Effective Bandwidth Prediction through Statistical Technique over Heterogeneous Networks

Renuka Deshpande, Lata Ragha, Satyendra Kumar Sharma

Abstract*: *Real time Streaming Media (Video Streaming) applications are mostly popular on the mobiles and computers using Internet. Due to higher demand of video streaming through wireless network and mobile devices, video are being transmitted through various heterogeneous networks so as to efficiently deliver to the clients devices. This has resulted in the lower quality of real time video, since real time streaming media has quality of parameter requirements like high bandwidth, low packet loss ratio, higher delay and jitter. Streaming media such as video through heterogeneous networks has more challenges due to unreliable wireless networks and device mobility; moreover bandwidth, delay and loss are unknown in advance and are unbounded. In this paper, effective bandwidth prediction through statistical technique over heterogeneous wireless communication networks is proposed. Statistical technique offers computationally efficient bandwidth prediction with reasonably better accuracy. Especially with mobile devices with limited computational power and battery life, necessitates better bandwidth prediction with efficient but computationally simpler algorithms. Bandwidth predictions assist in selecting effective network for video streaming when various heterogeneous networks are available. Detailed bandwidth prediction algorithm is presented with use of quality of service (QoS) parameters data sets available online.

Keywords*: *Bandwidth prediction, quality of service parameters, statistical technique, heterogeneous networks.

I. INTRODUCTION

Advances in networking technologies and video encoding / decoding algorithms in last few decades facilitated the real time video streaming, video calls and conferencing [1 - 3]. Due to popularity of wired and wireless networks such as WiFi, Wimax and Bluetooth, real time video streaming and video delivery applications such as Youtube and Netflix have found to be mostly used through cellular networks. The essential task for real time video streaming through cellular networks is to achieve at the same time high data rate, bandwidth and low delay for complete video transmission over the extremely volatile cellular networks with totally unknown quality of service parameters such as bandwidth, packet delay and loss. One of the most important issue for transmission of video over cellular networks is with increasing the data rate beyond the available bandwidth leads to self-congestion, and insupportable packet delays, and subsequently frame delays [4 – 5]. It results in loss of frames due over delay in receiving frames. Whereas a conventional data rate completely leads to under-utilization of the cellular networks and finally results in lower quality than that would be possible. However with the available massive information about the network, accurate topology inference and up-to-date estimation of every link over the network may be not possible as well. But fortunately it may also be not necessary to estimate [6].

It is essentially required that the video buffering data rate must be greater than or equal to bandwidth for real time video streaming. Movement of a mobile data-enabled device from a SSA to a WSA has a significant detrimental effect on the network bandwidth available to the device. Since the bandwidth was greater in the SSA, the bit-rate of the video will likely be significantly higher than the bandwidth available in the WSA. The sudden bandwidth deficit creates QoS issues for the stream service once the stream is starved of buffered data specifically pauses in playback [7 – 9]. Mostly data rate limitation techniques and bandwidth sharing are applied in wireless networks. However it is necessary to consider real time and future bandwidth constraints, location of the device specific to cellular networks [10]. Adaptive bit-rates have now been standard for many real time video streaming applications, with the standardization of the Scalable Video Content (SVC) MPEG-4 (H.264) extension. It thus allows for an appropriate quality of video to be chosen with respect to the available bandwidth. SVC is especially beneficial and effective for video streaming with various video qualities to viewers with chosen high or low bandwidth availability, without the need of separate encoded video files for each data rate [11].

However with the availability of effective and sufficient real time bandwidth fluctuation algorithm, the received video may suffer from poor quality of service parameters especially with the sudden drop in the bandwidth occurs. Switching to WSA does initiate lower bit rate thereby increasing frame loss. But if the sudden drop in bandwidth is due to loss of mobile signal would indefinitely delay the video stream and introduce pause in the playback. Thus during both the issues of switching to WSA and loss in mobile signal would lead to frame loss and starvation of the

Revised Manuscript Received on October 05, 2019.

