Journal of Theoretical and Applied Information Technology
10th August 2014. Vol. 66 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

CONGESTION PREDICTION IN WIRELESS NETWORK USING GENE EXPRESSION PROGRAMMING TECHNIQUE

[1]Dr. S. KANAGA SUBA RAJA, [2]C.VISWANATHAN, [3]Dr.D.SIVAKUMAR, [4]V. BALAJI
[2,4]ASSISTANT PROFESSOR, EASWARI ENGINEERING COLLEGE, CHENNAI, INDIA
[1,3]PROFESSOR, EASWARI ENGINEERING COLLEGE, CHENNAI, INDIA
E-mail: [1] skanagasubaraja@gmail.com, [2] vishwachakra_2k@yahoo.com
[3]dgsivakumar@sify.com , [4] balaji.iniyan@gmail.com,

ABSTRACT

Congestion Control is very important in any network to provide a good quality of service. This paper implementing a Network based Congestion Control technique using Gene Expression Programming. Congestion is caused when the number of packets stored at the router buffer exceeds the total capacity of the buffer. Under this state the additional packets received at the router are lost. In any Network, the measured Buffer Utilization value can be used to identify congestion. Whenever congestion occurs there is a drastic loss of data packets. To overcome this problem this work tries to implement a method where the congestion is predicted before it occurs and to avoid it. To achieve this, here a summary of the past and present buffer utilization value and the corresponding parameters that determine the buffer utilization are collected and this information is used by the Gene Expression Program to predict the future buffer utilization value. This value is used to identify the occurrence of Congestion in the network in the near future. Once Congestion is predicted, less drastic measures can be taken to avoid it

Keywords: *Buffer, Congestion, GEP, ORF, Prediction.*

1. INTRODUCTION

Congestion is a problem that occurs on shared networks when multiple users contend for access to the same resources (bandwidth, buffers, and queues).In packet-switched networks, packets move in and out of the buffers and queues of switching devices as they traverse the network. Buffers help routers absorb bursts until they can catch up. If traffic is excessive, buffers fill up and new incoming packets are dropped. Increasing the size of the buffers is not a solution, because excessive buffer size can lead to excessive delay.

Our proposed technique uses Network-based congestion avoidance system. Here the basic idea is to predict the level of future buffer utilization and to take congestion prevention control measures accordingly the following sections we deal with the existing systems of Network-based congestion avoidance system. The main objective of our work is to implement a congestion control technique for LAN using Gene Expression Programming An electronic copy can be downloaded from the conference website. For questions on paper guidelines, please contact the conference publications committee as indicated on the conference website. Information about final paper submission is available from the conference website.

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1.1 Gene Expression Programming [GEP]

Gene Expression Programming is another congestion avoidance mechanism which uses prediction of the occurrence of congestion .In contrast to its analogous cellular gene expression, GEP is rather simple. The main players in GEP are only two: the chromosomes and the expression trees (ETs), being the latter the expression of the genetic information encoded in the chromosomes.. The genetic code is very simple: a one-to-one relationship between the symbols of the chromosome and the functions or terminals they represent. The rules are also very simple: they determine the spatial organization of the functions and terminals in the Ets and the type of interaction between sub-ETs. In GEP there are therefore two languages: the language of the genes and the

Journal of Theoretical and Applied Information Technology
10th August 2014. Vol. 66 No.1

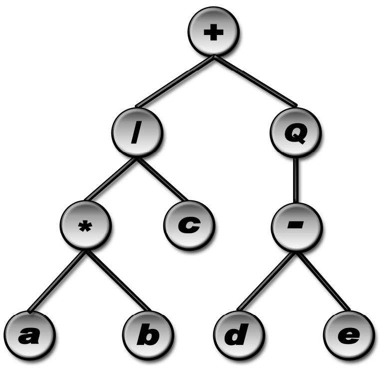
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

language of ETs, and knowing the sequence or structure of one, is knowing the other. The genome or chromosome consists of a linear, symbolic string of fixed length composed of one or more genes. Despite their fixed length, GEP chromosomes code for ETs with different sizes and shapes.

