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MANAGING QUEUE STABILITY USING ART2 IN ACTIVE QUEUE MANAGEMENT FOR CONGESTION CONTROL

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ABSTRACT

Congestion occurs on a link when the traffic is exceeding the maximum capacity of that link which is a major problem in today's world of internet. If the incoming link is larger than that of the outgoing link, it leads to congestion. Active Queue Management (AQM) schemes allow router to proactively respond to congestion by increasing the average length of its queue. Random Early Detection (RED) AQM algorithm a solution for congestion has difficulties in setting the parameters for bursty traffic. Hence an intelligent AQM technique is needed to reduce the packet loss by stabilizing the queue. The proposed Adaptive Resonance Theory 2 (ART 2) RED based AQM an unsupervised intelligent neural network stabilizes the queue and reduces the queue oscillations. The results are tested using network simulator ns 2 and prove that the proposed ART 2 RED AQM best suits for maintaining the queue stability by reducing the packet loss.

Keywords: active queue management, random early detection, neural networks, kohonen self organizing map, adaptive resonance theory (ART).

INTRODUCTION

ART self-organizes stable pattern recognition. This recognition code is done in real time based on the arbitrary input pattern sequences. Due to its self stabilization ART does not possess the local minimum problem. It is an unsupervised paradigm and is based on competitive learning method, capable of finding categories and creating new categories when needed automatically. ART is a type of incremental clustering paradigm. The standard feed forward network suffers a stability problem for which ART was developed. During the training process the old weights that were captured may be lost when new weights come in. The process of maintaining the old weights with that of the new weights is called the stability-plasticity dilemma which is the main concept used in this neural network. Its principles helps in the parametric behavioral and brain data in the areas like object recognition, visual perception, variable-rate speech auditory source identification, and word recognition and adaptive sensory motor control [1, 2]. It is used to represent the hypothesized processes like learning, attention, search, recognition and prediction. ART is a family of different neural architectures among which ART1 is the first network which learns binary patterns. ART 2 [3] can learn arbitrary sequences of analog input patterns. Other ART models include ART3 and ARTMAP [4].

An ART2 has two interconnected layers F1 and F2 as shown in the Figure-1. F1 indicates the characteristic representation layer and F2 indicates the category representation layer. The dimension of the input vector represents the number of nodes in the F1 layer. Node in the F2 layer represents a category given by its top-down and bottom-up weights. These weights are known as the Long Term Memory (LTM) of the network. When new categories patterns arrive, nodes will be dynamically created in F2. Vigilance parameter gives the coarseness of the categories. In the F1 layer, normalization and feature extraction are the number of operations performed on the input pattern. The pattern code in the F1 layer is sent out to the F2 layer through the bottom-up weights. The F2 node with the bottom-up weights which matches with the F1 pattern code is declared as winner and its top-down weights are sent out back to the F1 layer. When the resonance between F1 and F2 stabilizes the reset assembly which evaluates the F1 pattern code and the input vector. The winning F2 node is reserved if the resemblance is too low and a new F2 node indicating a new category is created. The adaptation of weights progress according to the differential equation and is executed on the winning node. Node which has the largest inner product of its weights and the F1 pattern code is known as winning node in F2. Reset has been made by using a clever angle measure between the input vector and the F1 pattern code. The ART2 NN is an unsupervised classifier that accepts input vectors. It classifies the next vector according to the stored pattern in which it resembles. If the input vector is totally of a different pattern it creates a new cluster corresponding to the input vector. This is achieved by a vigilance threshold ρ [4]. Thus the ART2 NN [8] allows the user to control the degree of similarity patterns placed in the same cluster.

Learning mode of ART 2

The prime ART system is an unsupervised learning model. It usually consists of a comparison field, a vigilance parameter, a recognition field composed of neurons and a reset module. The vigilance parameter has great effect on the system. Higher vigilance results in highly detailed memories (fine-grained categories), while lower vigilance produces more general memories (more-general categories). The comparison field gets an input vector (one-dimensional array of values) and transmits it to the best match in the recognition field. Set of weights (weight vector) in single neuron matches well with the input vector. Each recognition field neuron produces a negative signal (proportional to that neuron's quality of match to the input vector) to all other recognition field neurons and consequently reduces their output. The recognition field displays lateral inhibition which allows each neuron to represent a category by which input vectors are classified. The reset module then compares the strength of the recognition match with the vigilance parameter. Training commences when the vigilance threshold is met. If it does not match with the vigilance parameter, the firing recognition neuron gets reduced until a new input vector is applied. Training starts only when search procedure completes. Recognition neurons are disabled one by one in the search procedure using the reset function until the vigilance parameter is satisfied by a recognition match. If there was no committed recognition neuron's match encounters the vigilance threshold, an uncommitted neuron is committed and it is adjusted to match with the input vector.

