

3.3. Traffic Forecasting Performance Evaluation Metrics

The performance analysis in this study takes into account a number of parameters that have been proposed in the literature. Selecting the right parameter is crucial for comparing the suggested model to the ones that already exist. Forecasting accuracy may be expressed using a variety of criteria. A brief overview of the parameters explained by authors in their papers is listed below:

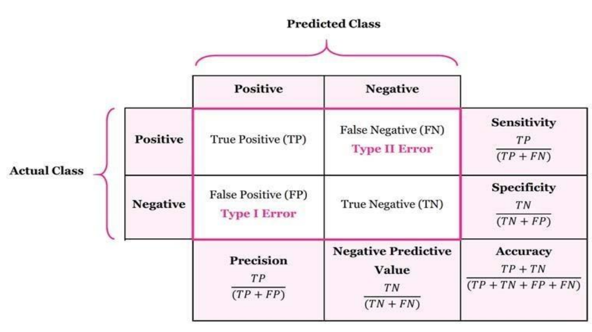
i. **Confidence Intervals**: It is considered as the most widely used parameter for network traffic forecasting. A confidence interval quantifies the uncertainty on an estimated traffic, such as the mean or standard deviation (Salas et al., 2003). Confidence intervals are most commonly used when forecasting with a regression model, where a quantity is being predicted. Confidence intervals tell how well the model has determined a parameter of interest, such as a mean or regression coefficient (Bartkiewicz, 2000).

ii. **Safe Zone**: Network administrators can successfully employ the safe zone—identified by the forecasting model—as an alarm system. It may be described as the area of network traffic that is within typical bounds. In the safe zone, there are no traffic spikes that might cause network-wide congestion or other associated issues. In order to take the proper steps to address this issue, it is utilized to pinpoint the precise moment the network peaked.

iii. **Mean Square Error (MSE)**: In forecasting, MSE is a frequently used performance metric. The mean square error (MSE) is one of the main metrics used to assess predicting effectiveness (Thompson, 1990). The average of the sum of squares of forecast errors is used to compute the MSE (Ahmar, 2020).

iv. **Root Mean Square Error (RMSE):** It is the predicting mistakes' standard deviation. The distance between the data points and the regression line is measured by forecasting errors. It indicates the degree of data concentration around the line of best fit. The square root of MSE is the mathematical definition of RMSE (Kumar et al., 2021b).

v. **Confusion Matrix:** The forecasting model's prediction accuracy is expressed using this statistic. A confusion matrix, where N is the number of target classes,



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is a □ × □ matrix used to assess a forecasting model's performance (Patro & Patra, 2014). The forecasting model's anticipated values and the actual target values are compared in the matrix. This provides a comprehensive picture of the model's performance and the kind of mistakes it is making. The confusion matrix, which includes the number of true positives, true negatives, false positives, and false negatives, is displayed in Figure 6. The following equations can be used to assess a forecasting model's performance in terms of sensitivity or true positive rate, specificity, accuracy, and precision

Figure 6. Confusion Matrix.

True Positive (TP) indicates that both the model's predicted and actual values were positive.

True Negative (TN) indicates that the model anticipated a negative value, while the actual result was negative.

False Positive (FP) occurs when the model predicted a positive result but the actual value was negative.

False Negative (FN) occurs when the model predicted a negative result but the actual value was positive.

vi. **True Positive Rate (TPR) or Sensitivity or Recall**: This is an additional metric used to assess a forecasting model's performance. It is calculated by dividing the total number of FP by the total number of TP. The likelihood that a real positive will test positive is known as TPR.

vii. **False Positive Rate**: It is calculated by dividing the total number of incorrect positive forecasts by the total number of negative forecasts.

viii. **Accuracy**: It is the main metric used to compare the performance of various models. Its definition is the proportion of cases that were accurately anticipated.

ix. **Precision**: The percentage of true positives reported by the suggested model relative to all positives is known as precision.

x. **F1-Score:**The F1 Score is the weighted average of Precision and Recall. Therefore, both false positives and false negatives are taken into account in this score. F1 is more helpful, particularly in situations when the distribution of classes is uneven. Accuracy performs best when the costs of false positives and false negatives are equal.

xi. **Execution Time:**CPU cycles are used to compute the execution time. It is equivalent to the number of CPU cycles required to run the model with a size n dataset.

xii. **Computational Complexity:**It has a direct correlation with the quantity of resources needed to execute an algorithm.

4. Result and Discussion

4.1 Total Traffic Forecast

Several metrics are used to compare the predicting outcomes produced by the suggested and current models during the testing period with the actual total traffic data. The y-axis shows the amount of traffic, while the x-axis shows the time in hours. To see how well each model performs, the prediction is placed next to the real traffic data. The graph gives a clear visual depiction of each model's accuracy by highlighting differences between expected and actual values. Algorithms for training and optimization make up forecasting models.ACO (Ant Colony Optimization), PSO (Particle Swarm Optimization), WOA

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(Whale Optimization Algorithm), IWOA (Improved Whale Optimization), and AGO (Adaptive Gradient Optimization) are utilized as optimization algorithms, while LSSVM (Least Square Support Vector Machine) is employed for training. Figure 7 displays the convergence curve for both the suggested and current models.

