International Journal of Future Generation Communication and Networking
Vol. 14, No. 1, (2021), pp. 795-808

Adaptive Framework for Predicting Cellular Network Traffic Bursts

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Abstract

Predicting the traffic in cellular networks is becoming increasingly important because of the explosively growing demand and limited availability of resources. The need for prediction of traffic patterns gains ground during seasonal burst or in case of special events. A huge increase in demand of network resources is observed occasionally which otherwise are under-utilized in other time frames. Also, it is noticed that the prediction performance of 5G and LTE networks varies from model to model. The linear model is better for predicting traffic for longer time frames, while the exponential fitting performs well only during shorter time frames. To address these issues in 5G networks, a new adaptive gradient based prediction model (AGBPM) has been proposed. The proposed algorithm (AGBPM) is compared with linear least square support vector machine (LS-SVM) hybridized with particle swarm optimization(LS-SVM-PSO) and ant colony optimization (LS-SVM-ACO) for analyzing the traffic dynamics and predictions. In order to smoothly perform prediction analysis of the proposed AGBPM algorithm, the traffic patterns of various virtual machines have been collected during normal and bursty periods using a tool Wireshark. These traffic patterns are then preprocessed using a newly proposed protocol namely, Adaptive Time Window Protocol (ATWP). Simulation has been done to test the predictive performance of the proposed AGBPM, LS-SVM-PSO and LS-SVM-ACO models using metrics TPR (True Positive Rate), FPR (False Positive Rate), confusion matrix and MSE (Mean Square Error). The results shown in the paper indicate the supremacy of AGBPM.

Keywords: *Traffic classification, Machine Learning, Prediction, ACO, PSO*

1. Introduction

The analysis and prediction of cellular network traffic patterns is the need of an hour. It is helpful in utilizing the limited network resources provided by infrastructure and carefully planning for the data transfers involving large amount of data. As the surge in network traffic involves increased radio spectrum consumption and more energy usage, it results in requirement of effective planning for network resources. The network traffic is immensely non-uniform in both space and time, making it difficult to predict. The challenge cellular networks are facing is, how to efficiently handle data oriented mobile communications, i.e. how to provide reasonable data performance to customers in networks when the cell sites experience significant amount of data traffic, resulting in call drops. Addressing this challenge requires a concrete understanding of the behavior of traffic networks and accurate mobile traffic forecast for efficient network planning and operations.

The estimation of the mobile traffic for a large time window with a certain probabilistic tolerance error enables better data routing and transfers in general sense.

ISSN: 2233-7857 IJFGCN

The short term prediction of network traffic guides several immediate traffic bursts in the network. This understanding has helped in proposing a new adaptive time window protocol(ATWP) which is used alongside of proposed adaptive gradient based prediction model (AGBPM).

Major salient features of the presented work can be identified as follows:

(i) An Adaptive Time Window protocol(ATWP) for cellular network traffic patterns based on identification of brusty traffic time frames has been proposed.

(ii) A new low complexity prediction model, namely, adaptive gradient based prediction model (AGBPM) is developed which is a combination of Adaptive Gradient Based (AGB) optimizer and modified LS-SVM.

(iii) Analysis of the proposed AGBPM is done with two other bio-inspired prediction models i.e. LS-SVM-PSO and LS-SVM-ACO using various parameters.

The rest of the paper is organized as follows. In Section 2, an overview of related works in traffic prediction has been presented. Section 3 describes the proposed methodology. Section 4 explains the data collection and preprocessing. Detailed explanation of the proposed ATWP which is needed for generation of bursty traffic is presented in Section 5. Section 6 gives details about proposed AGBPM and also explains the two bio-inspired techniques used for analysis. Various results of the proposed prediction model along with two other bio-inspired models are shown in Section 7. Performance analysis of the proposed model(AGBPM) is done with LS-SVM-PSO and LS-SVM-ACO in Section 8 in terms of mean squared error (MSE), prediction accuracy, confusion matrix(CM), execution time and computational complexity. The conclusion of the work with future aspects is presented in Section 9.

2. Related work

The authors have developed an efficient mechanism for the detection of outbreaks in traffic and subsequent traffic classification by using Support Vector Machine (SVM) as a classifier [1]. This algorithm reduced the false alarms to a certain extent. Also authors in paper [2] constructed an Adaptive Bacterial Foraging Optimization (ABFO) algorithm and redefined its computation rules to solve the MOCP (Multi Objective Computational Problem). ABFO based MOCP algorithm had improved performance and was more efficient than the existing ones.

For voice traffic in traditional circuit-switched networks, the use of the Box-Jenkins model yielded reasonable prediction performance [3,4]. However, it was shown that the internet traffic exhibited both long-range dependence and statistical self-similarity [5, 6]. The origins of self-similarity in the internet traffic was mainly attributed to the heavy-tailed probability distributions [6-8]. Karagianniset.alin [9] reexamined the Poisson assumption and refuted the assumption of the Poisson distribution by applying the Kolmogorov-Smirnov test [10, 11]. Author in paper [12] used Transmission Control Protocol. Author in paper [13] studied usage of application for patterns recognition and communication interval of 255 Smartphone users. Author in paper [14] developed a 3G application for an iPhone. Performance of Transmission Control Protocol(TCP) and various rush hour traffic irregularities in the network were examined in [15].

