Analysis of Users Web Browsing Behavior Using Markov chain Model

Diwakar Shukla
Department of Mathematics and Statistics, Sagar University, Sagar M.P. 470003, India.
e-mail: diwakarshukla@rediffmail.com
Rahul Singhai
International Institute of Professional Studies, D.A.V.V. Indore, (M.P.), India.
e-mail: singhai_rahul@hotmail.com

---ABSTRACT---
In present days of growing information technology, many browsers available for surfing and web mining. A user has option to use any of them at a time to mine out the desired website. Every browser has pre-defined level of popularity and reputation in the market. This paper considers the setup of only two browsers in a computer system and a user prefers to any one, if fails, switches to the other one .The behavior of user is modeled through Markov chain procedure and transition probabilities are calculated. The quitting to browsing is treated as a parameter of variation over the popularity. Graphical study is performed to explain the inter relationship between user behavior parameters and browser market popularity parameters. If rate of a company is lowest in terms of browser failure and lowest in terms of quitting probability then company enjoys better popularity and larger user proportion.

I. INTRODUCTION

A browser has many salient features like user friendliness, portability, hardware freedom, efficiency, legal precedence, low cost, data privacy etc. One of the efficiency parameter relates to quick and speedy connectivity of web sites. When connectivity fails with certain probability it is termed as browser failure (BF). Features for attractiveness of a browser in the market is termed as quality of service (QOS).

Stochastic modeling approach to a computer system is due to Naldi (2002), Shukla and Gadewar (2007), Shukla et al. (2007). In contribution Shukla and Jain (2007) stochastically modeled multilevel queue scheduling and one more similar extended by Shukla et al. (2010 d & g) in the data model setup. Catledge and Pitkow (1995) examinied browsing stratigies by a method of characterization. A Markov model application is adopted by Deshpande and Karpis (2004) over web page access for computing and prediction purpose. A usefull contribution in similar lines is due to Pirolli (1996). In web mining area, Pitkow (1997) presented a search procedure in the scenario of World Wide Web. Detailed description over different data mining techniques is due to Han and Kamber (2001) and over the topic of stochastic process is due to Medhi (1991).

Application of Markov Chain model on ready queue processing time estimation presented by Shukla et al. (2010

b & c). Srivastav, Despande and Tan (2000) discussed basic concepts on discovery and applications of usage pattern for web mining. Shukla et al. (2010 g) applied the Markov Chain model approach on message flow probability computations and Shukla et al. (2009 a, b, c) have similar application over the study of Internet share distribution.

Motivation derived from these to model the user browsing behavior for web-site of Internet. This paper presents a simple stochastic model when two browser owner companies are in competition for more and more popularity and attractiveness in the market. We define browser failure as the failure of opening web site, non-compatibility to operating system, lack of appropriate software and its complexity. The general behavior of a user is to choose one browser out of two which is most popular among people and provides lowest failure rate (or blocking). Objectives of this content are:

1. To examine the effect of Quality of Service (QOS) on browser popularity in public;

2. To study the effect of browser failure on browser sharing.

Let $\{X_n , n \geq 0\}$ be a Markov chain with state space $\{C, Q, B_1, B_2 , S\}$ where

State C: represents connecting state.
State Q: user quitting from the process.
State B_1: user attempts to surf through browser B1.
State B_2: user attempts to surf through browser B_2.

State S: success for connectivity and surfing.

The Xn denotes the position of random variable X in the state space at the nth connectivity attempt made by the user.

II. ASSUMPTIONS FOR USER BROWSING BEHAVIOR

(1) The user attempts for dial up connection to use internet. If the connection is not established, user quits with the probability Pc.

(2) When connection is made user chooses any one of browsers B_1, B_2 with the probability P and 1–P respectively.

(3) User navigates to any one browser at a time when successfully opened.

(4) B_i (i=1,2) failure occurs due to non-opening of any site through B_i. Then user either quits (with probability Pq) or switches to the next browser.

(5) Switching between browsers are on attempt by attempt basis (n=1,2,3….).

(6) Initial preference is based on quality of services and variety of facility features contained in both browsers.