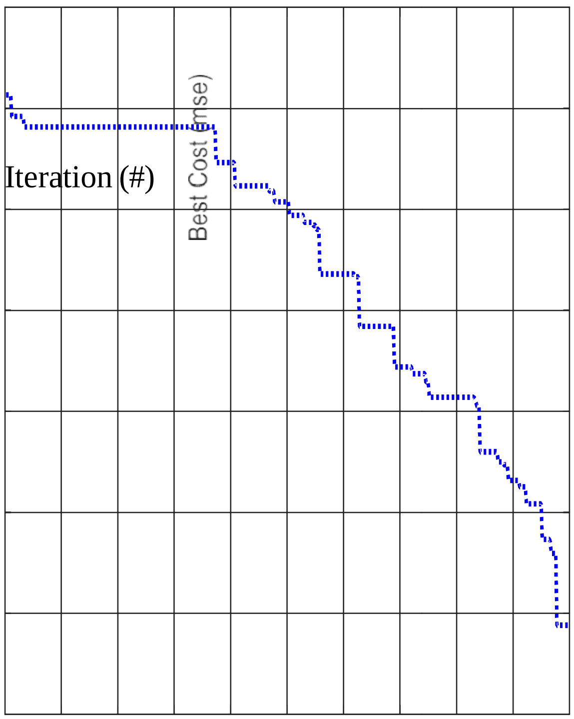

Figure7. LSSVM-ACO Convergence Curve

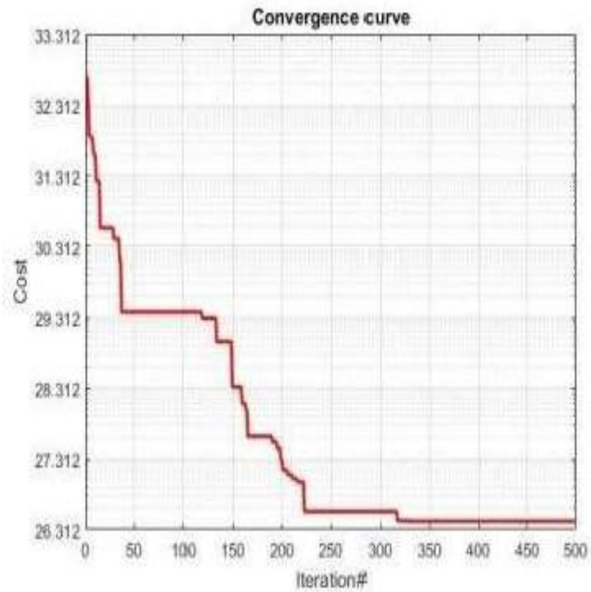

Figure 8. LSSVM-PSO Convergence Curve

Figures 7 and 8 display the optimal optimization cost that may be achieved with the LSSVM classifier utilizing ACO and PSO. Even after 50 iterations, ACO Pareto optimization was not obtained. As a result, LSSVM-ACO has higher optimization efficiency. This is a result of ACO's slower search parameters. Figures 9, 10, 11, 12, and 13 display the confusion matrix for LSSVM-ACO, LSSVM-PSO, LSSVM-WOA, AGBFM, and IWOFM for scenarios 1 and 2, respectively.

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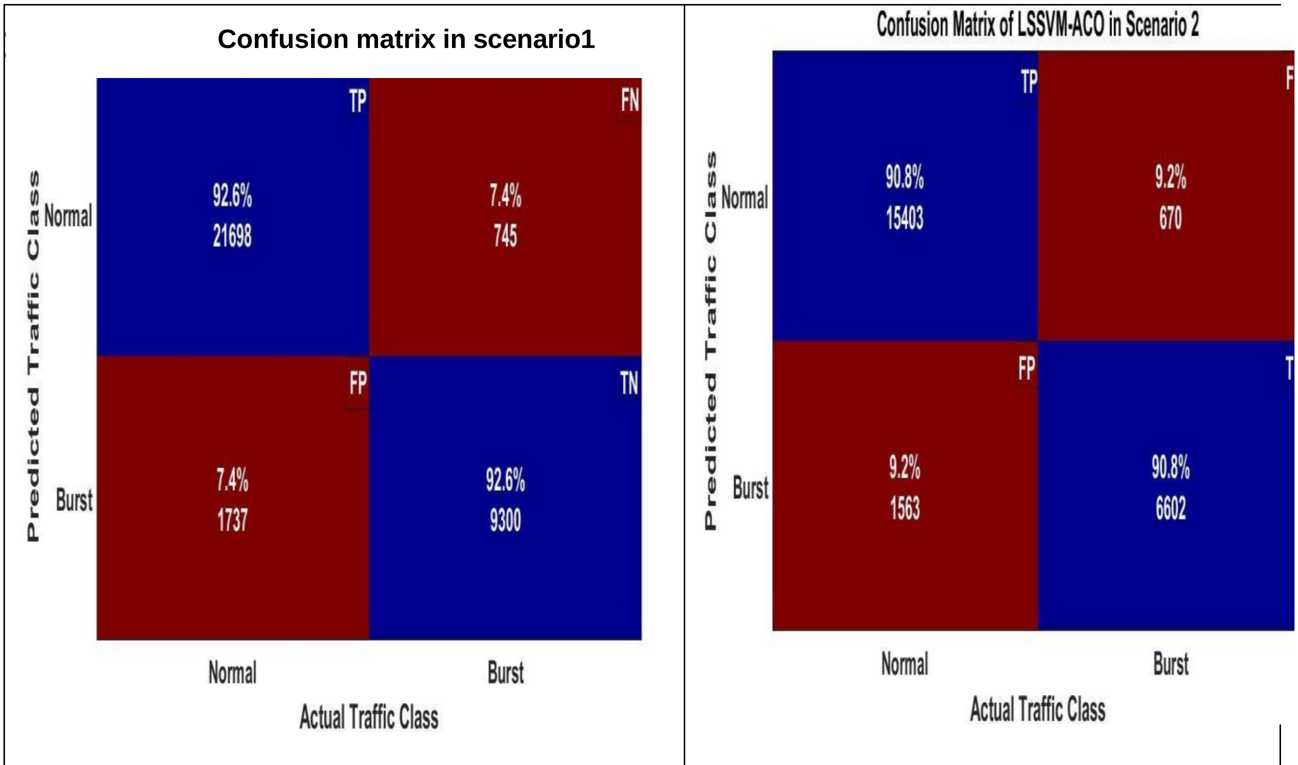