1.2 Open Reading Frames

The structural organization of GEP genes is better understood in terms of open reading frames (ORFs). In biology, an ORF or coding sequence of a gene begins with the 'start' codon, continues with the amino acid codons, and ends at a termination codon. Although in GEP the start site is always the first position of a gene, the termination point not always coincides with the last position of a gene. for example, the algebraic expression can be represented in the form of a tree diagram.

$$\frac{a*b}{c}+\sqrt{d-e} \qquad (1)$$



This kind of diagram representations is in fact the phenotype of GEP chromosomes as follows

0123456789

+/Q*c-abde (2)

Which is the straightforward reading of the ET from left to right and from top to bottom. The expression 1.2 is an ORF, starting at '+' (position 0) and terminating at 'e' (position 9). These ORFs are named as K-expressions (from Karva notation).

1.3. The GEP Genes

GEP genes are composed of a head and a tail. The head contains symbols that represent both functions and terminals, whereas the tail contains only terminals. For each problem, the length of the head h is chosen, whereas the length of the tail t is a function of h and the number of arguments of the function n, and is evaluated by the equation:

$$t = h\,(n\text{-}1) + 1 \qquad (3)$$

Consider a gene for which the set of functions F = {Q, *, /, -, +} and the set of terminals T = {a, b}. In this case, n = 2; and if we chose an h = 15, then t = 16. Thus, the length of the gene g is 15+16=31. { where g=h+t }

One such gene is shown below (the tail is shown in bold):

0123456789012345678901234567890

/aQ/b*ab/Qa*b***-ababaababbbabbb**

The Expression Tree for the above gene is shown below.

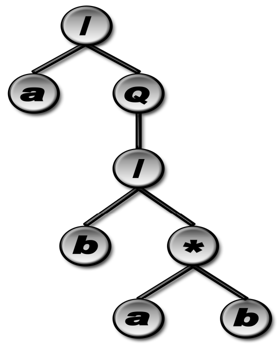


Figure 1.3: Expression Tree

A number of genes of the same size are combined together to form a single GEP chromosome or individual. The Ets of each of the gene are combined using a suitable linking function that is usually a Binary function from the function set of the GEP.

1.4. Equations GEP Congestion Avoidance

Several methods have been proposed to avoid congestion. Most of them are network based congestion avoidance methods i.e. these methods work at the router in the network. The Buffers present at the routers are responsible for avoiding congestion in the networks by buffering the excess packets that are received at the router and preventing them from being lost. One way by which we can avoid congestion is to increase the buffer size. But this is not a viable measure. The other way is to introduce suitable queue management methods that can identify or guess when congestion can occur and can avoid it by taking the suitable control measures. Hence the first step to avoid congestion is to identify congestion. Measuring the buffer utilisation value at the routers in the network can identify congestion in networks. Existing queue management techniques identify

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

congestion by assuming that the future buffer utilisation value is same as the current buffer utilisation value. This idea has shown considerable performance improvement over the traditional Drop Tail method. But what will be the level of performance improvement if the routers can predict the future buffer utilisation level and this is the idea being explored in this method "Congestion Control using GEP"

This method uses Gene Expression Programming to Predict the future buffer utilisation value based on the current and past buffer utilisation values. GEP is used to generate a prediction model that can predict the future buffer utilisation value. The predicted value of buffer utilisation is used to take the corresponding control measures to avoid congestion.

2. RELATED WORK

The quality-centric congestion control for multimedia streaming over wired IP networks, which we refer to as media-TCP-friendly congestion control(MTCC). The solution adapts the sending rate to both the network condition and the application characteristics by explicitly considering the distortion impacts, delay deadlines, and interdependencies of different video packet classes. The sufficient conditions for multiple multimedia users to achieve quality-based fairness using MTCC congestion control. Note that the proposed solution only modifies the adaptation mechanism of the TCP congestion window size at the sender, without changing the design at the receiver side [1].The problem of time series prediction provides a practical benchmark for testing the performance of evolutionary algorithms. Which compare various selection methods for genetic programming, an evolutionary computation with variable-size tree representations, with application to time series data. Selection is an important operator that controls the dynamics of evolutionary computation. A number of selection operators have been so far proposed and tested in evolutionary algorithms with fixed-size chromosomes. However, the effect of selection schemes remains relatively unexplored in evolutionary algorithms with variable-size representations.[2].Time related association rule mining is a kind of sequence pattern mining for sequential databases. Which introduce a method of generalized association rule mining using genetic network programming (GNP) with time series processing mechanism in order to find time related sequential rules efficiently. GNP represents solutions as directed graph structures, thus has compact structure and implicit memory function. The inherent features of GNP make it possible for GNP to work well especially in dynamic environments. GNP has been applied to generate time related candidate association rules as a tool using the database consisting of a large number of time related attributes. The generalized algorithm which can find the important time related association rules is described and experimental results are presented considering a traffic prediction problem[3]