(7) Failure probability of a browser B_1 is b_1 and of B_2 is b_2.

(8) Transition probability of surfing through B_1, being completed in a single attempt is $(1 - b_1)$.

(9) Absorbing state (transition from a state to itself) probability is 1. No transition from this state occurs.

Under these assumptions user's browsing behavior is discussed by a Markov Chain Model (see fig.2.1) in which the transition probabilities are on the arcs connecting the circles and representing the chain states.
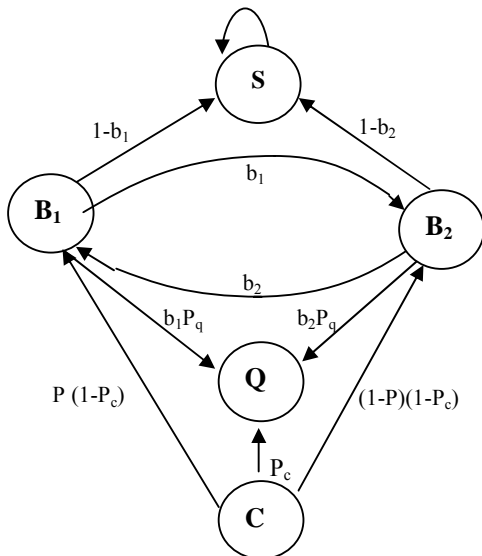

Fig. 2.1 [Transition Diagram of user browsing]

The initial conditions n=0, (state probability before the first surf attempt) are:

$$P[X^{(0)} = C] = 1$$
$$P[X^{(0)} = B_1] = 0$$
$$P[X^{(0)} = B_2] = 0 \qquad \Biggr\} \quad …(2.1)$$
$$P[X^{(0)} = S] = 0$$
$$P[X^{(0)} = Q] = 0$$

The unit-step transition probability matrix is:

	B_1	B_2	S	Q	C
B_1	0	$b_1(1-b_1)$	$(1-b_1)$	$b_1 P_q$	0
B_2	$b_2(1-P_{q1})$	0	$(1-b_2)$	$b_2 P_q$	0
S	0	0	1	0	0
Q	0	0	0	1	0
C	$P(1-P_c)$	$(1-P)(1-P_c)$	0	P_c	0

…(2.2)

Table: 2.1 [Transition Probability Matrix]

Transition probabilities over multiple attempts are:

For n=1,

$$P[X^{(1)} = B_1]$$
$$= P[X^{(0)} = C]P[X^{(1)} = B_1 | X^{(0)} = C]$$
$$= P.(1 - P_c) \qquad …(2.3)$$

$$P[X^{(1)} = B_2]$$
$$= P[X^{(0)} = C]P[X^{(1)} = B_2 | X^{(0)} = C]$$
$$= (1 - P)(1 - P_c) \qquad …(2.4)$$

$$P[X^{(1)} = Q]$$
$$= P[X^{(0)} = C] P[X^{(1)} = Q | X^{(0)} = C]$$
$$= P_c \qquad …(2.5)$$

For n=2,

$$P[X^{(2)} = B_1]$$
$$= P[X^{(1)} = B_2]P[X^{(2)} = B_1 | X^{(1)} = B_2]$$
$$= P[X^{(0)} = C]P[X^{(1)} = B_2 | X^{(0)} = C][b_2(1 - P_q)]$$
$$= 1.[(1 - p)(1 - p_c)]b_2(1 - p_q)$$
$$= [b_2(1 - P)(1 - P_c)(1 - P_q)] \qquad …(2.6)$$