Training in ART2

Basically there are two methods of training ART-based neural networks. They are slow and fast. The degree of training of the recognition neuron's weights towards the input vector is calculated in slow learning method by continuous values using differential equations and it depends on the length of time the input vector is presented. Algebraic equations are used to calculate degree of weight adjustments in fast learning and it uses binary values. Fast learning is effective and efficient for several tasks, while the slow learning method is more biologically probable and it can be used with continuous-time networks (i.e., while the input vector varies continuously).

Queue stability using ART2 RED

ART2 RED [3] self organizes stable recognition categories in response to arbitrary sequences of analog input patterns as well as binary input patterns. The capability of recognizing analog patterns represents a significant enhancement to the system. ART2 RED also recognizes the underlying similarity of identical patterns superimposed on constant backgrounds having different levels. ART2[7] includes.

- Allowance for noise suppression.
- Normalization (i.e.,) contrasts to enhance the significant parts of the vector.
- Comparison of top-down and bottom-up signals to reset the mechanism.
- Dealing with real valued data that may be arbitrarily close to one another.

ART2 RED inputs data from the various environments categorizes the input internally and recognizes similar data in the future. Its plasticity allows the system to learn new concepts and stabilizes the previously learned information without destroying the learned data. ART2's self regulating control structure allows autonomous recognition and learning. Its speed, stability, feature amplification and noise reduction features along with its plasticity and stability produces a well suitable training process for the proposed methodology. ART2 learned information is not washed out due to the stability. This proposed method reduces noise and drop ratio compared to KRED.

EXPERIMENTAL RESULTS

The performance of the proposed ART2 RED approach is determined by comparing the performance with the conventional techniques. In case of small number of patterns, the performance of the proposed technique is almost same as the conventional techniques. When the number of inputs increases rapidly, the performance of the proposed technique also differs rapidly. The experimentation is performed upto 25 sample patterns to learn at a time. The dumbbell topology is used for the test experiments. The TCP flows are New Reno with 10000 packets. Two types of traffic flow are used in the experiment. First the number of traffic flow is increasing from 50 to 250 flows with identical Round Trip Time (RTT). The second type the traffic flow is varied every 50 seconds in which each flow has a RTT ranging from 64 to 102ms. The traffic pattern is used to evaluate the proposed methods under wide traffic variation. It is implemented in network simulator (NS-2.33) [5]. The results obtained by using the ART2 RED training method perform much better than that of the existing KRED [6]. The queue is stabilized in both the scenarios used shown in Figure-1. The training steps involved is less compared to that of the previous methods.

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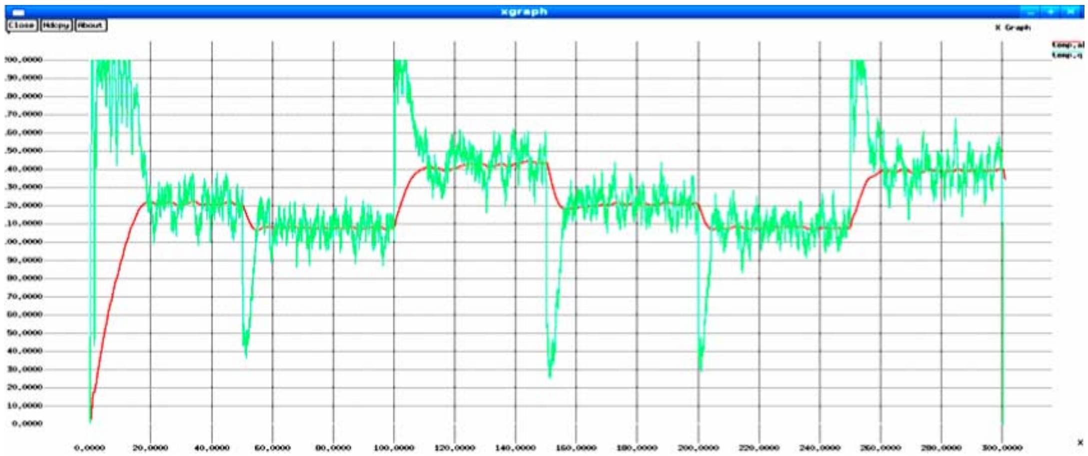
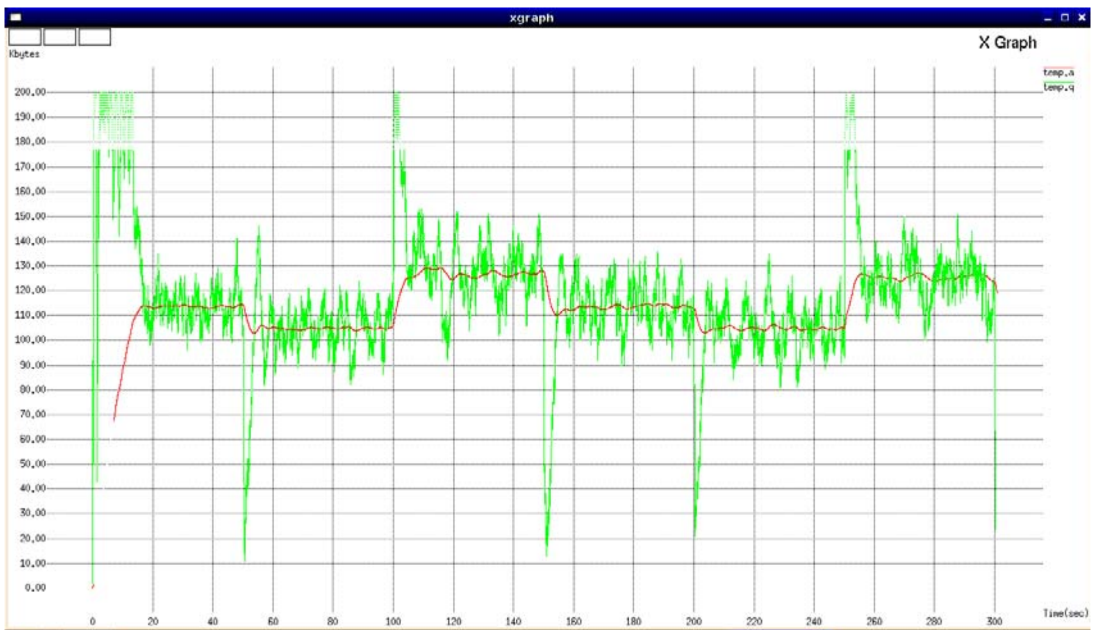