The major limitations of the existing algorithms were that many of these models were based only on some heuristic rules and did not actually rely on training the model based on past datasets and then predicting the future based on smart choice by modifying the model automatically as per the need of an hour. Also, these models had not considered any peaks in the traffic bursts. Therefore, a more traffic aware adaptive algorithm is proposed which tries to accommodate the traffic peaks and manage resources accordingly.

3. Proposed Methodology

The existing study presents various challenges and problems in identifying traffic patterns during seasonal events in cellular networks. Therefore, a methodology is proposed so as to identify both short and long term traffic fluctuations and to predict appropriately. The detailed methodology is shown in figure 1. The real time data is captured through *Wireshark* [16] using virtual machines scenario. As per norms 70% of the data is used for training and 30% is used for testing of the proposed prediction model.

A new ATWP (Adaptive Time Window protocol) is also proposed to identify classes of traffic, to generate traffic bursts and to get initial value of parameters, thereafter prediction is done by traffic classes using initial value of the tuning parameters. The proposed AGBPM uses adaptive gradient based (AGB) optimization technique for optimizing the tuning parameters along with modified LS-SVM for training the model. AGBPM is applied to data coming from ATWP and their individual obtained predicted value are compared with the testing value. The accuracy is checked using confusion matrix. The sections below are describing the individual components of proposed methodology.

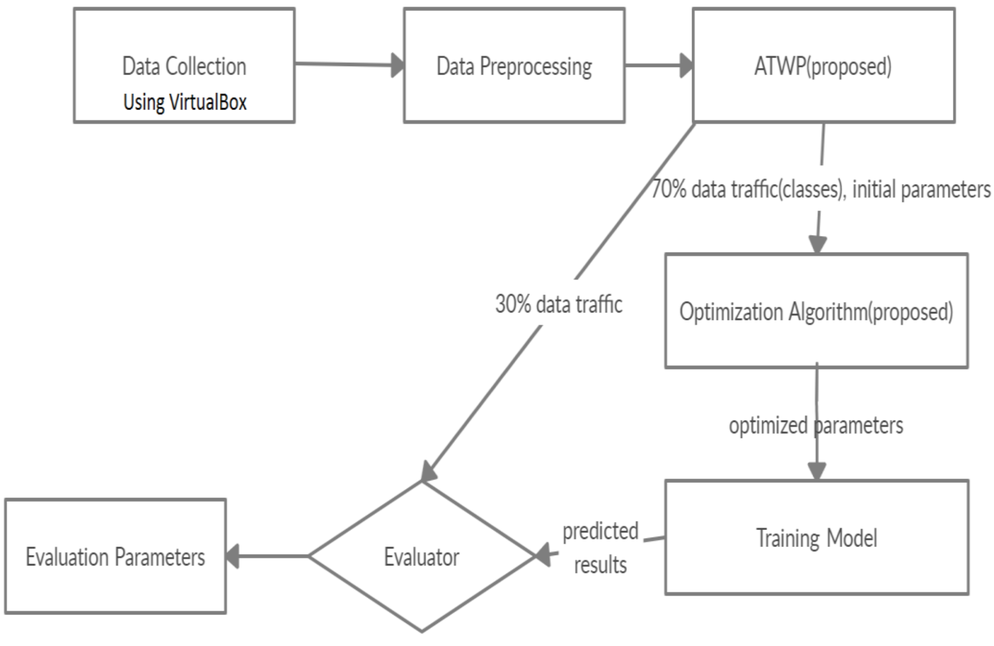


Fig. 1. Flow in proposed methodology

4. Data Collection & Preprocessing

The data which is used for comparison is generated by flooding various virtual machines with network traffic. This network traffic could be generated by running various commands at command prompt of the host machine. Here "ping command" and "apache server" commands are run again and again to flood network with traffic. These bursts of data are captured by the host machine by using *Wireshark*. The Wireshark capture engine captures live network data simultaneously from multiple network interfaces.

5. ATWP (Adaptive Time Window Protocol)

The property of the time series data is that they exhibit predictable and recurring behavior. The seasonal bursts are more evident in the 5G traffic patterns and are often large enough to mask other patterns of the time series data. By identifying these seasonal components from the gathered traffic patterns, a seasonally adjustment of these traffic patterns can disclose the actual current traffic trends. Also, by identifying seasonality, its relationship with other time frames can also be easily measured. Therefore, a novel approach for identification of seasonality in the 5G network traffic has been considered. The Adaptive Time Window Protocol (ATWP) works by identifying basic patterns in the time series dataset and dividing the data into set of classes for prediction by the proposed AGBPM.

ATWP is proposed to generate traffic peaks for a certain time interval. These traffic peaks are identified using a threshold value of data traffic. This threshold value is obtained by $\boldsymbol{\mu}+\boldsymbol{\delta}$**,** where $\boldsymbol{\mu}$ is the mean and $\boldsymbol{\delta}$ is the standard deviation of the traffic data. Thereafter, network nodes are informed of the peaks in the network.