For n=3,

$$P\left[X^{(3)} = B_1\right]$$

$$= P\left[X^{(2)} = B_2\right]P\left[X^{(3)} = B_1 \mid X^{(2)} = B_2\right]$$

$$= P\left[X^{(1)} = B_1\right]P\left[X^{(2)} = B_2 \mid X^{(1)} = B_1\right]\left[b_2\left(1 - P_q\right)\right]$$

$$= \left[P\left(1 - P_c\right)\right]b_1\left(1 - P_q\right)\left[b_2\left(1 - P_q\right)\right]$$

$$= b_1 b_2 P\left(1 - P_c\right)\left(1 - P_q\right)^2 \qquad \ldots(2.7)$$

$$\boxed{\begin{array}{l} P\left[X^{(2n)} = B_1\right] \\ = b_1^{n-1} b_2^n (1-P)(1-P_C)\left(1-P_q\right)^{2n-1}; n > 0 \end{array}} \qquad \ldots(2.8)$$

$$\boxed{\begin{array}{l} P\left[X^{(2n+1)} = B_1\right] \\ = \left(b_1 b_2\right)^n P\left(1 - P_C\right)\left(1 - P_q\right)^{2n}; n > 0 \end{array}} \qquad \ldots(2.9)$$

Similarly, for browser B_2

$$P\left[X^{(2n)} = B_2\right]$$

$$= b_1^n b_2^{n-1} P\left(1 - P_C\right)\left(1 - P_q\right)^{(2n-1)}; n > 0 \qquad \ldots(2.10)$$

When n is odd

$$P\left[X^{(2n+1)} = B_2\right]$$

$$= \left(b_1 b_2\right)^n (1-P)\left(1 - P_C\right)\left(1 - P_q\right)^{2n}; n > 0 \qquad \ldots(2.11)$$

III. CATEGORIZATION OF USER:

Based on blocking in web surfing user categories are

(1) **Faithful Browser User:** - who sticks with any one browser chosen in first attempt (the user who is not interested to toggle in between browsers).

(2) **Impatient Browser User:** - who frequently switches between two available browsers. He does not stick surff with any one browser.

If B_1 selected, it's browser failure probability is b_1 and if B_2 selected, blocking probability is b_2. Average blocking probability for faithful users (when $n > 1$) is

$$B_f = Pb_1 + \left(1 - P\right)b_2 \qquad \ldots(3.1)$$

For Impatient user the browser failure probability depends on number of attempts. At the nth attempt this is (when $n > 1$)

$$B_i^{(n)} = \frac{P[X^{(n-1)} = B_1].b_1 + P[X^{(n-1)} = B_2].b_2}{P[X^{(n-1)} = B_1] + P[X^{(n-1)} = B_2]} \ldots(3.2)$$

Since the state probability for B_1 & B_2 at the nth attempt depends whether n is even or odd, we can have two expressions.

$$B_i^{(n\ even)} = \frac{(1-P_c)(1-P_q)^{n-1}b_2}{\left\{\begin{array}{l}(1-P)(1-Pc)\sqrt{b_1^{\,n-2}}\sqrt{b_2^{\,n}}(1-Pq)^{n-1}\\ +P\sqrt{b_1^{\,n}}\sqrt{b_2^{\,n-2}}(1-P_c)(1-P_q)^{n-1}\end{array}\right\}}$$

$$= \frac{b_1 b_2}{Pb_1 + (1-P)b_2} \qquad \ldots(3.3)$$

$$B_i^{(n\ odd)} = \frac{\left\{\begin{array}{l}P\sqrt{(b_1 b_2)^{n-1}}(1-P_c)(1-P_q)^{n-1}.b_1\\ +(1-P)\sqrt{(b_1 b_2)^{n-1}}(1-P_c)(1-P_q)b_2\end{array}\right\}}{\left\{P\sqrt{\begin{array}{l}(b_1 b_2)^{n-1}(1-P_c)(1-P_q)^{n-1}\\ +(1-P)\sqrt{(b_1 b_2)^{n-1}}(1-P_c)(1-P_q)^{n-1}\end{array}}\right\}}$$

$$= \frac{Pb_1 + (1-Pb_2)}{P + (1-P)} = \left[Pb_1 + (1-P)b_2\right] \qquad \ldots(3.4)$$

With equations (3.1) & (3.4) the average blocking (congestion) probabilities of faithful user (B_f) are equal. Since the geometric mean of the blocking probabilities b_1 and b_2 is smaller than their weighted sum (if $b_1 \neq b_2$) i. e.