The next method deals with the problem of ramp metering along with speed limit control of the freeway networks in order to reduce the peak hour congestion. An adaptive fuzzy control is proposed to solve the problem. To calibrate the fuzzy controller, genetic algorithm is used to tune the fuzzy sets parameters so that the total time spent in the network remains minimum. A macroscopic traffic model is used for tuning the controller in an adaptive scheme and for presenting the simulation results. This method concludes that the adaptive genetic-fuzzy control is expected to enhance the performance of the freeway traffic network[4].The next method explores the utilization of discrete sliding mode control approach for the congestion control in communication network. For the past several years many feedback control methods have been used for the control of various parameters of Communication Networks like Traffic Control, Congestion Control and Power Control. The work presented here proposes a new application of sliding mode control for congestion control in communication network. Thus, it has been shown that the discrete sliding mode control can be used in control of various parameters of communication network[5].The quality-centric congestion control for multimedia streaming over wired IP networks, which we refer to as media-TCP-friendly congestion control(MTCC). solution adapts the sending rate to both the network condition and the application characteristics by explicitly considering the distortion impacts, delay deadlines, and interdependencies of different video packet classes. The media-aware solution is able to provide differential services for transmitting various packet classes and thereby, further improves the multimedia streaming quality compared to the conventional network-aware congestion control. We use finite-horizon Markov decision process (FHMDP) to determine the optimal congestion control policy that maximizes the long-term multimedia quality, while adhering to the horizon-K TCP-friendliness constraint, which ensures long-

Journal of Theoretical and Applied Information Technology
10th August 2014. Vol. 66 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

term fairness with existing TCP applications. Moreover, the proposed MTCC is able to achieve quality-based fairness among multimedia users[6].Dynamic system identification algorithm is developed using the basic mechanisms of clonal selection and idea of a new evolutionary computing paradigm - gene expression programming. On the basis of the algorithm developed a computer based system is implemented for making decisions relevant to forecasting of single variable and multivariate time series. The results of computing experiments achieved with the system developed show high quality of short and medium period forecasts[7]The media-aware congestion control problem is formulated as a Partially Observable Markov Decision Process (POMDP), which maximizes the long-term expected quality of the received multimedia application. The solution of this POMDP problem gives a policy adapted to multimedia applications' characteristics (i.e., distortion impacts and delay deadlines of multimedia packets). Note that to obtain the optimal congestion policy, the sender requires the complete statistical knowledge of both multimedia traffic and the network environment, which may not be available in practice. Hence, an online reinforcement learning in the POMDP-based solution provides a powerful tool to accurately estimate the environment and to adapt the source to network variations on the fly[8].

3. SYSTEM MODEL

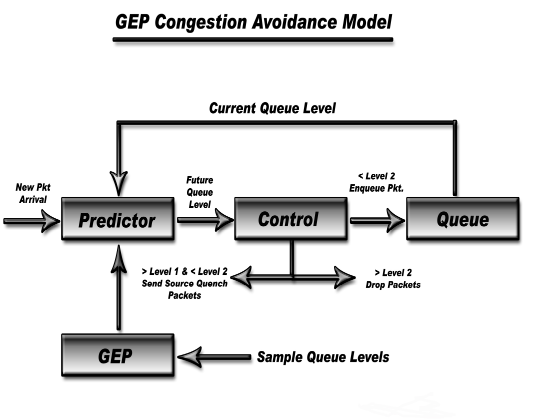


Figure 3: GEP Congestion Avoidance Model

Based on the above said idea the GEP Congestion Avoidance System has been developed. The above figure shows the block diagram representation of the GEP Congestion Avoidance System. The GEP uses predictor that uses the current & past buffer utilisation levels to predict the future buffer utilisation level for every new packet arrival. The Predicated value is then used by the control unit for making a decision on the packets. The main components are