6. Optimized Prediction Model

After dataset normalization and obtaining data traffic patterns, the prediction model is proposed. The prediction model broadly includes training and testing. For training these models 70% of data patterns are utilized and remaining 30% data patterns are used for testing. These models are defined as follows:

6.1. Adaptive Gradient based Prediction Model(AGBPM)

In the proposed model, firstly a new gradient based optimizer for tuning the prediction's parameter is considered. The training process is carried out using modified LS-SVM model which results into a nonlinear regression curve. The proposed AGBPM selects the most suitable regularization and classification width parameters.

The proposed AGBPM model optimizes the regularization parameter and classification width automatically and selects the proper training function for classification, which is a step forward, in comparison to SVM and LS-SVM. Complete flow of AGBPM is as described in the figure 2 below.

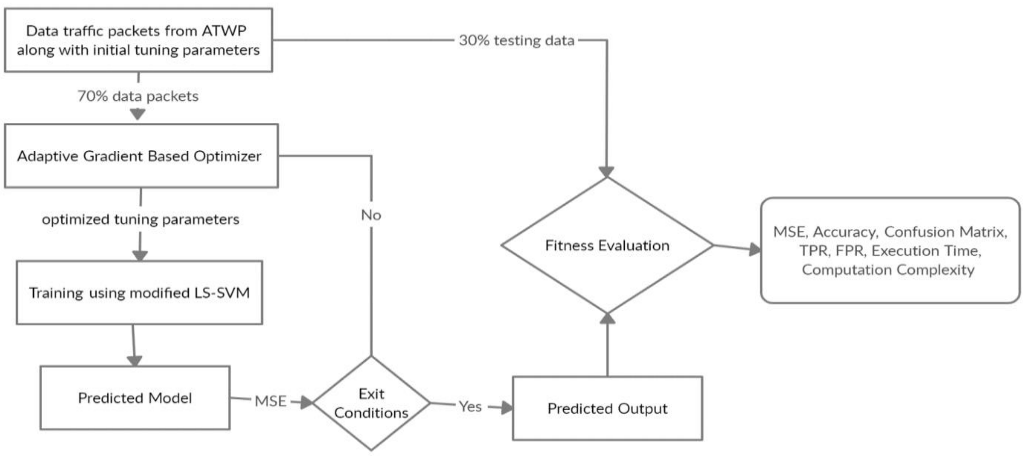


Figure 2. Detailed Flow of proposed AGBPM

6.2. Training of AGBPM

In AGBPM, partitioned time windows are fed to the classifier for efficient analysis. The AGBPM uses optimized tuning parameters and time frames constructed from the datasets to model the solution. A sparse matrix is obtained by refining the sample dataset rather than using the whole data samples. A subset of datasets is taken into consideration for training. AGBPM uses data packets constructed through adaptive time window protocol. Now, the initial value of tuning parameters needs to be fine-tuned. With the prediction process, values of prediction parameters i.e. γ and $\sigma2$ are generated. AGBPM parameter selection is carried out by applying a new gradient based optimization technique as these parameters effects the overall efficiency and accuracy of the prediction models. The two parameters, regularization parameter (γ) manages the penalty given to vector space that drift from the regression curve. Likewise, the classification width parameter ($\sigma2$) effects the smoothness of the regression curve. If classification width parameter ($\sigma2$) value is high, normal and abnormal traffic classes mixes into a single class and cannot be identified. Hence, in order to achieve the appropriate performance parameters, these two needs to be adjusted accordingly using any optimization technique. After getting optimized parameters, model is trained with 70% of datasets and then testing of the proposed model is done to check various parameters like accuracy, true positive rate, false positive rate, confusion matrix and mean square error.

Parameters: ϑ (number of Support Vectors), r Traffic Feature Vectors,
Input: Traffic Dataset with η data points
Output: Class assignment for each data point i in dataset($\mathbb{C} \in$ Classes identified by ATWP)

Partition the dataset into training set X and test set $\widehat{\boldsymbol{X}}$
identify mean μ and standard deviation δ in the dataset
normalize the dataset using min-max normalization
Using Algorithm Time window Protocol ATWP estimate class ranges
Initialize classifier parameters γ and σ
for k 1 to K (K-Fold validations)
    ***e** = train and test AGBPM on the traffic dataset* * modified LS-SVM*\
if change in error e is greater than threshold or stopping conditions of optimization technique have not met
then
        re-initiate AGBPM training parameter $\boldsymbol{\gamma}$ and $\boldsymbol{\sigma^2}$ * AGBO *\
    else

optimal classifier has been received
exit for
end for
test AGBPM classifier on test dataset $\hat{\boldsymbol{X}}$
get estimated traffic ranges $\widehat{\mathcal{Y}} = ATWGO(\hat{\boldsymbol{X}})$, $\hat{\mathcal{Y}}$ *consists of* $\mathbb{C}$ *classes*
evaluate using true class $\mathcal{Y}$ ***and predicted class*** $\hat{\mathcal{Y}}$

6.3. Fitness Evaluation of AGBPM

After training of model gets completed, it is tested with the remaining 30% of datasets. The predicted values which are coming from the proposed model and the actual values are compared to calculate the performance parameters namely, MSE, accuracy, true positive alarms and execution time. The two existing bio-inspired optimization model LS-SVM-ACO [17][18] and LS-SVM-PSO[19] are described for comparison purposes. In these existing algorithms, whole training data is fed again and again to the classifier to produce outcome.