* Correspondence Author

Renuka G. Deshpande*, Research Scholar, Pacific Academy of Higher Education and Research, Udaipur, India. Email:renukagdeshpande@gmail.com

Dr. Lata Ragha, Head of Department, Department of Computer Engineering at Fr. C. Rodrigues Institute of Technology, Vashi, Navi Mumbai, Maharashtra, India. Email: lata.ragha@gmail

Dr. Satyendra Kumar Sharma, Director, Modern Institute of Technology, Research Centre, Alwar ,Rajasthan, India**.** Email: skpacific323@gmail.com

existing video stream buffer, and thus cause a pause in playback of video. Also there is possibility of no attempt to prevent pause through any methods to access data or restore lost bandwidth and signal [12]. In this paper, location based bandwidth prediction technique is proposed. It demonstrates that allows for dynamic data transmission rate limitations within a video streaming service. In this paper, effective bandwidth prediction through statistical technique over heterogeneous wireless communication networks is proposed. Statistical technique offers computationally efficient bandwidth prediction with reasonably better accuracy. Especially with mobile devices with limited computational power and battery life, necessitates better bandwidth prediction with efficient but computationally simpler algorithms. Bandwidth predictions assist in selecting effective network for video streaming when various heterogeneous networks are available. Detailed bandwidth prediction algorithm is presented with use of quality of service (QoS) parameters data sets available online.

II. Related Work

Adaptive bit-rates have now been standard for many real time video streaming applications, with the standardization of the Scalable Video Content (SVC) MPEG-4 (H.264) extension. It thus allows for an appropriate quality of video to be chosen with respect to the available bandwidth. SVC is especially beneficial and effective for video streaming with various video qualities to viewers with chosen high or low bandwidth availability, without the need of separate encoded video files for each data rate [11]. A HTTP based video-streaming service was demonstrated in [13] that practices a client-side algorithm to determine worst, best and appropriate bandwidth for the available networks. Extensive simulations of the above algorithm were successfully performed on the mobile networks with varying bandwidths. It was observed that the instant when mobile network bandwidth becomes restricted or drops, the request for the SVC begins to omit layers to lower the bit-rate in an attempt to ensure the bandwidth is equal to, or greater than, the received bit-rate. A proactive congestion control scheme for real time video streaming in cellular networks was demonstrated in [14]. The proposed model considers a cellular links as single-server queues emptied out by a doubly stochastic service process [14]. For the available bandwidth estimation, no particular time-evolution model for the link capacity is explored and it only focuses on congestion control without considering video adaptation rate. Work on complete bandwidth estimation using end-to-end bandwidth measurements is mostly not addressed, it may be due to complete measurement of bandwidth is not possible or identical. In paper [15 - 16] performed coarse grained bandwidth estimation based on clustering measurements between peer-to-peer clients. The issue of bandwidth estimation on multicast tree requires active probing. Mostly data rate limitation techniques and bandwidth sharing are applied in wireless networks. However it is necessary to consider real time and future bandwidth constraints, location of the device specific to cellular networks [10]. Computationally efficient bandwidth prediction with reasonably better accuracy is necessary especially with mobile devices with limited computational power and battery life. Statistical algorithms assist in low computational complexity as compared with other algorithms.

III. BANDWIDTH PREDICTION CRITERIA

In this paper, we adopt simple and generic statistical model for heterogeneous networks for bandwidth prediction. Statistical technique is precisely the tool to give us approximate solutions when the processes we're interested in are highly complex or unknown in their true forms. The end to end bandwidth observations are modeled as realizations of independent random variables Y generated along the path A, each network component J produces a bandwidth contribution, which is a realization of a random variable drawn independently from a probability distribution associated with component. Then, for the non-additive metric bandwidth,

$$Y_i = \min X_{ij\ j \in A} \tag{1}$$

It is necessary to understand that there is no reasonable transformation that makes bandwidth additive, since bandwidth is determined by the smallest restricted access on the path. It makes the problem more difficult problem, therefore a likelihood function needs to be derived. The end-to-end bandwidth is given by the smallest component as mention in equation (1). Thus the probability that component J delivers high bandwidth to produce desire Y is given as equation (2).

$$P = \int_{y_i}^{\infty} p_j(x)dx \tag{2}$$

Thus the probability that all the components deliver high bandwidth is given as equation (3)

$$P = \prod_{j \in A_i} \int_{y_i}^{\infty} p_j(x)dx \tag{3}$$

Finally to determine the likelihood function by applying derivative, we obtain equation (4) as

$$P_i(y_i) = \frac{d}{dy_i} \prod_{j \in A_i} \int_{y_i}^{\infty} p_j(x)dx \tag{4}$$