3.1 The Predictor Generator

The Prediction Model uses a function that is used to predict the future buffer utilisation value using the past and the current buffer utilisation values. The Gene Expression programming is used to generate the prediction model uses Time Series Prediction

3.2 Definition Of Time Series Prediction.

The task of one-step-ahead prediction is to map points from lag space (input parameters of the model, , i.e. current input and L past input values from the series) to an estimate of the future value, that is, the prediction

$$\hat{x}_{n+1} = f(x_n, x_{n-1}, x_{n-2}, \ldots\ldots\ldots\ldots, x_{n-L}) \quad (3)$$

where L is the order of the model and n denotes current time index. The prediction model building consists of determining the structure and parameters of this mapping. The parameters in this case are the past and current buffer utilisation values. The Structure has to be generated by the GEP. Since this time series prediction has to continuously predict the future buffer value, this has been used in the Sliding window prediction mode for Time series prediction. With sliding window prediction, the prediction function slides over the time axis as a window of size, L+1.

3.3 Generating The Initial Population

Before generating the initial population the size of the gene and hence that of the individual or the chromosome has to be fixed. To decide on the size of the gene, the size of the head is decided and the size of the tail is calculated from the size of the head. The sum of the size of the head and the tail is taken as the size of the gene. Then the number of genes that make up the chromosome is decided.

As the second step in generating the Initial population, the set of functions and the set of terminals is decided. The function set consists of +, -, *, /, Q. The terminal set consists of the independent variables of the predictor function i.e. the input values to the predictor function. The number of terminals is same as the window size.

While generating the initial population the following rules are to be followed for constructing each gene The root element of each gene should be a function.

The remaining positions in the head can be a function or a terminal The positions on the tail should all be from the terminal set. The initial

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

population is generated using the pseudo random number generator. A fixed number of individuals i.e., equal to the population size, is generated using the Initial population generator.

3.4 Evaluating The Fitness & Selection

As GEP is an evolutionary process at each stage of evolution the best individuals have to be selected for evolution. For this, the fitness of the individual has to be measured. In this case the fitness of the individual is inversely proportional to the amount of deviation between the actual value and the predicted value of buffer utilisation.

Mean Squared Error (MSE) Function is used for measuring the fitness of the individual. A fitness function using this error function is called an Mean Squared Error Fitness Function. This type of fitness function can easily handle both the positive and negative deviations of the predicted value.

The mean squared error, Ei of an individual program is evaluated by using the equation.

$$E_i = \frac{1}{n}\sum_{j=1}^{n}(P_{ij} - T_j)^2 \qquad (4)$$

Where Pij is the predicted value for the individual,i for the fitness case j, and Tj is the target value or the actual value for the fitness case j. For a perfect fit the value of Pij = Tj and Ei = 0. So the MSE index ranges from 0 to infinity, with 0 corresponding to the ideal case. The value of Ei cannot be directly used as fitness because for fitness proportionate selection, the fitness value should increase with efficiency. Thus for evaluating the fitness fi ,of an individual,i the following fitness function is used,

$$f_i = 1000 * \frac{1}{1 + E_i} \qquad (5)$$

With the value of fitness fi ranging from 1000 to 0, and 1000 being the ideal case. The coefficient value of 1000 allows a fairer distribution of fitness for selection.

The selection is based on Roulette Wheel method which ensures that probability of selection is directly proportional to fitness.

$$p_{selection_j} = \frac{fitness_j}{\sum_{i=1}^{n} fitness_i} \qquad (6)$$

Mutations can occur anywhere in the chromosome. However, the structural organization of chromosomes must remain intact. In the heads, any symbol can change into another (function or terminal); in the tails, terminals can only change into terminals. This way, the structural organization of chromosomes is maintained, and all the new individuals produced by mutation are structurally correct programs. The mutation operator is applied on an individual with a probability of Pm.