7. Results

The following results can be formulated from the proposed model:

7.1. Simulation Parameters

Real time datasets with 100k instances are utilized to evaluate the performance of selected prediction model. The dataset is divided into instances starting from 10% up to 100% of datasets incremented by 10%. Thus total 10 sets of datasets are utilized. For the performance evaluation, MATLAB 2016 on Intel i5 processor with 8GB of RAM is used. The parameters used in the implementation are listed in table 1:

Table 1. Simulation parameters considered in proposed work

Parameter	Value
TWP Window	$1e^{-4}$
K-Cross validation folds	15
No of iterations	100
Maximum Function evaluation	1000
Tolerance	$1e^{-6}$
Cost Function	MSE
Dataset size	100K instances in 10% to 100% sets
Training Classifiers	LS-SVM,AGBPM
Optimization functions	PSO and ACO for LS-SVM, AGBO(Adaptive Gradient Based Optimizer) for AGBPM
PSO Particles	2-4
Exploration-Exploitation Ratio (ACO, PSO)	0.1/0.9

7.2. Optimization Results

The effectiveness of optimizer in minimizing the mean squared error cost associated with prediction of the traffic is shown in figure 3. As simulation is a gradient decent algorithm, the cost of optimizer used is the MSE of the proposed prediction model. Thus,

ISSN: 2233-7857 IJFGCN

the task of optimizer is to minimize MSE of prediction model in minimum number of iterations. This can be seen by analyzing the curve received, the proposed optimizer(AGBO) is able to achieve Pareto front based optimization in less than 10 iterations.

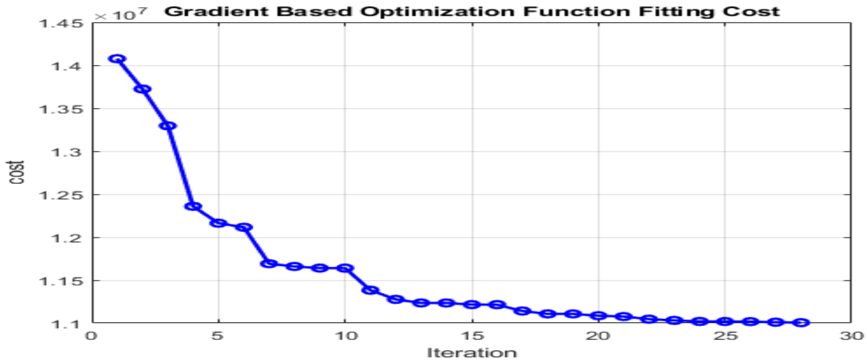


Figure 3. Gradient based optimizer fitting cost over AGBPM

Here, the fitting cost(MSE) or the optimization cost refers to difference in the predicted and actual traffic patterns of gradient based model, it is clear from the figure that the cost (i.e. difference in prediction) gradually gets lower as the algorithm progresses.

$$Fitting\ Cost(MSE) or\ Optimization\ Cost\ =\ Actual\ traffic - Predicted\ traffic \tag{1}$$

The best achievable optimization cost using ACO with LS-SVM classifier is shown in fig. 4. ACO Pareto optimization is not received even until 50 iterations, because of the slower search criteria and the nature of meta-heuristic algorithms in general. This makes AGBPM based implementation better than the LS-SVM-ACO based implementation in terms of optimization efficiency. Best cost is the lowest MSE (difference in prediction) received over a number of iterations during the optimization process.

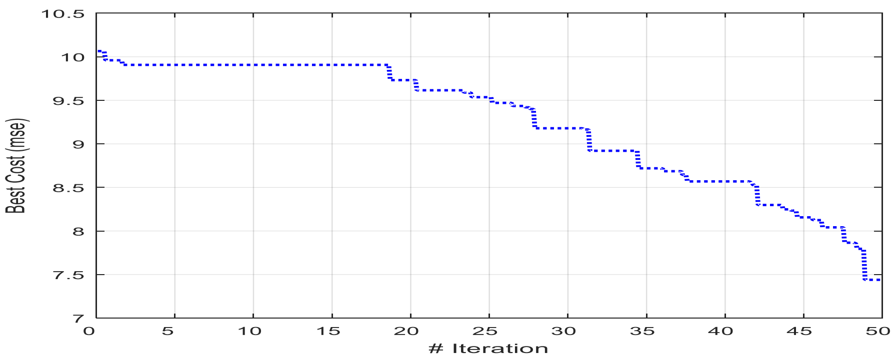
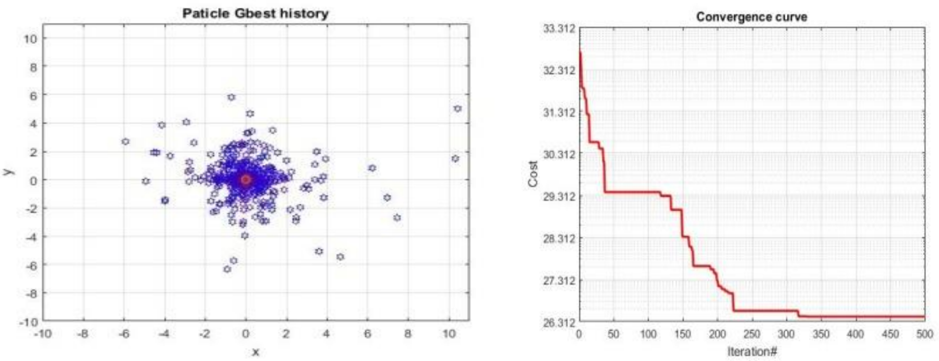