This requires a proper design of the study, an appropriate selection of the study sample and choice of a suitable statistical test. The extent to which the observations cluster around a central location is described by the central tendency and the spread towards the extremes is described by the degree of dispersion. If we rank the data and after ranking, group the observations into percentiles, we can get better information of the pattern of spread of the variables. To make the interpretation of the data simple and to retain the basic unit of observation, an exponential moving average (EMA) is a type of moving average (MA) that places a greater weight and significance on the most recent data points. The exponential moving average is also referred to as the exponentially weighted moving average. An exponentially weighted moving average reacts more significantly to recent value changes than a simple moving average (SMA), which applies an equal weight to all observations in the period. The EMA gives a higher weighting to recent values, while the SMA assigns equal weighting to all values. The weighting given to the most recent value is greater for a shorter-period EMA than for a longer-period EMA. For example, an 18.18% multiplier is applied to the most recent value data for a 10-period EMA, whereas for a 20-period EMA, only a 9.52% multiplier weighting is used. The major difference between an exponential moving average and a simple moving average is the sensitivity each one shows to changes in the data used in its calculation. More specifically, the EMA gives a higher weighting to recent values, while the SMA assigns equal weighting to all values. Since EMAs place a higher weighting on recent data than on older data, they are more reactive to the latest value changes than SMAs are, which makes the results from EMAs timelier and explains why the EMA is the preferred average.

IV. EXPERIMENTAL RESULTS

Web service QoS dataset describes real-world QoS evaluation results from 339 users on 5,825 Web services [17] and Web service QoS dataset describes real-world QoS evaluation results from 142 users on 4,500 Web services over 64 different time slices (at 15-minute interval) [18]. The presented algorithm was evaluated on the above two QoS datasets. Web service QoS datasets includes a number of properties, such as response time and throughput. QoS parameters such as response time and throughput that includes bandwidth may change randomly for various users. Mainly it depends on unpredictable internet connections and heterogeneous network environment. The estimation of throughput is focused in this work. Throughput is defined as the average rate of successful message size (here in bits) delivery over a communication channel per second. In this experiment bandwidth prediction was performed based on the statistical technique through calculation of various parameters such as mean, min, max, mod, median, standard deviation, variance and covariance. The entire dataset in web services consist of 5825 and 4500 entries of throughput and response time. These throughput entries were divided into segments of data consisting 100, 250 and 400 entries. Each segments were analyzed through calculation of statistical parameters as given in equation (5) mean (m), (6) median (mn), (7) max, (8) min, (9) median and (10) mod.

$$m(x) = \frac{1}{n}\sum_{i=1}^{n} x(i) \tag{5}$$

$$mn(x) = median\big(x(i)\big) i = 1, - - -, n \tag{6}$$

$$max(x) = max\big(x(i)\big) i = 1, - - -, n \tag{7}$$

$$min(x) = max\big(x(i)\big) i = 1, - - -, n \tag{8}$$

$$med(x) = median\big(x(i)\big) i = 1, - - -, n \tag{9}$$

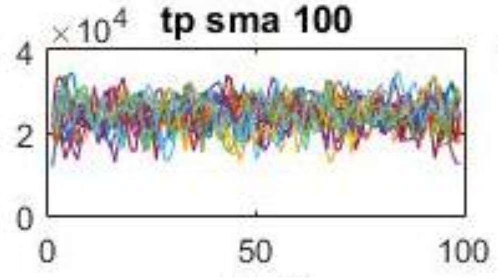
$$mod(x) = \Big(mean\big(x(i)\big) - median\big(x(i)\big)\Big) \tag{10}$$

It forms the fundamental statistical approach towards prediction which was supported through standard deviation, variance and covariance given equation (11), (12) and (13) respectively.

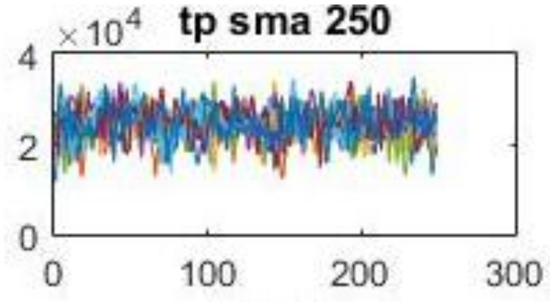
$$\mathrm{sd}(x) = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}\big(x(i) - mn(i)\big)^2} \tag{11}$$

$$\mathrm{var}(x) = \frac{1}{n-1}\sum_{x_i x_{i+1} \in A}\Big(x(i) - \frac{1}{n-1}\sum_{i=1}^{n} x(i+1)\Big)^2 \tag{12}$$

