Network Bandwidth Predictor (NBP):
A System for Online Network performance Forecasting

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Abstract

The applicability of network-based computing depends on the availability of the underlying network bandwidth. However, network resources are shared and the available network bandwidth varies with time. There is no satisfactory solution available for network performance predictions. In this research, we propose, design, and implement the NBP (Network Bandwidth Predictor) for rapid network performance prediction. NBP is a new system that employs a neural network based approach for network bandwidth forecasting. This system is designed to integrate with most advanced technologies. It employs the NWS (Network Weather Service) monitoring subsystem to measure the network traffic, and provides an improved, more accurate performance prediction than that of NWS, especially with applications with a network usage pattern. The NBP system has been tested on real time data collected by NWS monitoring subsystem and on trace files. Experimental results confirm that NBP has an improved prediction.

Index Terms— Performance prediction, Network bandwidth, Artificial Neural Network, Distributed computing

1. Introduction

Performance monitoring and forecasting is an active area of research. In the growing world of networking, more emphasis is being placed on speed, connectivity, and reliability. When network problems occur, they often result in catastrophic breakdowns. Due to the heterogeneity and the constantly varying nature of the network traffic, there are only a few works available to provide prediction of network performance in terms of available bandwidth and latency in a heterogeneous environment, such as Grid computing.

Network Weather Service (NWS) [1, 2] is a well-used network performance measurement and prediction system in Grid computing. However, its simple prediction methods cannot satisfactorily capture the complicated short and long-range temporal dependence characteristic of heterogeneous network traffic.

In this paper, we design and implement NBP for online performance forecasting that uses artificial neural network based mechanism for bandwidth prediction. NBP forecasts the available bandwidth, the maximum rate that the path can provide to a flow, without reducing the rate of rest of the traffic in the path. The system employs NWS for traffic monitoring and a neural network based approach for bandwidth predictions.

NBP is more powerful than simple statistical models and exhibit excellent learning ability. The system can capture complex communication patterns more effectively. NBP employs a non-linear representation that alleviates the problems of linear models.

Section 2 discusses the overall architecture of the NBP implementation; Section 3 presents the experimental results with the data collected using the NWS monitoring system. Section 4 concludes and summarizes the work and discusses future research.

2. Component Design and implementation of NBP

We propose the design of the Network Bandwidth Predictor (NBP) system for network bandwidth prediction. NBP has the following different interacting modules: Network Traffic Monitor, Network Traffic Pre-Processor, Network Traffic Predictor, Database and a GUI that work together to provide network traffic forecast. NBP uses NWS for network traffic monitoring and uses neural network for forecasting.

Network traffic data are compiled into a database to serve as inputs to the neural network based forecasting model. Each sensor periodically takes a performance measurement from the network link it is monitoring and stores the bandwidth information with a time stamp in the database. The resulting collection of measurements, ordered by time stamp, forms a training input to the forecasting subsystem (Neural network based) which generates a prediction of what the performance will be during a given time period.

2.1. Network Traffic Monitor

The network traffic must be periodically monitored and collected. NWS monitoring sub-system provides this functionality. It is an active measurement methodology that estimates the hop-by-hop available bandwidth between a source and the destination node on a single link. To monitor network links, the NWS conducts end-to-end network probes. One host opens a connection with another and sends a small message to measure the link round-trip time, and sends a large message to measure the throughput. Setting up the NWS to start monitoring the network traffic involves starting the NWS daemon processes that provide directory services, persistent storage, resource monitoring, and forecasting. Each of these hosts listens for service requests on a particular port. NWS host can be specified by giving the underlying machine and the port it's listening to. For measuring the network's TCP traffic, the TCP message monitor is the skill that needs to be employed. This skill monitors the TCP bandwidth and latency between each pair of a set of machines [3].

2.2. Network Traffic Pre-Processor

The main functionality of the network traffic data pre-processor is to process the raw traffic data collected by the NWS subsystem and produce a processed training data set [4]. This component has been implemented in java. The processData API takes the input file that contains the raw traffic data collected by the network traffic monitor and the bin size which is the frequency at which the user wants to make predictions as input and output a file that contains the timestamp, minimum, maximum, and average number of bits in one second in the specified bin size. The output is then passed into the generateFinalInputANN API which then produces the final input that contains all the information (timestamp, month, day, hour, minute, minimum number of bits in one second in that bin size, maximum number of bits in one second in that bin size, average number of bits in the past 1 row, 2 rows, ... 6 rows, average number of bits in one second in that bin size and the value to be predicted in step one) that are needed for neural network training.