(a)



(b)

Figure-1. Queue stability in a) KRED and b) ART2 RED.

The trained network can be used for any type of traffic. The time taken to train the given network is much lesser compared to that of KRED. Table-1 discusses the results obtained for both KRED and ART2 RED. The QoS parameters are discussed in Table-1 for existing KRED and ART2 RED.

Table-1. Training Time, Average Queue Delay, Jitter and PDR of KRED and ART2 RED

Methods	**Time** (ms)	**Queue delay** (ms)	**Jitter** (ms)	**PDR**
KRED	301.4626	0.283853	0.0031342	0.9731
ART2 RED	110.5288	0.199942	0.0019157	0.9691

It has been noticed from Table-1 that the performance compared to KRED, ART2 RED produces a better training time, minimum queue delay for heavy traffic and variance of queue delay is less. The training time, average queue delay, variance of queue delay and PDR is shown in Figure-2 through 6. It is clear that the ART2 RED gives a better result than KRED competitive learning neural network method. The number of bytes sent and received from the scenarios with RTT of 50 flows is shown in Figure-5.

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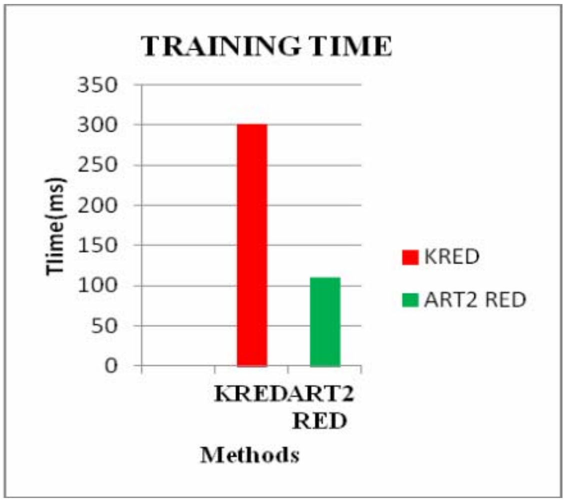

Figure-2. Training Time of KRED and ART2 RED.

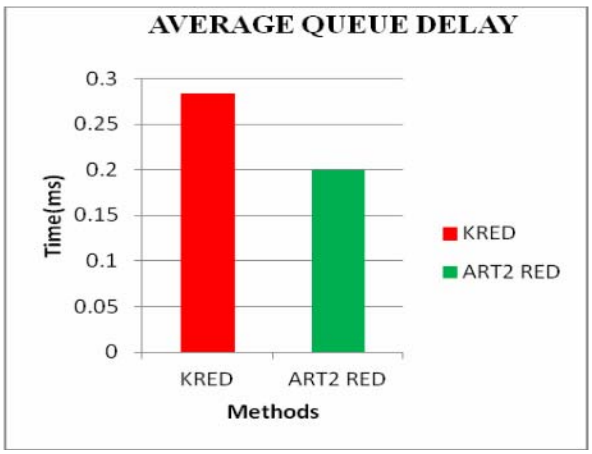

Figure-3. Average Queue Delay of KRED and ART2 RED.