Figure 9: Confusion Matrix of LSSVM-ACO

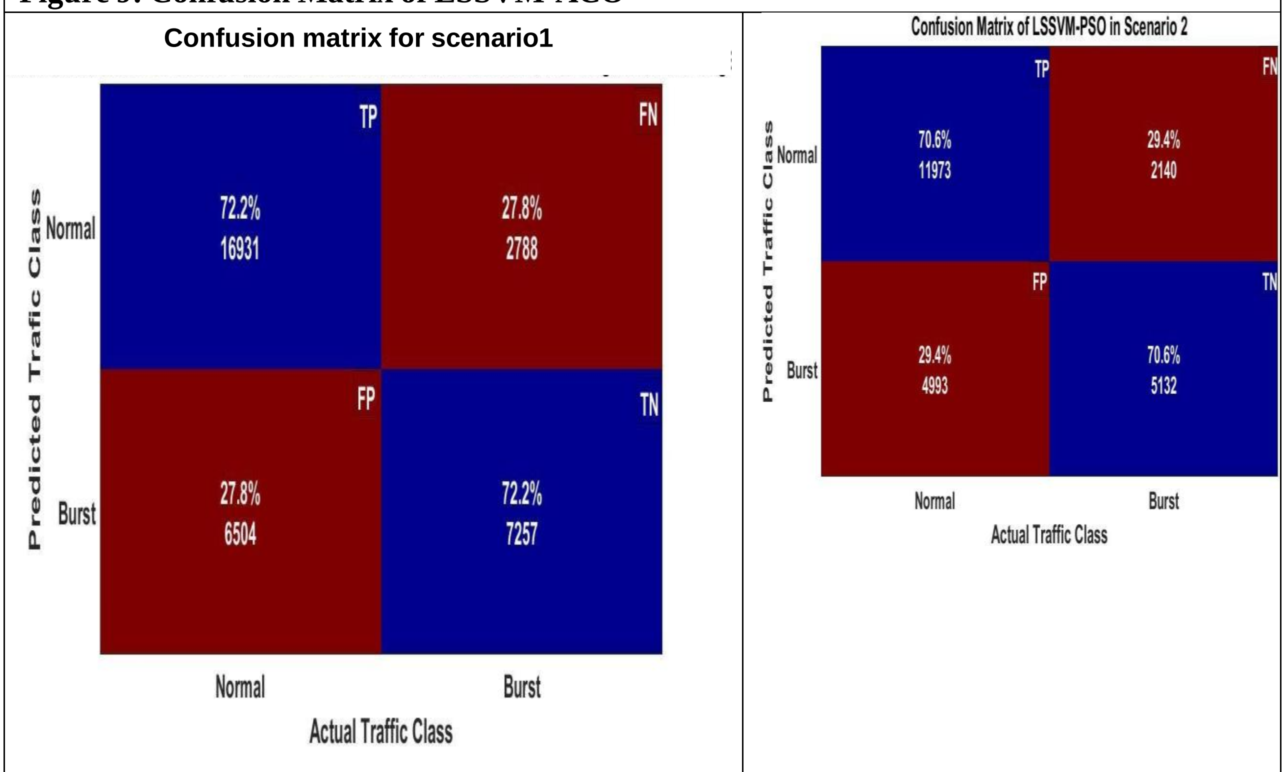

Figure 10: Confusion Matrix of LSSVM-PSO

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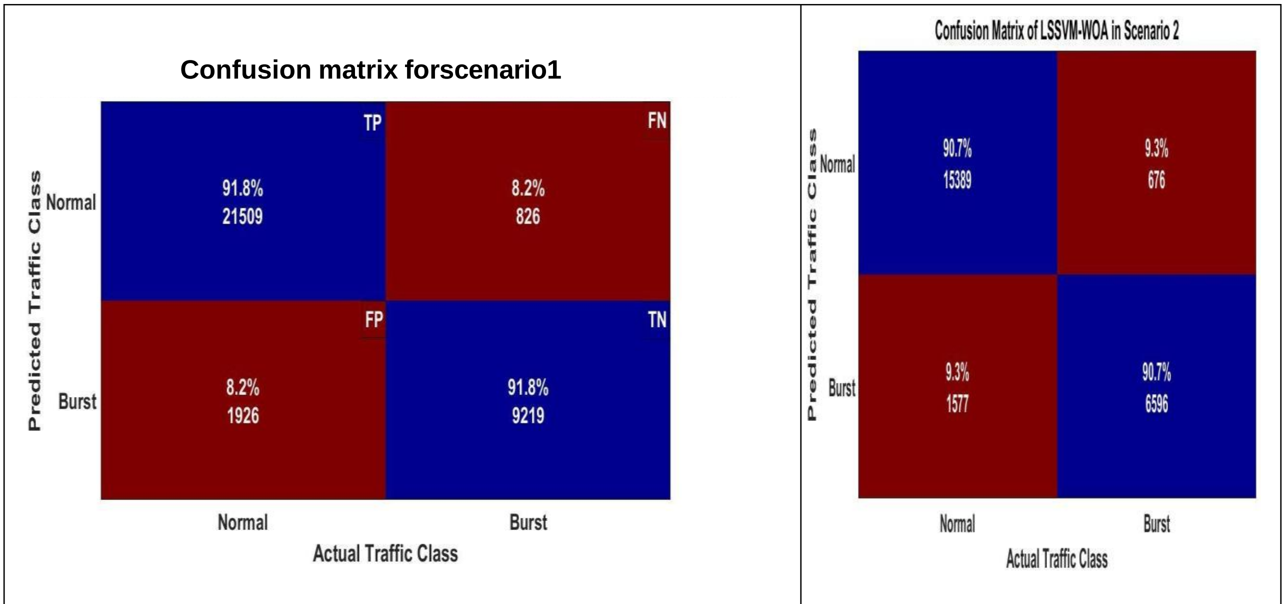
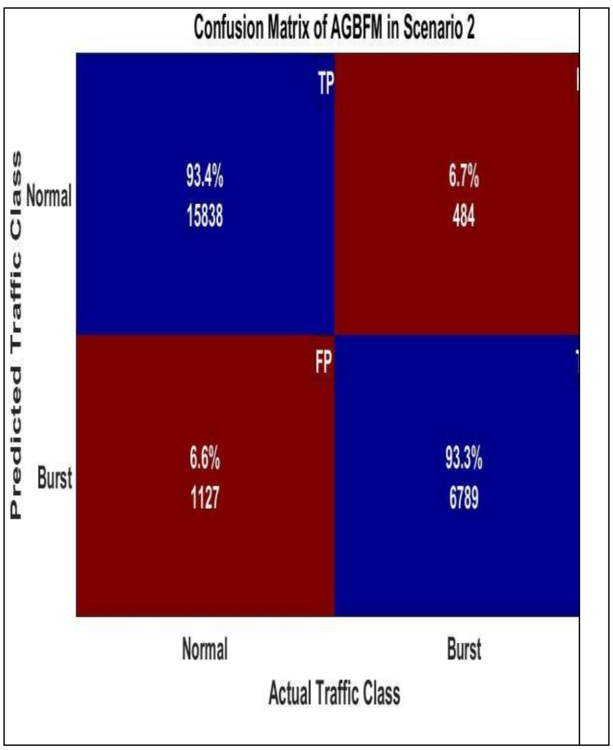