Figure 4. Best optimization cost(MSE) achievable using the ACO optimizer over LS-SVM classifier

Also, In LS-SVM-PSO, the particle gbest history is used to show how far each particle is from the best solution (minimum MSE) at any given iteration. The result shown below in figure 5(a) are of final iteration still many particles lie far away from the global best which is also clear from convergence curve in figure 5(b).



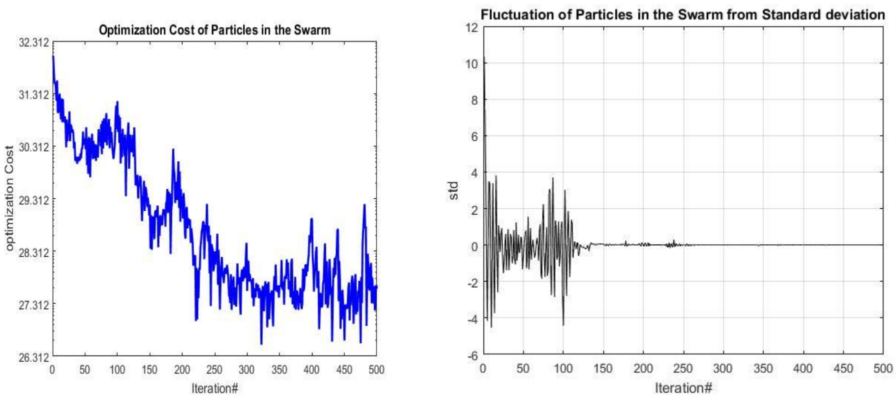
(a) (b)

Figure 5. LS-SVM-PSO particle (a) Gbest history (b) Convergence curve

PSO is not suitable as a minimizing function for LS-SVM as minimum of 25% errors are achieved in PSO. This may be because of the fact that each particle behaves independent of each other. Also the average optimization cost in PSO based optimization does not reduce as much as it did in ACO. The optimization cost is shown in equation (2) and plotted in fig. 6(a).

$$optimization\ cost = \frac{total\ cost\ received}{number\ of\ iterations\ done\ to\ reach\ optimality} \tag{2}$$

The fluctuations of particles from standard deviation can be clearly seen from fig. 6(b). It clearly shows highly unstable nature of PSO.



(a) (b)

Fig. 6. LS-SVM-PSO (a) Particle optimization Cost(MSE) (b) Fluctuations of Particles from standard deviation

From above discussion, it is clear that AGO based implementation is better for optimization as compared to bio-inspired techniques in the case of time based network traffic predictions. This is because of the fact that bio-inspired techniques use whole data traffic to be fed to the optimizer again and again which results in degraded performance of the optimizer and minimum MSE is achieved in more number of iterations. But, in AGBO based proposed model, only the tuning parameters needs to be modified with each iteration, so minimum MSE is achieved in lesser number of iterations.

The traffic range in MB/s of the dataset is plotted along with mean (μ), standard deviation (δ), proposed AGBPM and classification of the traffic in safe zone and abnormal peaks. The time t is divided into different time frames by ATWP as plotted in x-axis. The traffic is estimated using proposed prediction model bounded by the confidence of two

ISSN: 2233-7857 IJFGCN

standard deviations i.e. (μ+δ) and (μ-δ) where (μ) is the mean value and (δ) is the standard deviation. Any traffic outside the confidence bounds is considered as abnormal traffic. The details are shown in figure 7.

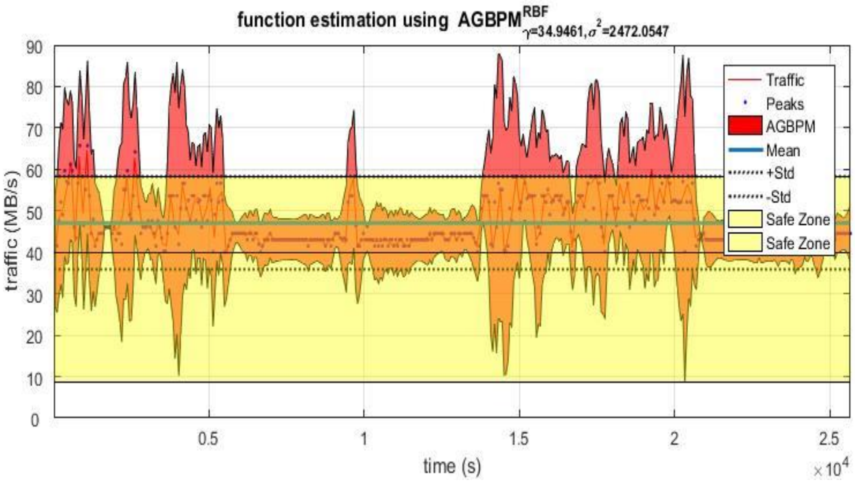


Figure 7. AGBPM classification of the traffic in safe zone and identification of abnormal peaks in traffic.