2.3. Network Traffic Predictor

The main functionality of this component is to give a forecast of the network traffic using the traffic history collected by the Network Traffic Monitor. We use neural networks, with their remarkable ability to learn from examples and derive meaning from complicated or imprecise data, to extract patterns and detect trends of available bandwidth. Thus, this component uses multilayer perceptron neural network with backpropagation training in order to make the predictions. This component of NBP uses weka, a collection of machine learning algorithms for solving real-world data mining problems [5]. This component has been implemented in Java. This component creates a neural network. The neural network is then trained [4] using the processed data obtained by the network traffic pre-processor. The trained neural network is then used to make the actual predictions. The BandwidthPredictor class provides a wrapper over the weka's neural network implementation classes.

The ANN is trained and continually to be trained during the time. In general, the continued training process is incremental and can overlap with prediction. However, when a sharp change of communication occurs, a longer time is needed to retrain the ANN from the scratch. Simple statistic methods are temporarily used during the retaining period for online real time prediction when necessary, so the training and prediction process can be overlapped.

The exposed API is get_estimate and this method is a wrapper over weka's classifyInstance method of the class classifiers. The classifyInstance method then classifies the given instance and returns the most likely class for the instance.

2.4. Graphical User Interface

The GUI initiates the traffic prediction as a result of user input, trains the neural network and finally performs the prediction of the future traffic based on the past traffic data. The results are presented as a report in the GUI for user's analysis. The GUI also provides users with the accuracy of prediction. The GUI allows a user to choose NWS based predictions too. The GUI will initiate the real time traffic monitoring using the NWS monitoring sub-system.

The GUI gives the main functionalities such as Configuration, Traffic Monitoring and Prediction. The configuration panel allows the users to set the system configuration details. The monitor panel invokes the NWS time series query that leads to collecting data and performing NWS forecast. The prediction panel allows the user to perform the ANN based prediction. Table 1 shows the implementation specifications.

Table 1. Implementation Specifications

Implementation	Tools
Programming Language	Java
Programming Platform	Windows, Unix
Database Connectivity	JDBC
GUI Components	Swing and Awt
Charting Tool	Jchart
SSH Library	Mindterm's Secure Shell
Neural Network Toolkit	Weka

3. Experimental Results

We have conducted experiments with NBP to capture the online traffic and make predictions. To verify the efficiency of NBP, comparison is made with that of NWS.

The network traffic between mgt5.dotresearch.org and iit01.dotresearch.org has been monitored and captured using the NWS monitoring subsystem. The collected traffic is then fed into Network Traffic Predictor component of NBP in order to make NBP forecasts and the results are generated. Figure 1 shows the measured versus predicted bandwidth for various bin sizes. The traffic data size with one second interval measurement is 6.29MB. From the graphs, we can infer that the prediction results are better than the prediction result of NWS forecast for the same traffic data.

We have also conducted experiments on the NSF TeraGrid environment between different clusters [6]. TeraGrid is the world's largest, most comprehensive, distributed infrastructure for open scientific research. It is funded by NSF and currently includes nine partners: NCSA, SDSC, Argonne, CACR, PSC, ORNL, Purdue, Indiana, and TACC. Linux clusters at each site are tightly connected through a network that operates at 40 gigabits and has a total of more than 20 teraflops computing power. A comparison of NBP prediction with NWS forecasting is done on TeraGrid and the prediction results are presented below.