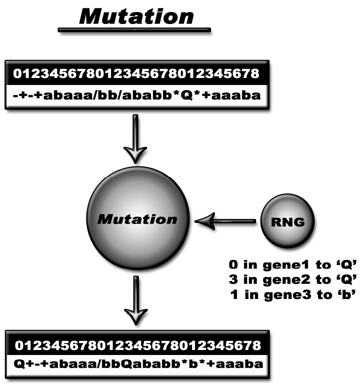


Figure 1.3: Mutation Computation

The transposable elements of GEP are fragments of the genome that can be activated and jump to another place in the chromosome. In GEP there are three kinds of transposable elements: i) IS Transposition; ii) Root IS Transposition; iii) and Gene Transposition. Any sequence in the genome might become an IS element, being therefore these elements randomly selected throughout the chromosome. A copy of the transposon is made and inserted at any position in the head of a gene, except the first position. The transposition operator randomly chooses the chromosome, the start of the IS element, the target site, and the length of the transposition. The IS Transposition operator is applied on an individual with a probability of Pis.. All RIS elements start with a function, and thus are chosen among the sequences of the heads. For that, a point is randomly chosen in the head and the gene is scanned downstream until a function is found. This function becomes the start position of the RIS element. If no functions are found, the operator does nothing. This operator randomly chooses the chromosome, the gene to be modified, the start of the RIS element, and its length. This probability that this operator is applied on an individual is given by Pris.

In gene transposition an entire gene functions as a transposon and transposes itself to the beginning of the chromosome. In contrast to the other forms of transposition, in gene transposition, the transposon (the gene) is deleted at the place of origin. Gene transposition is very important when

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

coupled with other operators, for it allows not only the duplication of genes but also a more generalized recombination of genes or smaller building blocks. The chromosome to undergo gene transposition is randomly chosen, and one of its genes is randomly chosen to transpose. The Gene Transposition operator is applied on an individual with a probability of Pgis..

In GEP there are three kinds of recombination: one-point recombination, two-point recombination and gene recombination. In all types of recombination, two chromosomes are randomly chosen and paired to exchange some material between them, creating two new daughter chromosomes. In one-point recombination the chromosomes are paired and split in the same point. The material downstream of the recombination point is afterwards exchanged between the two chromosomes. The One Point Recombination operator is applied on an individual with a probability of P1r.

In 2-point recombination the chromosomes are paired and two points are randomly chosen as crossover points. The material between the recombination points is afterwards exchanged between the two parent chromosomes, forming two new daughter chromosomes. The following diagram shows a two generic Two Point Recombination. The Two Point Recombination operator is applied on an individual with a probability of P2r.In the third kind of GEP recombination, gene recombination, entire genes are exchanged between two parent chromosomes, forming two daughter chromosomes containing genes form both parents. The exchanged genes are randomly chosen and occupy the same position in the parent chromosomes. The Gene Recombination operator is applied on an individual with a probability of Pgr. The Following figure shows a two genetic Gene Recombination.

3.5 Control And Avoidance

Once the Future Level of buffer utilisation has been predicted it can be used to take the control measures. For this purpose two different threshold levels have been defined and named as Level 1and Level 2. The following threshold policy is followed to control congestion

If Predicted Level < Level 2, then Enqueue the packets.

If Predicted Level > Level 2 and Predicted Level < Level 1, then Enqueue the Packets but set a Congestion notification bit in the packet header of packets from CCGA-capable host. Then the packets are forwarded to the receiver, which then sends an ACK to the sender that contains the congestion indicator. This ACK is called a CCGA-Echo. When the sender receives this explicit signal, it halves the rate at which it sends packets.

If Predicted Level > Level 1, then Drop the Packets.

The above said control measures have already been describes under RED and ECN queue management techniques. The methods of their implementation have been widely covered under RFC 2309 and RFC 2481 respectively. Hence in this project only the Prediction part of CCGA has been implemented and the results of their implementation have been shown in the following section.