This figure 7 clearly shows the effectiveness of the AGBPM prediction model in identification of high burst traffic. The yellow safe zone identified by the AGBPM can be effectively used as an alarm system by the network administrators. It can be defined as the network traffic zone in the normal ranges. There are no traffic bursts that might lead to network wide congestions and other related problems in safe zone. So it can be used to identify exactly when the network peaked and thus appropriate actions can be taken to mitigate this problem.

8. Performance Analysis

The proposed prediction model(AGBPM) is compared with two other models namely LS-SVM-ACO and LS-SVM-PSO. Although the meta-heuristic algorithms work really well in many domains of application, however, it is observed that both LS-SVM-ACO and LS-SVM-PSO does not perform well as compared to AGBPM, in predicting traffic bursts. This is because gradient based optimizer can be directly integrated with proposed prediction model using parameter optimization (gamma and sigma) whereas ACO and PSO cannot. Secondly, the search criteria of ACO and PSO includes exploration and exploitation instead of inherent gradient based optimization in AGBPM. Thirdly, the usage of input data for effective tuning of parameters makes the proposed algorithm adaptive and efficient. The extra searches make the ACO and PSO loosely coupled optimizers. In case of PSO the convergence did happen faster, but it did not achieve good MSE. Compared to ACO, the PSO achieved lower average MSE i.e. lower efficiency but not better than AGBPM.

The performance evaluation of AGBPM, LS-SVM-PSO and LS-SVM-ACO is done using various evaluation parameters, namely dataset size, MSE, confusion matrix, accuracy, execution time and computational complexity.

8.1 Dataset Size

In this, the dataset is divided into varying sizes of instances. The dataset is varied from 10% to 100% in increments of 10% totaling 10 partitions(p). The MSE of each algorithm is evaluated. This is done by identifying the nature of algorithms, when small and large amount of data is available for training. The increase in the dataset size in both ACO and

PSO results in degraded performance whereas only AGBO algorithm shows decreasing MSE. MSE with respect to dataset is evaluated using the formula as given below.

$$MSE_p = \frac{1}{p}\sum_{i=1}^{n}(t_i - o_i)^2 \quad (3)$$

where n is the number of instances in database and p is the subset of n. t_i is the expected traffic class and o_i is the predicted traffic class. The comparison of three algorithms at varying dataset sizes is shown in figure 8. The dataset is partitioned into 10 sets. Each partition p is the subset of total instances n. In this work, 78120 total instances are considered i.e. n = 78120.

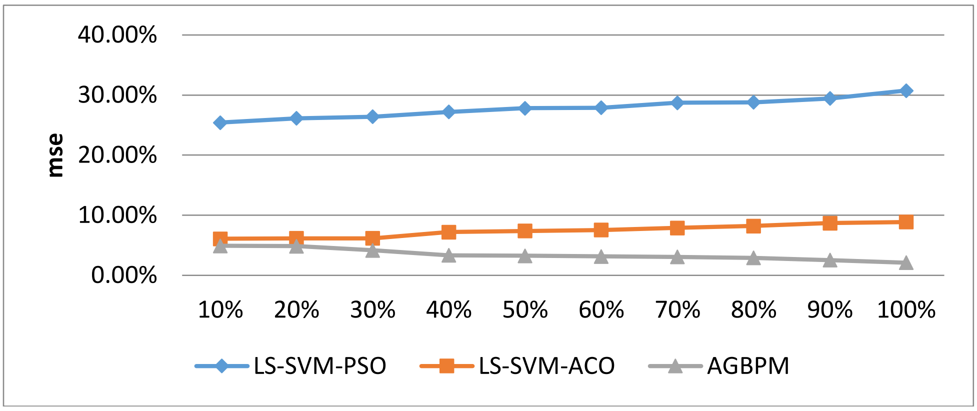


Figure 8. MSE of three algorithms for different dataset sizes.

8.2 Accuracy, Confusion Matrix, True Positive Rate(TPR) and False Positive Rate

The accuracy is evaluated for all three algorithms and is depicted in figure 9.