Figure 11: Confusion Matrix of LSSVM-WOA



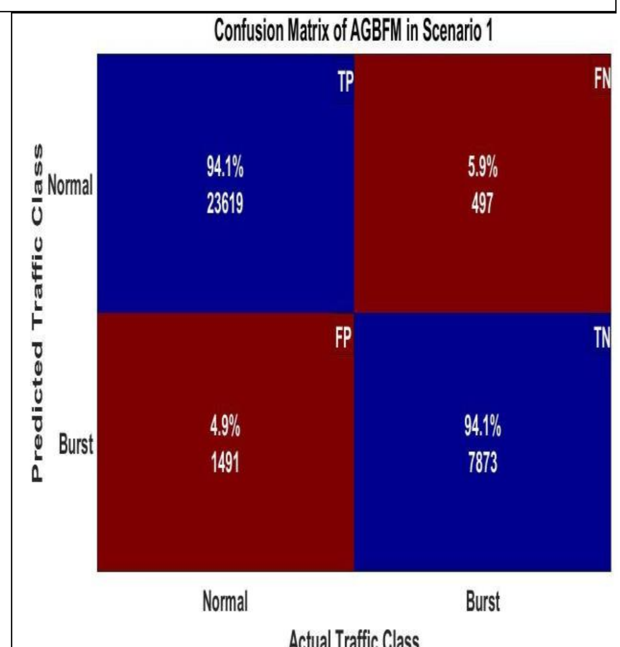


Figure 12: Confusion Matrix of AGBFM

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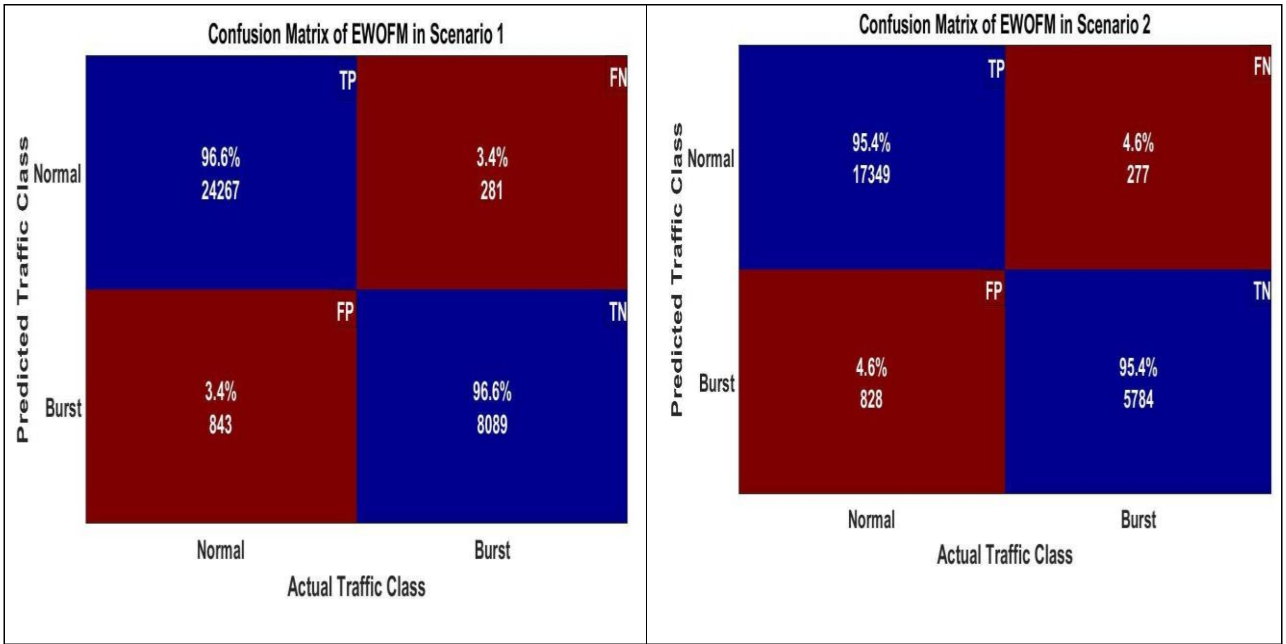

Figure 13: Confusion Matrix of IWOFM

4.2 Performance Analysis

The proposed forecasting models (AGBFM and IWOFM) are compared with three other models namely LSSVM-ACO, LSSVM-PSO and LSSVM-WOA. Despite the fact that meta-heuristic algorithms are highly effective in many application areas, it has been noted that LSSVM-ACO, LSSVM-PSO, and LSSVM-WOA perform worse than the suggested ones when it comes to traffic burst forecasting.This is because parameter optimization (gamma and sigma) may be used to directly integrate the first suggested model, the adaptive gradient based optimizer (AGBO), with the suggested prediction model. The second proposed model, EWOA enhances the exploration ability by using inertia weight factor whereas ACO and PSO cannot do optimization and proper exploration using LSSVM. Moreover, the search criteriaof ACO and PSO include exploitation instead of inherent gradient-based optimization in AGBFM. Also, the usage of input data for tuning of parameters makes the proposed algorithms (AGBFM and IWOFM) adaptive and efficient.