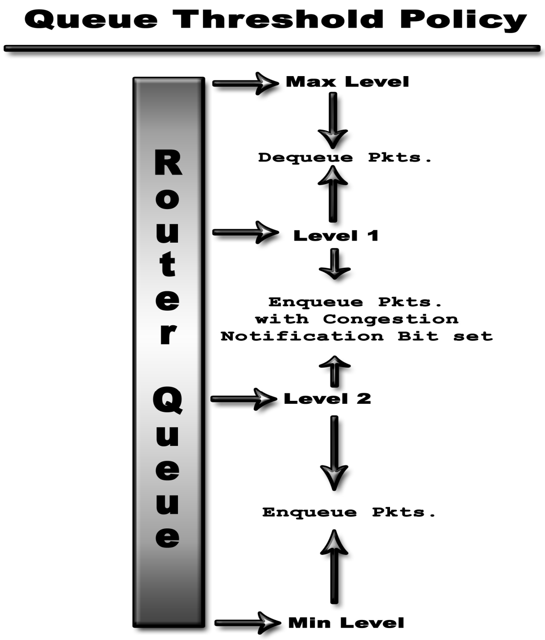


Figure 3.5: Queue Threshold Policy

4. DESIGN APPROACH

The present work envisages avoidance of congestion by predicting it before it occurs. To achieve this first a summary of the past and present buffer utilization values and the corresponding parameters that determine the buffer utilization are collected. This information is used by the GEP to identify the future buffer utilization value, which is then used to predict the occurrence of Congestion in the network. Once Congestion is predicted, measures can be taken to avoid it.

4.1 Congestion Prediction Using GEP Techniques

In order to predict short-term congestion in a network, AI techniques have been implemented. The

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prediction goal and input data are explained. Then, the AI technique will be introduced, focusing on its application in our problem.

4.2 Prediction Goal and Input Data

The system should predict when a short-congestion situation is going to occur. If this moment is foreseen before it happens, some measures can be taken in advance to avoid this future and undesirable situation. The system can predict it, using information based on the temporary evolution of the buffer utilization. AI techniques learn from past situations and apply their knowledge to predict new situations. The AI technique used is Genetic Programming (GP) GPs are a machine learning method useful for prediction model generation. In this case, it will predict the future buffer utilization. Like the majority of machine learning methods, GPs need a representative set of problem samples to be trained. Once the training phase is completed, the output (the model) is used to make the prediction. The test bed used to train the GP is made up of a set of samples, where every set of samples is included in a file. These samples come from previous network simulations obtained from OPNET. Thus a file contains a time-ordered list of buffer utilization states.

The GP system needs a data set that reflects not only the past and present situation, but also the future buffer utilization, in order to achieve a good training. Therefore, the data set will be fragmented in windows and every window will be processed as a new sample. Every window includes an account of buffer utilization in the previous instants as well as the future buffer utilization. The account is summarized in intervals and every interval is represented by the maximum, the minimum and the mean buffer utilization.

5. PERFORMANCE EVALUATION

The GEP Predictor Generator has been tested with two different types of traffic patterns and results are given below using NS2 Simulator. In order to test the GEP Predictor Generator a simple network has been chosen, with two Sources, a Router and a Destination. The Network model is as in figure 5.1

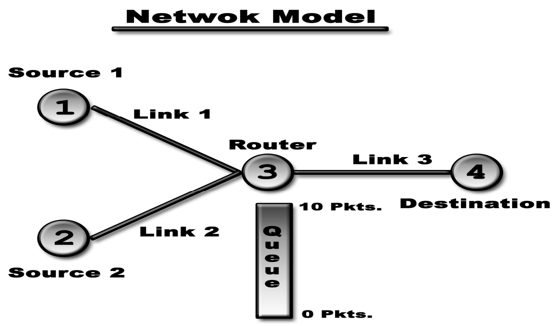

Figure 5.1: Network Model

Link 1: Line Rate: 2 mb: Line Delay: 10 ms.

Link 2: Line Rate: 3 mb: Line Delay: 10 ms.

Link 3: Line Rate: 1.7 mb: Line Delay: 10ms.

Queue Size: 10 Pkts.

5.1 Constant Bit Rate Traffic

Generates traffic according to a deterministic rate. Packets are constant size. Optionally, some randomizing dither can be enabled on the inter-packet departure intervals.