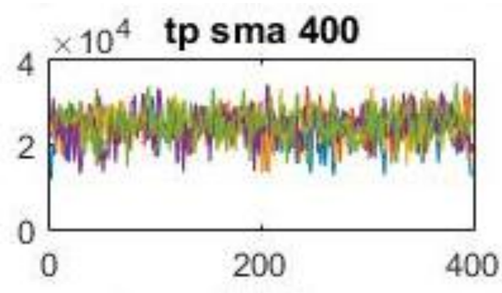
$$\mathrm{covar}(x) = \frac{1}{n}\sum\big(x(i) - mn\big)\big(x(i+1) - mn\big) \tag{13}$$



(a) Simple moving average for 100 samples



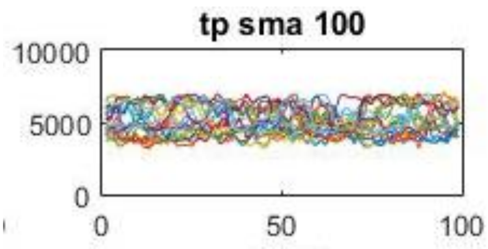
(b) Simple moving average for 250 samples



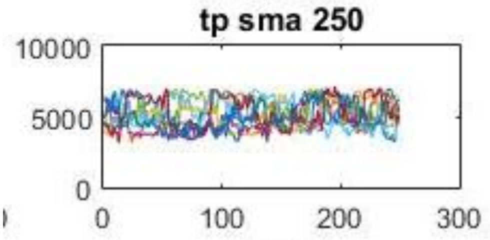
(c) Simple moving average for 400 samples

Fig. 1 Simple moving average for data set 1

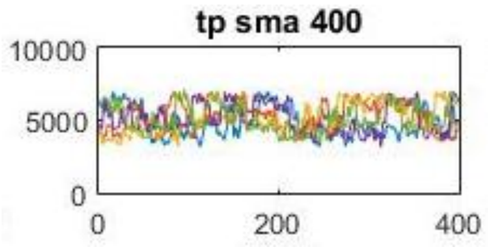
The above parameters were calculated to final evaluate the simple moving average (sma) and exponential moving average (ema). The simple moving average calculated for variations.



(a) Simple moving average for 100 samples

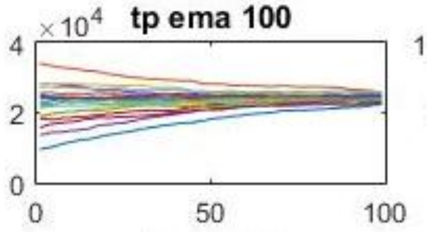


(b) Simple moving average for 250 samples

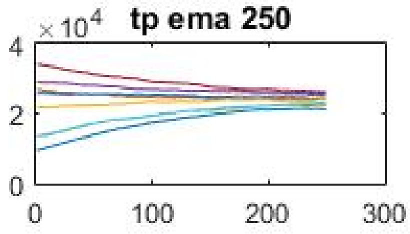


(c) Simple moving average for 400 samples

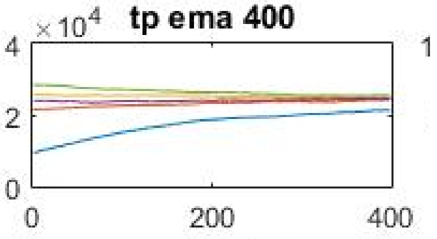
Fig. 2 Simple moving average for data set 2



(a) Exponential moving average for 100 samples

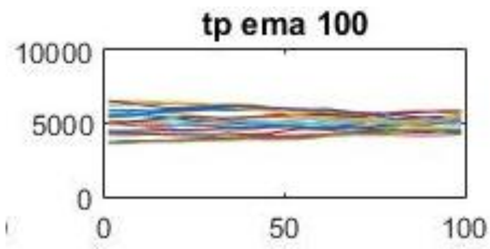


(b) Exponential moving average for 250 samples

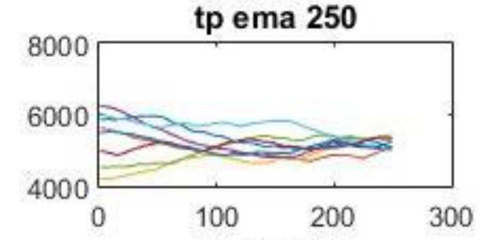


(c) Exponential moving average for 400 samples

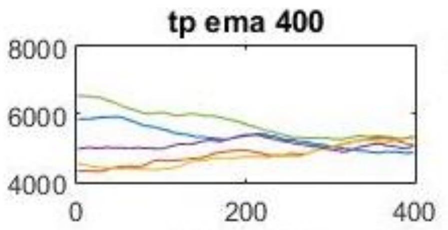
Fig. 3 Exponential moving average for data set 1