The ACO and PSO optimizers are loosely connected due to the additional searches. Although convergence occurred more quickly in the PSO instance, an acceptable fitting cost was not attained. The PSO obtained lower average fitting cost (i.e., lesser efficiency) than ACO, but it was not superior than AGBFM and IWOFM. For each of the current and suggested forecasting models, the evaluation parameters—MSE, accuracy, TPR, FPR, precision, and F1-score—are also computed.

4.2.1 Mean Square Error

Both the suggested and current algorithms' MSEs are assessed. Figure 14 displays the outcomes for scenarios 1 and 2. MSE is a method for assessing how well forecasts or estimates match actual values. This is used as a model assessment metric for regression

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models, where a lower value denotes a better fit. Because the improved whale optimization model is used to optimize the training model's hyperparameters, the IWOFM has the lowest MSE. Compared to other models, the IWOA optimizer may be closely integrated with the LSSVM training method, which makes this model suitable for forecasting.

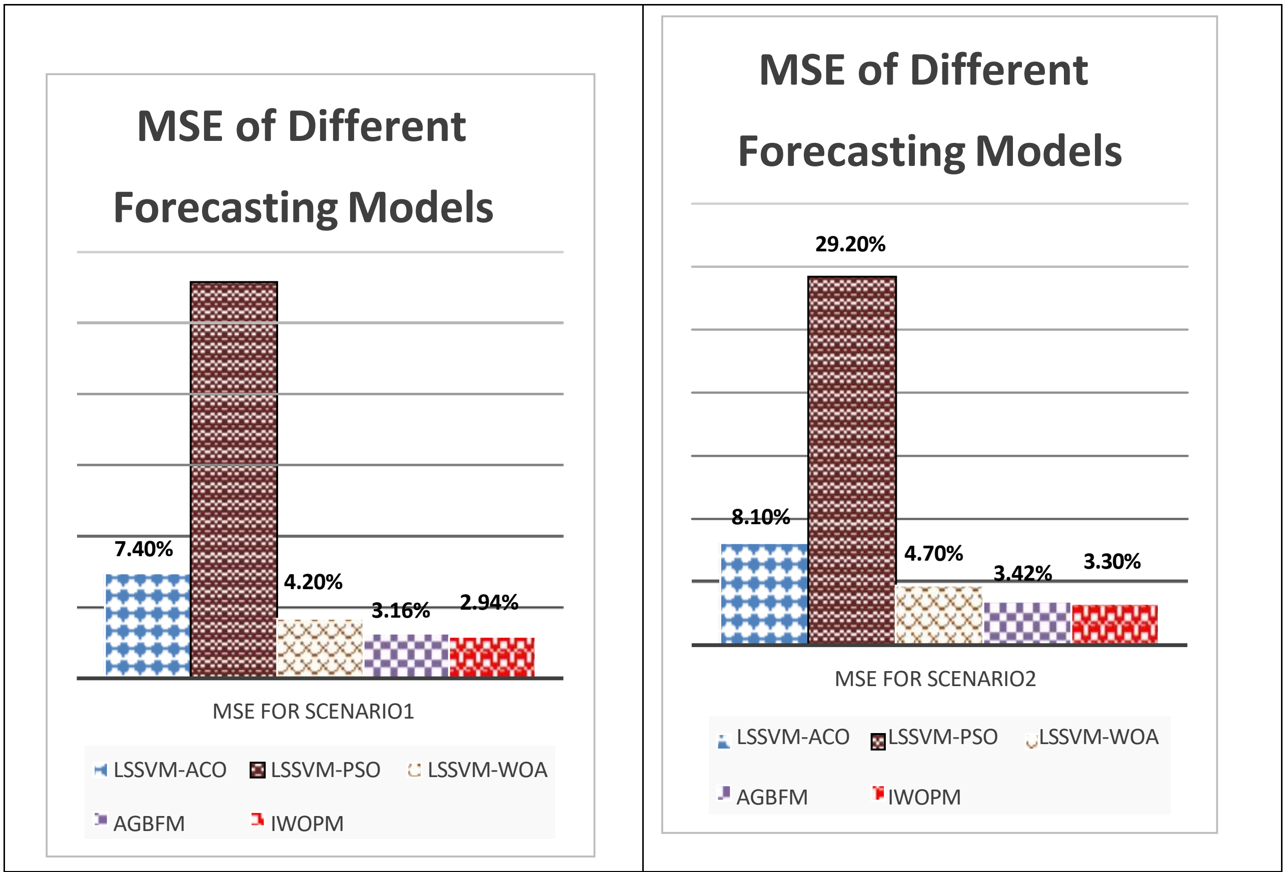

Figure14. MSE of forecasting models in scenario 1 and scenario 2

4.2.2. Accuracy

The accuracy is tested for the proposed and current algorithms. Figure 15 displays the outcomes for both scenarios 1 and 2. The three-dimensional search criteria in this model, which search agents utilize, improves their ability to explore the search space and, as a consequence, raises the overall accuracy of forecasting findings, which is why the IWOFM exhibits maximum accuracy.