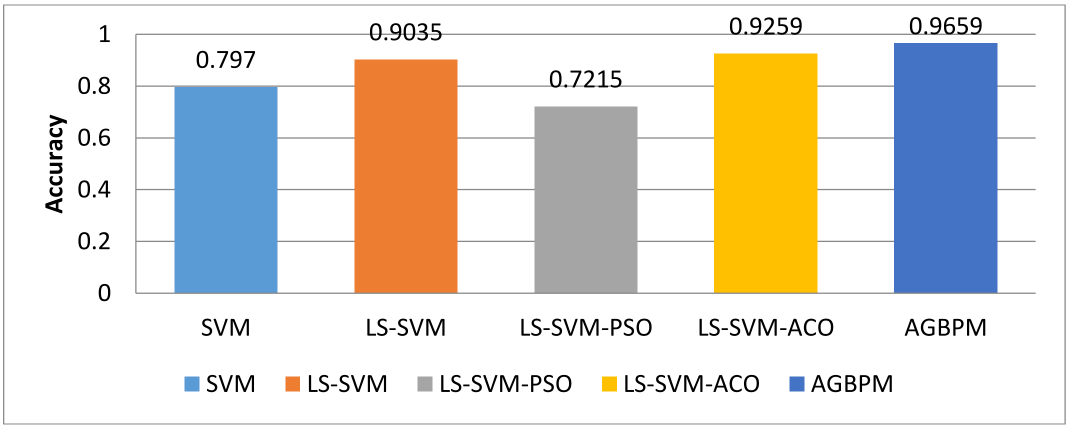
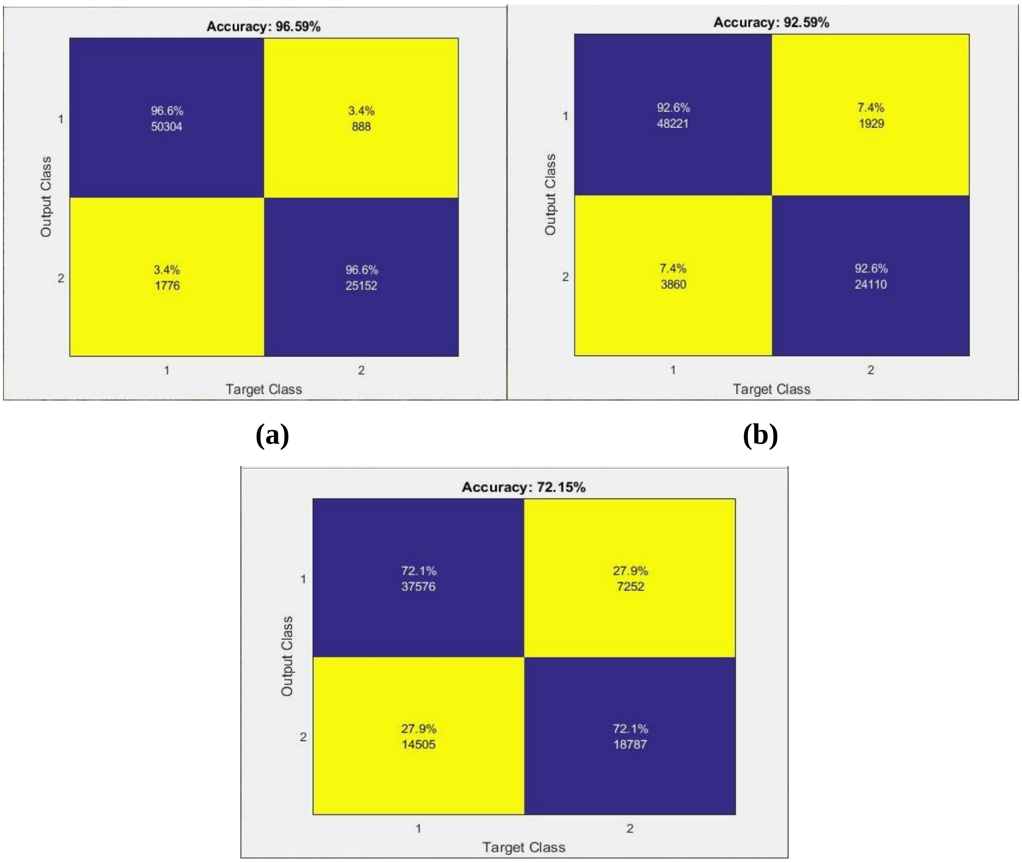


Figure 9. Accuracy of LS-SVM-PSO, LS-SVM-ACO and AGBPM

The confusion matrix helps in summarizing the classification performance of the selected classifiers when given test data is available. The confusion matrix is used to assign true classes separated by false classes. The confusion matrices for AGBPM, LS-SVM-ACO and LS-SVM-PSO are presented in fig. 10 (a), (b) and (c) respectively.



(a) (b)

(c)

Figure 10. Confusion Matrix for (a) AGBPM (b) LS-SVM-ACO (c) LS-SVM-PSO

As there are 78120 instances in the dataset considered in this paper, the quadrants of confusion matrix are placed with appropriate assignment by respective algorithm. For AGBPM, out of 78120 instances, 50304 are true positives. For LS-SVM-ACO, there are 48221(92.6%) true positives and for LS-SVM-PSO, there are 37576 (72.1%) true positives. Similarly, for false positive, only 888 instances are assigned for AGBPM compared to 1929(7.4%) false positives assigned by LS-SVM-ACO. The maximum of 7252(27.9%), a very large false positives are assigned by LS-SVM-PSO. True Positive Rate(TPR) or sensitivity can be calculated by using the following formula

$$TPR = TP/(TP + FN) \quad (3)$$

False Positive Rate(FPR) can be calculated by using the formula given below

$$FPR = FP/(FP + TN) \quad (4)$$

AGBPM possesses maximum TPR rate (98.27%) which is 2.12% greater than LS-SVM-ACO (96.15%) and 14.45% greater than LS-SVM-PSO (83.82%). Similarly, AGBPM has lowest (6.60%) FPR compared to LS-SVM-ACO (13.80%) which is about twice as much and compared with LS-SVM-PSO (43.57%). The AGBPM has 84.6% lower FPR. The TPR and FPR are shown below in figure 11.