(a) Exponential moving average for 100 samples



(b) Exponential moving average for 250 samples



(c) Exponential moving average for 400 samples

Fig. 4 Exponential moving average for data set 2

Fig. 1 and 2 shows the sma for all samples of data set segmented into 100, 250 and 400 entries for both web services. The figure 1 and 2 clearly indicates the change of predicted value from the actual value. Thus it is not efficient to predict correct results from it. It was observed that the exponential moving average shows the better conversion into the prediction of bandwidth. Figure 3 and 4 shows the ema for the samples of data set segmented into 100, 250 and 400 entries for both web services. Also it clearly indicates the conversion into the values for most of the cases. Exponential moving average predicts almost correct bandwidth for samples with 400 entries as compared to 100 and 250 entries. Comparison of the results for both the dataset is tabulated in table 1. Also it was observed that increasing the number of samples per segment increases better prediction rate or accuracy. Thus it is very much understood that statistical parameters assist in better bandwidth prediction with lower computational complexity that may be desired at the device given with limited battery life.

V. CONCLUSION

Streaming media such as video through heterogeneous networks has more challenges due to unreliable wireless networks and device mobility; moreover bandwidth, delay and loss are unknown in advance and are unbounded. In this paper, effective bandwidth prediction through statistical technique over heterogeneous wireless communication networks is proposed. Especially with mobile devices with limited computational power and battery life, necessitates better bandwidth prediction with efficient but computationally simpler algorithms. Bandwidth predictions assist in selecting effective network for video streaming when various heterogeneous networks are available. Detailed bandwidth prediction algorithm is presented with use of quality of service (QoS) parameters data sets available online. More specifically, the EMA gives a higher weighting to recent values, while the SMA assigns equal weighting to all values. Since EMAs place a higher weighting on recent data than on older data, they are more reactive to the latest value changes. . Exponential moving average predicts almost correct bandwidth for samples with 400 entries as compared to 100 and 200 entries. Also it was observed that increasing the number of samples per segment increases better prediction rate or accuracy. Statistical technique offers computationally efficient bandwidth prediction with reasonably better accuracy.

Table 1. Results obtained for bandwidth and its comparison with actual measured value.

(a) Dataset 1 bandwidth in KB

Samples	Measured	Calculated (SMA)	Calculated (EMA)
100	66.25	110	68.04
250	79.98	121	78.2
400	88.75	131	88

(b) Dataset 2 bandwidth in KB

Samples	Measured	Calculated (SMA)	Calculated (EMA)
100	5.444	5.033	5.445
250	4.606	5.117	4.97
400	5.048	5.736	5.13