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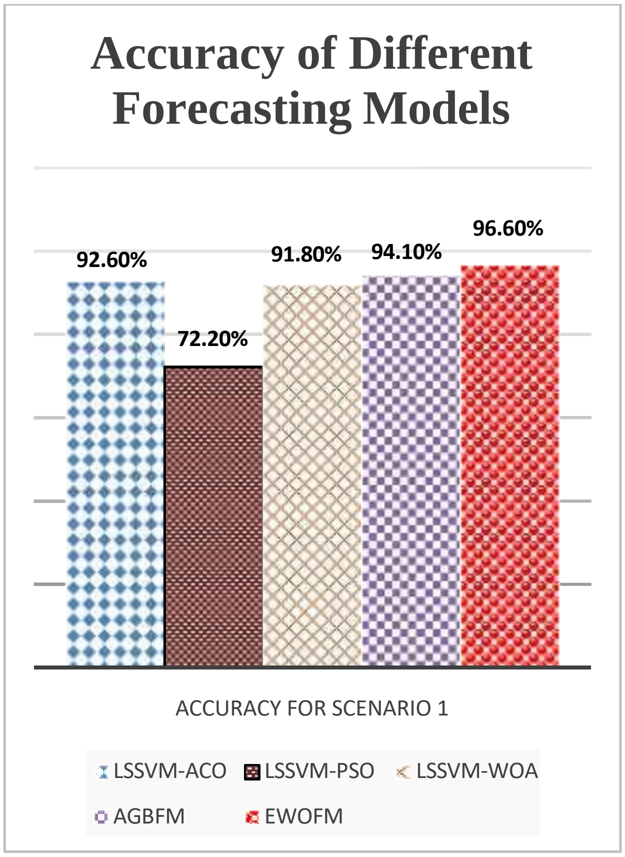

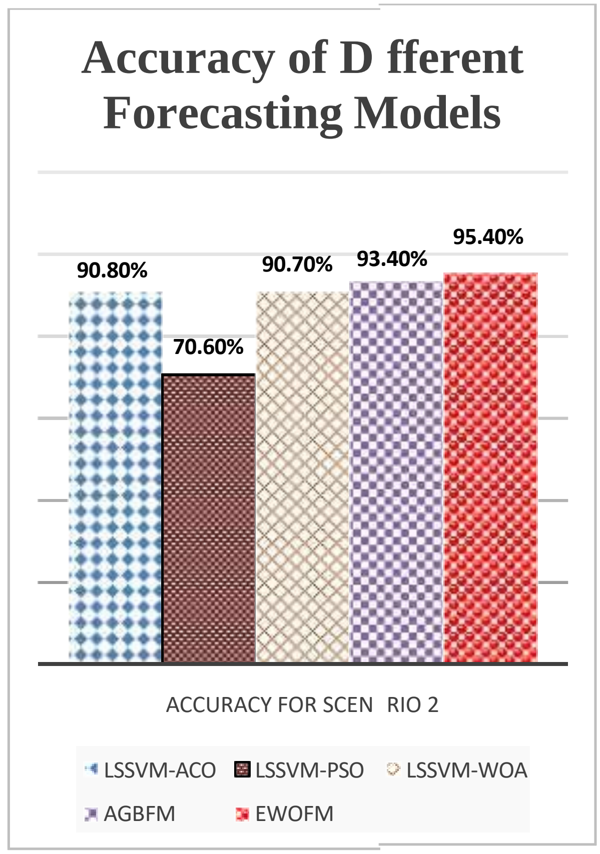

Figure15. Accuracy of forecasting models in scenario 1 and scenario 2

4.2.3. True Positive Rate (TPR) or Sensitivity or Recall and False Positive Rate (FPR)

Figure 16 displays the genuine positive rate for both the suggested and current methods. Figure 17 displays the false positive rate for both the suggested and current methods. Because there are more genuine alarms as the number of iterations rises, the TPR reaches its maximum in the case of IWOFM. Confirmation is shown by the increased TPR. In the case of IWOFM, the FPR is lowest. A lower FPR rating is preferable as it indicates inaccurate predictions.

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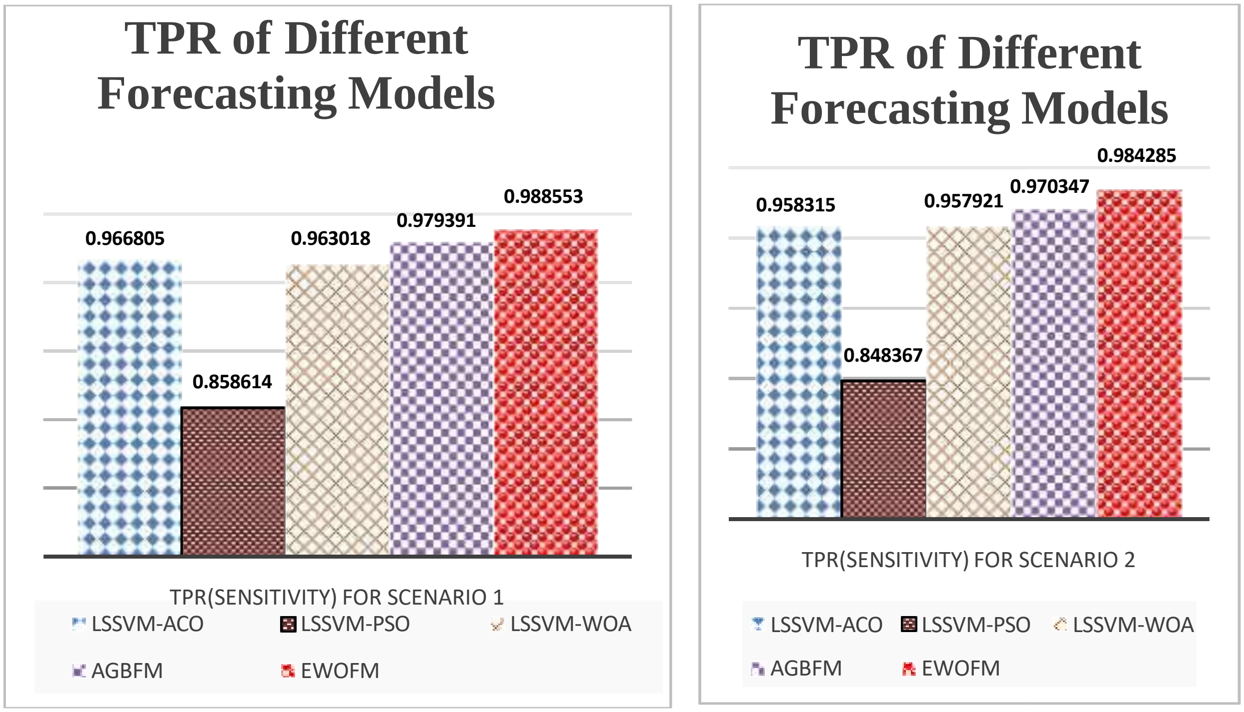