$$\sqrt{b_1 b_2} < Pb_1 + (1-P)b_2 \Rightarrow P(b_1 - b_2) > \sqrt{b_1 b_2} - b_2$$

$$\left.\begin{array}{ll}\Rightarrow P > \dfrac{\sqrt{b_1 b_2} - b_2}{(b_1 - b_2)} & \text{if}(b_1 > b_2)\\[4mm] \Rightarrow P < \dfrac{\sqrt{b_1 b_2} - b_2}{(b_1 - b_2)} & \text{if}(b_1 < b_2)\end{array}\right\} \qquad \ldots(3.5)$$

The equations (3.3) and (3.4) are similar to Naldi (2002).The strategy adopted by the impatient user is in fig. 3.1, 3.2 and 3.3 shown in the regions of (b_1, P) plane where the impatient user's behavior is favored when the B_2's blocking probability is 0.02, 0.04 and 0.08 respectively.
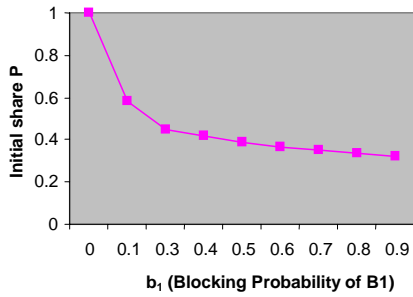
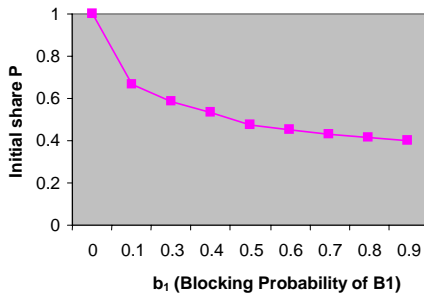**Fig. 3.1 Favoured strategies (when $b_2 = 0.02$)**

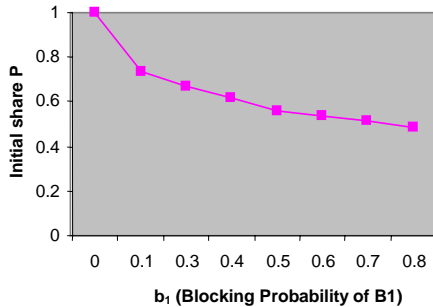**Fig. 3.2 Favoured strategies (when $b_2 = 0.04$)**

Fig. 3.3 Favoured strategies when ($b_2 = 0.08$)

The browser failure probability is inversely proportional to initial choice of user (see fig 3.1 to 3.3), but when blocking due to other browser is high the share of first browser increases. We can express that

$$P \propto \frac{1}{b_1} \quad and \quad P \propto b_2 \quad For \ B_1$$

The competitor browser failure if high, produces gain in user's proportion for that browser.

IV. BROWSER SHARING:

The probability that navigation successfully starts with browsers B_1 at the nth attempt is:

$$P_1^{(n)} = P\big[X^{(n-1)} = B_1\big] P\big[X^{(n)} = S \big| X^{(n-1)} = B_1\big]$$

$$n > 0 \quad ...(4.1)$$

$$P_1^{(n)} = (1 - b_1) \sum_{i=1}^{n} P\big[X^{(i-1)} = B_1\big] \qquad ...(4.2)$$

Let $\quad b_1 b_2 (1 - P_q)^2 = r$

$$P_1^{(1)} = (1 - b_1) \sum_{i=0}^{1} P\big[X^{(i)} = B_1\big] = (1 - b_1) = 0 \quad ...(4.3)$$

$$P_1^{(2)} = (1 - b_1) \sum_{i=0}^{1} P\big[X^{(i)} = B_1\big]$$

$$= (1 - b_1)\big[P\big(X^{(0)} = B_1\big) + P\big(X^{(1)} = B_1\big)\big]$$

$$= (1 - b_1)\big[0 + P(1 - P_C)\big] = (1 - b_1)\big[P(1 - P_C)\big] \quad ...(4.4)$$

$$P_1^{(3)} = (1 - b_1) \sum_{i=0}^{2} P\big[X^{(i)} = B_1\big]$$

$$= (1 - b_1)\big[P\big(X^{(0)} = B_1\big) + P\big(X^{(1)} = B_1\big) + P\big(X^{(2)} = B_1\big)\big]$$