REFERENCES

1. Mohammed A Qadeer, Rehan Ahmad, Mohd Siddique Khan, Tauseef Ahmad, “Real-Time Video Streaming over Heterogeneous Networks”, International Conference on Advanced Communication Technology, Vol.2, March 2009.
2. Scott Pudlewski, Nan Cen,Zhangyu Guan and Tommaso Melodia, “Video Transmis-sion Over Lossy Wireless Networks: A Cross-Layer Prespective”, IEEE Journal of Se-lected Topics in Signal Processing, Vol. 9, No. 1, Pg. 6-21, Feburary 2015.
3. Jaydip Sen and Shomik Bhattacharya, “A Survey on Cross-Layer Design Frameworks for Multimedia Applications over Wireless Networks”, International Journal of Com-puter Science and Information Technology, Vol. 1, No. 1, Pg. 29-42, June 2008.
4. Hongli Luo and Mei-Ling Shyu, “Quality of Service Provision in Mobile Multimedia –A Survey”, Human-centric Computing and Information Sciences, a Springer Open Journal, Vol. 1, No. 1, November 2011.
5. Jen-Yeu Chen, Chia-Wen Chiu, Gwo-Long Li, Mei-Juan Chen, “Burst-Aware Dy-namic Rate Control for H.264/AVC Video Streaming”, IEEE Transactions on Broad-casting, Vol. 57, No. 1,Pg. 89-93, March 2011.
6. Hilmi E Egilmez, Seyhan Civanlar and A. Murat Tekalp, “An Optimization Frame work for QoS-Enabled Adaptive Video Streaming Over OpenFlow Networks”, IEEE Transactions on Multimedia, Vol. 15, No. 3, Pg. 710-715, April 2013.
7. A. Balk, D. Maggiorini, M. Gerla and M. Y. Sanadidi, “Adaptive MPEG-4 Video Streaming with Bandwidth Estimation”, Quality of Service in Multiservice IP Net works, Second International Workshop, QoS-IP 2003, February 2003.
8. Wen Ji, Zhu Li and Yiqiang Chen, “Joint Source-Channel Coding and Optimization for Layered Video Broadcasting to Heterogeneous Devices”, IEEE Transactions on Multimedia, Vol. 14, No. 2, Pg. 443-455, April 2012.
9. Thomas Dreibholz, Martin Becke, Jobin Pulinthanath, Erwin P. Rathgeb, “Implemen-tation and Evaluation of Concurrent Multipath Transfer for SCTP in the INET Framework”, 3rd International ICST Conference on Simulation Tools and Techniques, March 2010.
10. Jianxin Liao, Jingyu Wang, Tonghong Li, Xiaomin Zhu, “Introducing multipath selec-tion for Concurrent Multipath Transfer in the Future Internet”, Elsevier Computer Networks 55 (2011), Pg. 1024–1035.
11. Jeeva Susan Jacob, Preetha K.G, “A QoS Based Network Selection Scheme for 4G Systems with Preplanner for Emergency Services,” in IEEE International Conference On Computing, Communication and Networking Technologies, India, 2013.
12. Liang Ma, Ting He, Ananthram Swami, Don Towsley, Kin K. Leung, and Jessica Lowe. Node failure localization via network tomography. In Proc. IMC. ACM, October 2014.
13. Tappayuthpijarn, K.; Stockhammer, T.; Steinbach, E., "HTTP-based scalable video streaming over mobile networks," Image Processing (ICIP), 2011 18th IEEE International Conference on , vol., no., pp.2193,2196, Sept. 2011.
14. K. Winstein, A. Sivaraman, and H. Balakrishnan, “Stochastic forecasts achieve high throughput and low delay over cellular networks,” in USENIX Symposium on Networked Systems Design and Implementation, 2013, pp. 459–471.
15. Kiril Dichev, Fergal Reid, and Alexey Lastovetsky, “Efficient and reliable network tomography in heterogeneous networks using bittorrent broadcasts and clustering algorithms’, in Journal Scientific Programming - Selected Papers from Super Computing, Volume 21 Issue 3-4, July 2013, pp 79-92.
16. E. Baralis, A. Bianco, T. Cerquitelli, L. Chiaraviglio and M. Mellia, "NetCluster: A Clustering-Based Framework for Internet Tomography," IEEE International Conference on Communications, Dresden, 2009, pp. 1-5.
17. Website http://wsdream.github.io/dataset/wsdream_dataset1.html
18. Website http://wsdream.github.io/dataset/wsdream_dataset2.html

AUTHORS PROFILE

Prof. Renuka G. Deshpande is Research Scholar at Pacific Academy of Higher Education and Research University, Udaipur .India. She has received her B.E. and M.E. degree in Computer Engineering from Pune and Mumbai University respectively. She is currently working as Associate Professor at Shivajirao S. Jondhale College of Engineering , Dombivli East, Maharastra. Her research interests include Heterogeneous Networks , System Security, Parallel and Distributed Computing.

Dr. Lata L. Ragha has received her Ph. D. degree from Jadavpur University, Kolkata in 2011. She received her B. E. and M.Tech degree in Computer Science and Engineering from Karnataka University in 1987 and Vishveshwarai Technological University, Karnataka, in 2000 respectively. She is currently working as Professor and Head, Department of Computer Engineering at Fr. C. Rodrigues Institute of Technology, Vashi, Navi-Mumbai. Her research interests include Networking, Security, Internet Routing, and Data Mining. She has more than 100 research publications in International Journals and conferences.

Dr. Satyendra Kumar Sharma has received his Ph. D degree from J R N Rajasthan Vidyapeeth (Deemed) University Udaipur. He has received his M.Tech. degree from Roorkee University, Roorkee. He has received his B.E. degree from Marathwada University, Aurangabad. He is currently working as Director at Modern Institute of Technology, Research Centre, Alwar ,Rajasthan, India. His research interests include Computer Networks, Heterogeneous Networks, System/ Information Security, Software Engineering, Wireless Sensor Networks. He has more than 50 research publications in International Journals and Conferences. He has written five books.