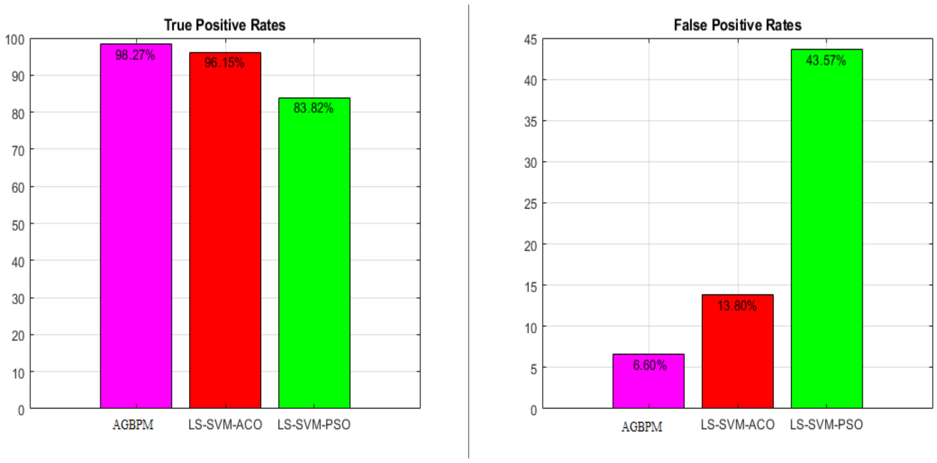


Figure 11. TPR and FPR of the proposed algorithm(AGBPM) along with LS-SVM-PSO and LS-SVM-ACO

8.3 Execution Time and Computational Complexity

The execution time is dependent on the computational complexity of the algorithm. The execution time is calculated using CPU cycles. The execution time is equal to number of CPU cycles to execute the algorithm using dataset of size n. The formula for execution time can be defined as follows

$$\text{Execution time} = \text{total CPU cycles} \times \tau \tag{5}$$

where τ is time taken by one CPU cycle. Since τ is constant for a machine, execution time is largely dependent upon number of CPU cycles. The CPU cycles taken by LS-SVM are 26 CPU cycles as computational complexity of LS-SVM [34] is n(logn). The computational complexity of the proposed AGBPM is also approximately equivalent to n(logn) where n is the number of instances. The computational complexity of LS-SVM with optimization algorithms ACO, PSO is shown in table 2. Inclusion of additional optimization algorithm adds additional computational complexity of the optimization algorithm to the classifier. This is clearly evident from execution time (in CPU cycles) taken by LS-SVM-PSO and LS-SVM-ACO. The computation complexity of the AGBPM is lowest because of the fact that the gradient based optimizer used by AGBPM itself has low computation complexity of θ(n^2) lower than ACO and PSO which makes the AGBPM faster. AGBPM takes 45 CPU cycles and LS-SVM-ACO takes slightly worse taking about 56 CPU cycles. The LS-SVM-PSO perform worst at 81 CPU cycles also reducing the accuracy at the same time.

9. Conclusions

This paper presents the prediction of network traffic using efficient prediction algorithm which do not suffer from long term or short term seasonality changes. ATWP has been proposed to identify and classify cellular network traffic patterns. To perform predictive analysis over the captured data, three algorithms has been implemented namely AGBPM, LS-SVM-PSO and LS-SVM-ACO. From the results, it is clear that AGBPM provides much more consistent results at acceptable computational complexity. The performance of AGBPM comes from the fact that gradient based optimization can be very effectively integrated with classifier used. Thus when trained the proposed AGBPM, is able to perform well as it updates the training parameters γ and σ^2 directly using gradient based optimization in contrast to ACO or PSO. Whereby, ACO and PSO need to rerun a new classifier for training in their next iteration. The AGBPM does this by utilizing the gradient nature. So the classifier does not need to re-trained again and again on the same data. AGBPM can work just by only changing training parameter γ and σ^2. Whereas ACO and PSO, being of stochastic nature and having exploration and exploitation cycles always need new classifier model for training. As indicated by the results, AGBPM offers improved accuracy (96.6%), reduced MSE and execution time (45 CPU cycles) than all classifiers considered in this work.

Table 2. Comparison of the algorithms using different parameters

Algorithms	**MSE**	**Accuracy**	**CPU Cycles**	**Computational Complexity**	**TPR**	**FPR**
LS-SVM [20]	9.7%	90.4%	26	O(n log(n))	81.75%	15.45%
LS-SVM-PSO [21]	27.9%	72.2%	81	$\theta(n^2 \log n)$	83.82%	43.57%
LS-SVM-ACO [22]	7.4%	92.6%	56	$\theta(n \log n) + \frac{\theta(n^2 \log n)}{\rho^2}$*	96.15%	13.80%
AGBPM	3.4%	96.6%	45	$\theta(n \log n) + \theta(n^2)$	98.27%	6.6%

* Where ρ is the evaporation factor

For future work, this proposed framework of traffic prediction may be further extended to support green computing.

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ISSN: 2233-7857 IJFGCN