Source 1:

Packet Size : 600 bytes
Data Rate : 1 mb
Random : 0.5

Source 2:

Packet Size : 1000 bytes
Data Rate : 1 mb
Random : 0.9

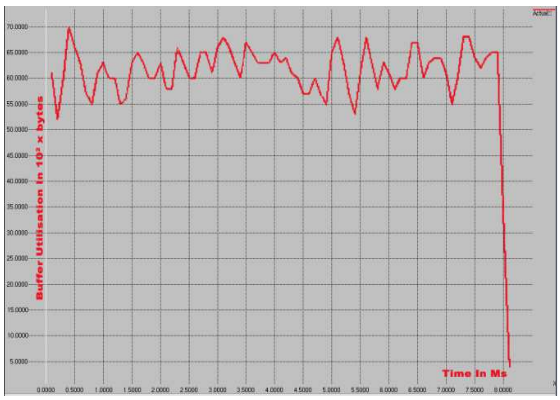

Figure 5.2: CBR: Actual Level

Journal of Theoretical and Applied Information Technology
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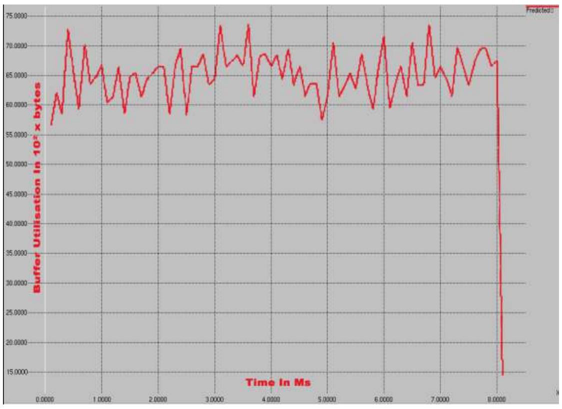

Figure 5.2: CBR: Predicted Level

5.2 Exponential Traffic

Generates traffic according to an Exponential On/Off distribution. Packets are sent at a fixed rate during on periods, and no packets are sent during off periods. Both on and off periods are taken from an exponential distribution. Packets are constant size.

Source 1:

Packet Size	:	500
Data rate	:	1 mb
Idle Time	:	0.2 ms
Burst Time	:	0.8 ms

Source 2:

Packet Size	:	1000
Data rate	:	1 mb
Idle Time	:	0.1 ms
Burst Time	:	0.5 ms

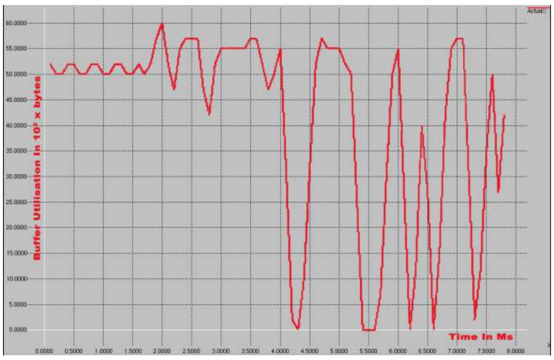

Figure 5.2: Exponential: Actual Level

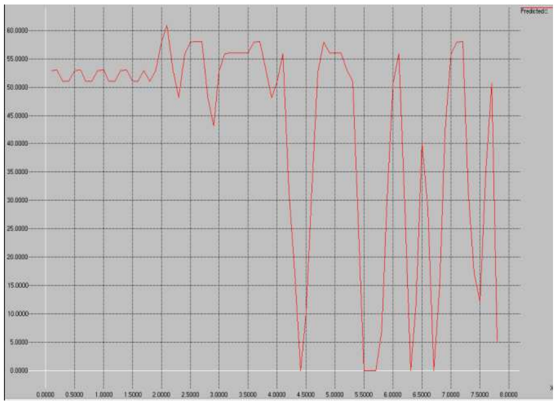

Figure 5.2: Exponential: Predicted Level

6. CONCLUSION

To predict and control short-term congestion in LAN network, a control method using GEP has been introduced in this Work. This algorithm works with buffer utilization and has been adapted in order to improve the congestion control. The prediction of the future buffer utilization is the main goal of this algorithm. Using past and present buffer utilization values, and corresponding parameters, Gene Expression Programming is used to predict the future buffer utilization in turn which is used to predict the occurrence of Congestion in the network. The algorithm uses the formula in order to foresee future states of network congestion. Then, it will apply this new knowledge with the purpose of minimizing the congestion effects.

7. FUTURE WORK

As an enhancement to this approach the static GEP can be replaced with a self-tuning GEP, which can change its parameters dynamically to adapt itself to varying traffic patterns. Also the GEP can be automated to switch between the training mode and the prediction mode to itself to large changes in the traffic pattern.

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