Figure 16. TPR of forecasting models in scenario 1 and scenario 2

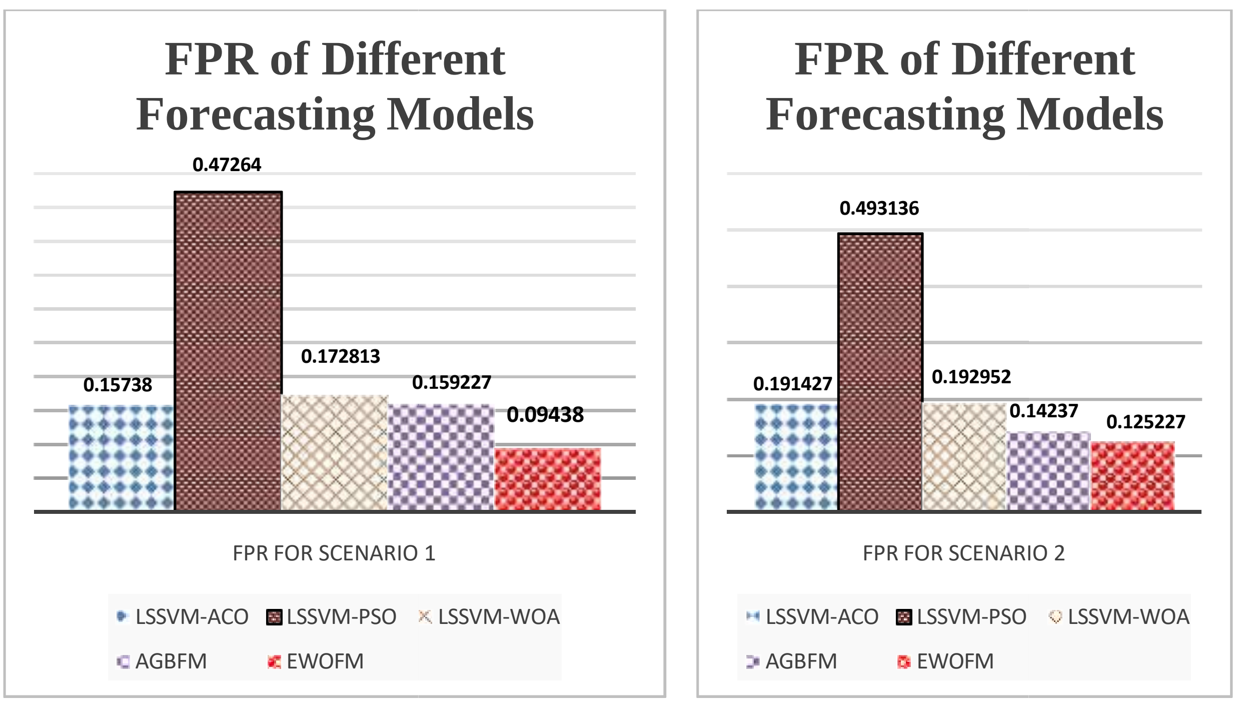

Figure 17. FPR of forecasting models in scenario 1 and scenario 2

4.2.4. F1-Score

Since the IWOFM model has the best TPR (or recall) and accuracy, its F1-score is marginally higher than those of the other models. The total value is superior than the other models since the F1-score provides the harmonic mean of these two. Figure 18 displays the F1-Score for the suggested and current methods.

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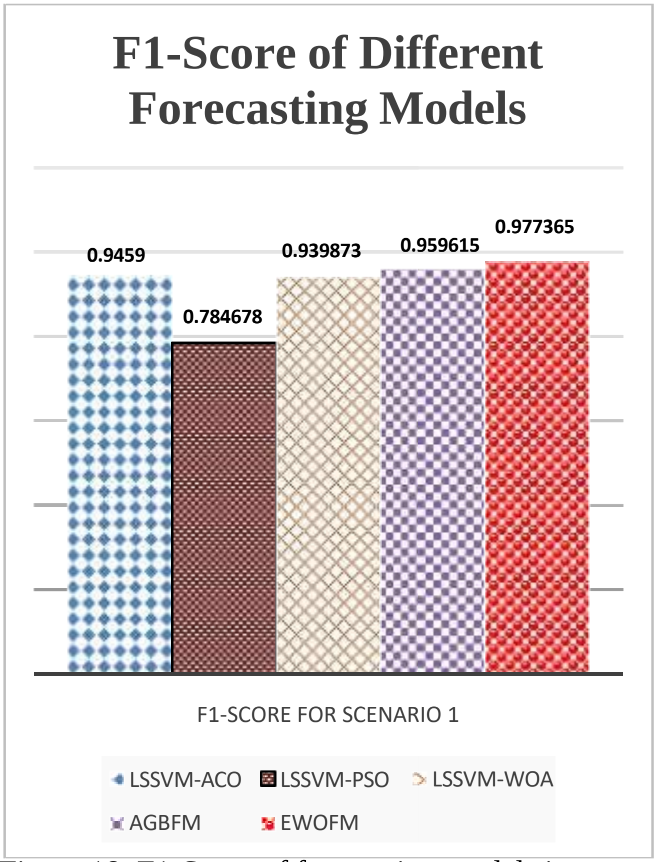