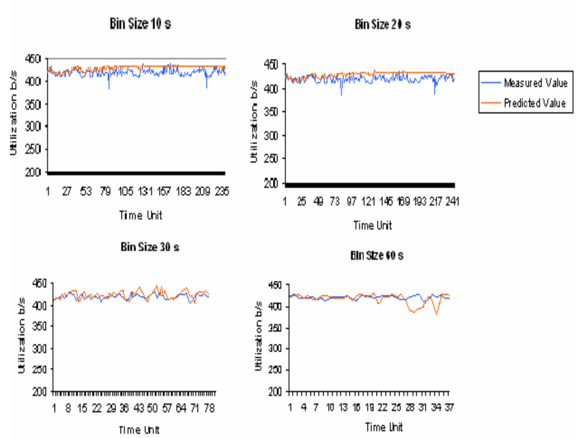

Figure 1. NBP Traffic Predictions

Table 2. NBP Vs. NWS Prediction Results

NBP PREDICTION COMPARISON WITH NWS					
ncsa.teragrid.org and sdsc.teragrid.org			sdsc.teragrid.org and uc.teragrid.org		
Bin Sizes	NWS	NBP	Bin Sizes	NWS	NBP
10	5.7%	5.4%	10	5.6%	4.1%
20	3.8%	3%	20	4%	2.6%
30	3.2%	2.4%	30	3.5%	3.6%
caltechncsa.teragrid.org and uc.teragrid.org			uc.teragrid.org and caltech.teragrid.org		
Bin Sizes	NWS	NBP	Bin Sizes	NWS	NBP
10	5.9%	5.8%	10	6.6%	5.4%
20	3.9%	3%	20	5.4%	4%
30	3.5%	2.6%	30	4.3%	6.6%
ncsa.teragrid.org and uc.teragrid.org			uc.teragrid.org and ncsa.teragrid.org		
Bin Sizes	NWS	NBP	Bin Sizes	NWS	NBP
10	4.1%	2.9%	10	7.3%	13.8%
20	2.8%	2.3%	20	3.5%	1.7%
30	2.4%	1.9%	30	3.4%	1.4%
sdsc.teragrid.org and ncsa.teragrid.org			uc.teragrid.org and sdsc.teragrid.org		
Bin Sizes	NWS	NBP	Bin Sizes	NWS	NBP
10	4.1%	3.6%	10	7.5%	4.1%
20	2.9%	2.3%	20	5.5%	4.5%
30	2.3%	2.3%	30	4.5%	3.8%

From Table 2, it can be inferred that the NBP prediction mechanism is superior to that of NWS. NBP is better than the NWS approach because the complex variable traffic can be well captured by the neural network. Performance predictions using NBP and NWS are made on the traffic data measured between the different nodes of the TeraGrid. The Figure 2 presents the comparison with NWS.

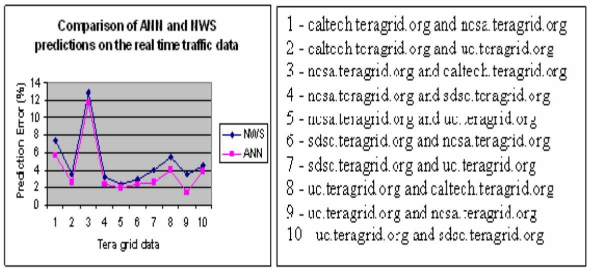

Figure 2. Comparison of NBP Prediction with NWS

We collected more traffic data between the different clusters of the TeraGrid infrastructure and carried out the traffic predictions. From the Table 3 and the Figure 3 it is obvious that NBP provides a better and consistent prediction results compared to that of NWS. Also, we can observe the NWS prediction error percent for 2 cases are over 100%. This is because of the high variability in the network traffic. The NWS fails to capture the pattern where as NBP can get trained with the traffic pattern and there by provide accurate results.

Table 3. Bandwidth Prediction on Tera Grid Data NBP Vs NWS

Different clusters of the Tera Grid	NBP	NWS
lemieux.psc.teragrid.org and sdsc.teragrid.org with message size 16	5.21%	10.25%
lemieux.psc.teragrid.org and sdsc.teragrid.org with message size 256	3.66%	3.54%
nsca.teragrid.org and sdsc.teragrid.org with message size 1	5.12%	121.9%
nsca.teragrid.org and sdsc.teragrid.org with message size 16	4.73%	109.7%
nsca.teragrid.org and sdsc.teragrid.org with message size 256	4.32%	4.45%
sdsc.teragrid.org and lemieux.psc.teragrid.org with message size 1	7.56%	8.65%
sdsc.teragrid.org and lemieux.psc.teragrid.org with message size 16	7.83%	8.48%
sdsc.teragrid.org and lemieux.psc.teragrid.org with message size 256	6.69%	7.5%
sdsc.teragrid.org and ncsa.teragrid.org with message size 1	3.54%	4.22%
sdsc.teragrid.org and ncsa.teragrid.org with message size 16	3.7%	4.15%

4. Conclusion and Future Work

Experimental results indicate that NBP provides an improved performance. The NBP prediction only takes 1.5 milliseconds in our experiments. The ANN mechanism used in NBP is a complement of the computing model proposed in [7] and will be used in Grid Harvest Service (GHS) [8] for performance prediction and task scheduling in a shared network environment. In the near future we plan to make NBP available online and work with network computing practitioners to apply NBP on engineering applications.

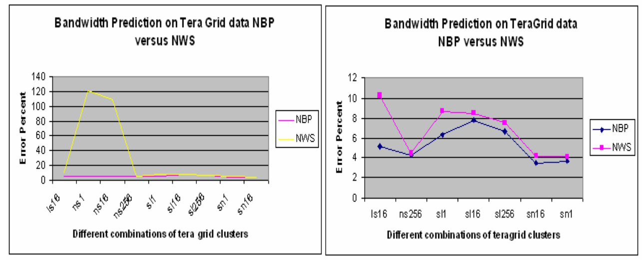

Figure 3. Bandwidth Prediction on Tera Grid data NBP Vs NWS

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