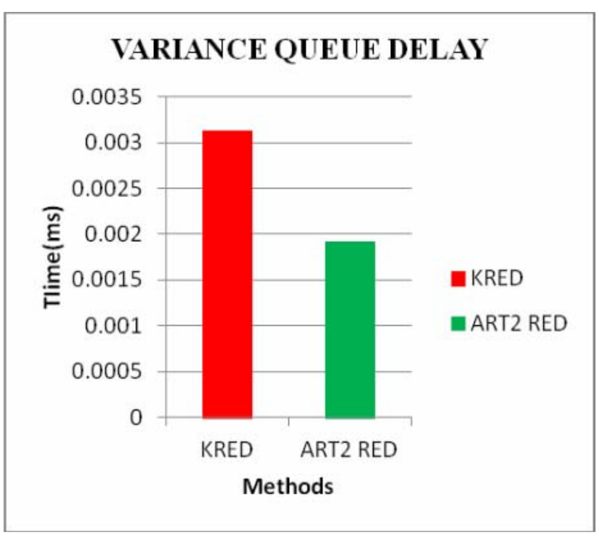

Figure-4. Variance of queue delay between KRED and ART2 RED.

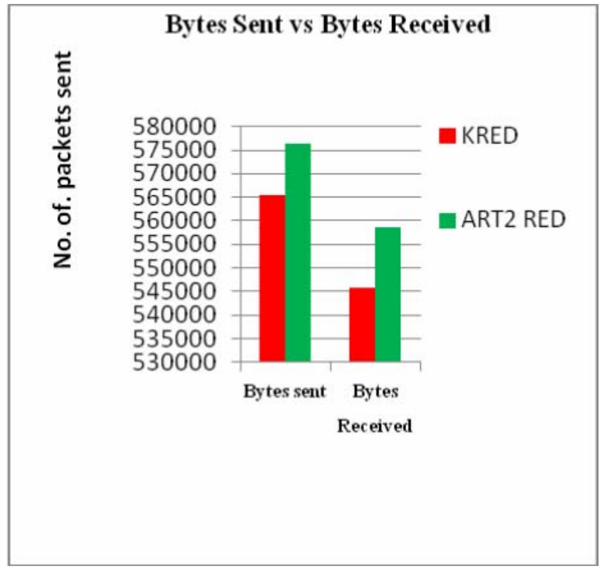

Figure-5. Bytes Sent vs Bytes Received in KRED and ART2 RED.

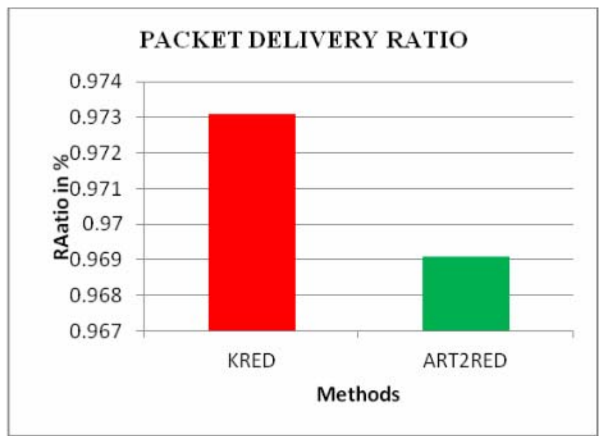

Figure-6. Packet Delivery Ratio of KRED and ART2 RED.

CONCLUSION

Adaptive Resonance Theory 2 uses the short term and the long term memory to keep the enhanced pattern and later the long term memory for the classification so that the stability and plasticity is maintained in this type of neural network. The performance when compared to the existing method is better in regard with average queue delay, jitter and the stability maintenance. The training time obtained by ART2 is very minimum when compared to the KRED mechanism. The number of bytes sent and received is very high in ART2 RED. The third approach, the intelligent learning using ART2 uses the stability plasticity dilemma henceforth having the previously learnt knowledge in the short term memory and long term memory for classification. This speeds up the learning time obtained for various input vectors ART2 [3] identifies and recognizes the object in general. Its top down approach of observing expectation and the bottom up sensory information compares with the actual features of the objects. When the sensory and expectation does not exceed the vigilance parameter the sensed object will be considered a member of the expected class. The stability-plasticity dilemma addresses how a learning system can preserve its previously learned knowledge while keeping its ability to learn new patterns ART architecture can self-organize in real time, producing stable recognition while getting input patterns and maintains the stability of the queue in a minimum training time. Hence proving better compared to the previous KRED method.

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