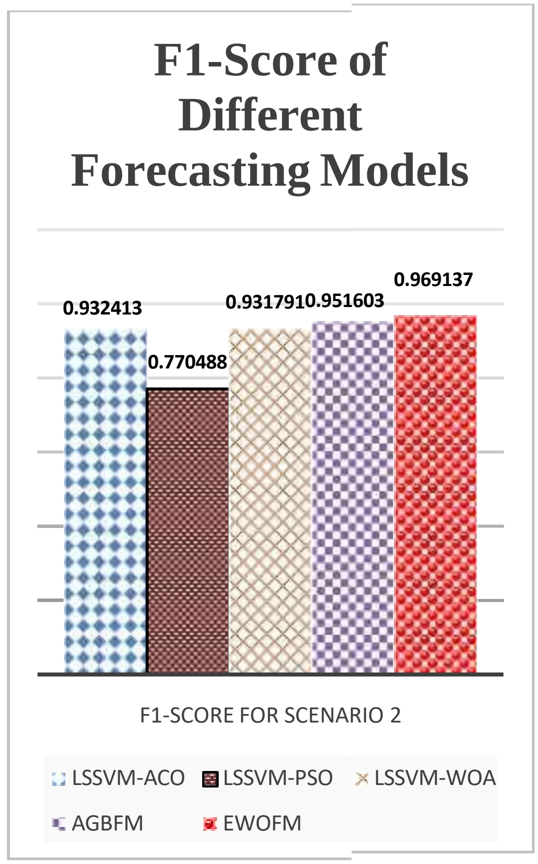

Figure 18. F1-Score of forecasting models in scenario 1 and scenario 2

The performance evaluation of IWOFM, AGBFM, LSSVM-PSO, LSSVM-ACO and LSSVM-WOA for both the scenarios of dataset is summarized in table 1 and table 2.

Table 1. Comparative an lysis of existing and proposed forecasting models for scenario 1

Parameters / Forecasting Models	LSSVM-ACO	LSSVM-PSO	LSSVM-WOA	AGBFM	IWOFM
Mean Square Error	7.4%	27.9%	4.2%	3.16%	2.94%
TP alarms	21698	16931	21509	23619	24267
FP alarms	1737	6504	1926	1491	843
TN alarms	9300	7257	9219	7873	8089
FN alarms	745	2788	826	497	281
Accuracy	92.60%	72.20%	91.80%	94.10%	96.60%
TPR (Sensitivity)	0.966805	0.858614	0.963018	0.979391	0.988553
FPR	0.15738	0.47264	0.172813	0.159227	0.09438
Precision	0.92588	0.722466	0.917815	0.940621	0.966428
F1-Score	0.9459	0.784678	0.939873	0.959615	0.977365
Execution Time*	56	81	49	45	41

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Computational Complexity	□(□ log □) + $\frac{\theta(n^2 \log n)}{\rho^2}$**	□(□^{2} log □)	□(□□□□ □) + □(□^{3})	□(□□□□ □) + □(□^{2})	□(□□□□ □) + □(□^{3})

Table 2. Comparative analysis of existing and proposed forecasting models for scenario 2

Parameters / Forecasting Models	LSSVM-ACO	LSSVM-PSO	LSSVM-WOA	AGBFM	IWOFM
Mean Square Error	8.1%	29.2%	4.7%	3.42%	3.30%
TP alarms	15403	11973	15389	15838	17349
FP alarms	1563	4993	1577	1127	828
TN alarms	6602	5132	6596	6789	5784
FN alarms	670	2140	676	484	277
Accuracy	90.80%	70.60%	90.70%	93.40%	95.40%
TPR (Sensitivity)	0.958315	0.848367	0.957921	0.970347	0.984285
FPR	0.191427	0.493136	0.192952	0.14237	0.125227
Precision	0.907875	0.705706	0.907049	0.933569	0.954448
F1-Score	0.932413	0.770488	0.931791	0.951603	0.969137
Execution Time*	60	85	53	51	46
Computational Complexity	□(□ log □) + $\frac{\theta(n^2 \log n)}{\rho^2}$**	□(□^{2} log □)	□(□□□□ □) + □(□^{3})	□(□□□□ □) + □(□^{2})	□(□□□□ □) + □(□^{3})

5. Conclusion and Future Scope

1. A study of the various machine learning algorithms is performed in order to choose the suitable algorithm for training. LSSVM machine learning algorithm is considered for training using dataset. Various optimization schemes are also studied to optimize the parameters of machine learning algorithm for better performance.
2. The proposed models have been compared on the evaluation parameters using confusion matrix namely MSE, TPR, FPR, accuracy, execution time and computational complexity precision, f1-score.
3. The two proposed models are compared with the existing models to show the effectiveness of the proposed ones using the performances matrices. The proposed forecasting models are compared with three existing models namely LSSVM-ACO, LSSVM-PSO and LSSVM-WOA. While meta-heuristic algorithms are effective in many areas of application, it has been found that both LSSVM-ACO and LSSVM-PSO perform worse than deterministic AGBFM in traffic burst prediction. IWOFM outperforms all models in forecasting because it concentrates on finding the near-optimal solution to the problem, and whale-based optimizers offer a high-level framework.
4. In future, IWOFM and AGBFM models can also be extended further, so as to

apply to different real world problems like image processing, data mining and feature selection.

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