$$= (1 - b_1)\big[0 + P(1 - P_C) + (1 - P)(1 - P_C)\,b_2(1 - P_q)\big]$$

$$= (1 - b_1)\big[P(1 - P_C) + (1 - P)(1 - P_C)\,b_2(1 - P_q)\big]$$

For $n > 0$; when n is even

$$P^{(2n)} = (1 - b_1)$$

$$\left[\begin{array}{l} P(1 - P_C)\left\{\dfrac{1 - r^n}{1 - r}\right\} \\[2mm] + (1 - P)(1 - P_C)(1 - P_q)b_2\left\{\dfrac{1 - r^{n-1}}{1 - r}\right\} \end{array}\right] \quad ...(4.6)$$

For $n > 0$; when n is odd

$$P^{(2n+1)} = (1 - b_1)\left\{\dfrac{1 - r^n}{1 - r}\right\}$$

$$\big[P(1 - P_C) + (1 - P)(1 - P_C)(1 - P_q)b_2\big] \quad ...(4.7)$$

These two equations exhibit the overall probability of sharing two browsers by user in a web environment. These two proportions also reflect how the sharing of two different browsers changes with respect to the initial preference.

The limiting cumulative probabilities of successfully surfing through the two browsers can be obtained by taking the limit of expression (4.6) & (4.7) over infinite attempts i.e. when the number of attempts are infinitely large.

When n is even

$$P_1 = \lim_{n\to\infty} \overline{P}_1^{(2n)}$$

$$= (1-b_1)(1-P_C)\left[\frac{P+(1-P)(1-P_q)b_2}{1-b_1b_2(1-P_q)^2}\right] \quad \dots(4.8)$$

When n is odd

$$P_1 = \lim_{n\to\infty} \overline{P}_1^{(2n+1)}$$

$$= (1-b_1)(1-P_C)\left[\frac{P+(1-P)(1-P_q)b_2}{1-b_1b_2(1-P_q)^2}\right] \quad \dots(4.9)$$

These expression are independent of parameter *n*. Browser sharing depends on P, P_q, b_1, b_2 and P_c. Both expressions (4.8) and (4.9) are same.
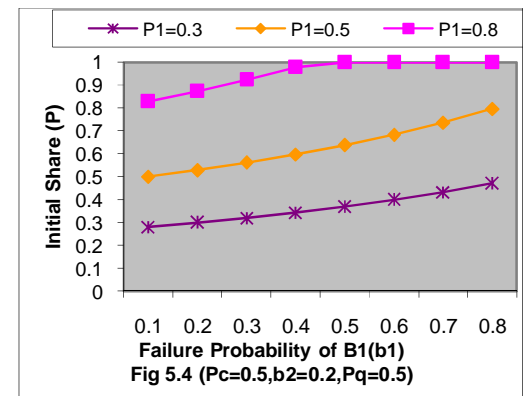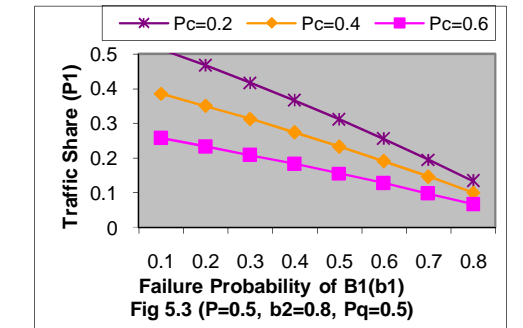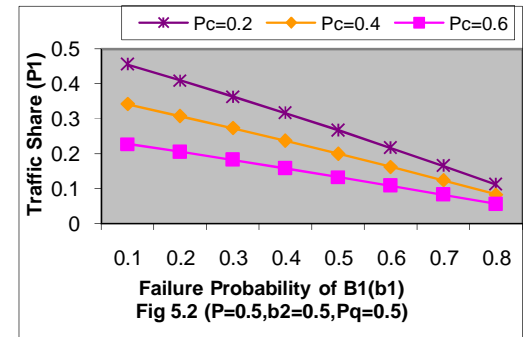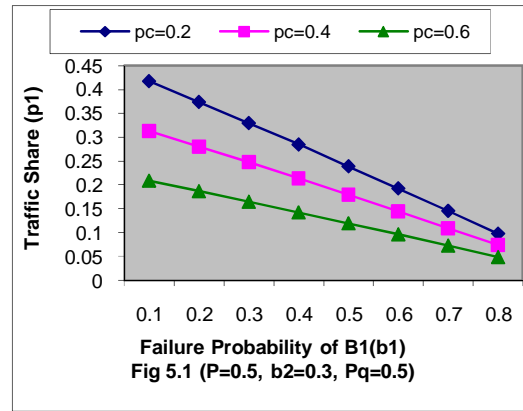
V. ISO-SHARE CURVES:

If we fix the final browsing share of user proportions then what shall be initial share to maintain the same ? This could be obtained by following equation.
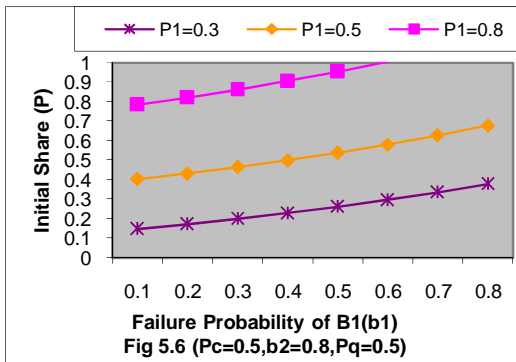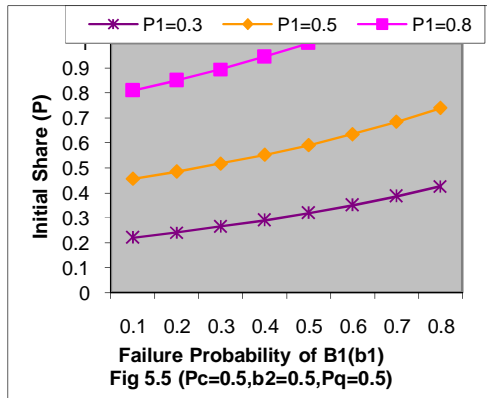
$$P = \frac{\left\{\begin{array}{c}b_1b_2\left[1-P_1+P_q\{2P_1-P_1P_q+P_C-1\}\right]\\ +P_1-b_2\left[1-P_q(1-P_c)-P_c(1-b_1)\right]\end{array}\right\}}{\left\{\begin{array}{c}(1-P_c)b_1\{b_2(1-P_q)-1\}\\ +1-b_2(1-P_q)(1-P_c)\end{array}\right\}} \quad \dots(4.10)$$

The initial share P is a function of final share P_1 with many other parameters. Iso-share curve indicates for what initial share of user proportion required if the final share level is fixed for both.

VI. GRAPHICAL STUDY:

From fig 5.1 to 5.3, increasing label of browser failure leads to loss of final browser user group share. If probability P_C is high, the fall in browser user proportion rate is also high. Moreover, if b_2 is high this loss is relatively lower.

Fig 5.1 (P=0.5, b2=0.3, Pq=0.5)

Fig 5.2 (P=0.5, b2=0.5, Pq=0.5)

Fig 5.3 (P=0.5, b2=0.8, Pq=0.5)

Fig 5.4 (Pc=0.5, b2=0.2, Pq=0.5)

Fig 5.5 (Pc=0.5,b2=0.5,Pq=0.5)

Fig 5.6 (Pc=0.5,b2=0.8,Pq=0.5)

The iso-share analysis (see fig 5.4 to 5.7) indicates that if final share is 30% and browser failure is 20% then the initial share must be around 30%. If browser failure is high then correspondingly the initial share should also be high. When competitor browser failure rate is high then the low initial share of user proportion is accomodable. More and more user's will opt that browser having the lower failure rate.

Fig 5.7 (Pq=0.5,b1=0.5,b2=0.5)
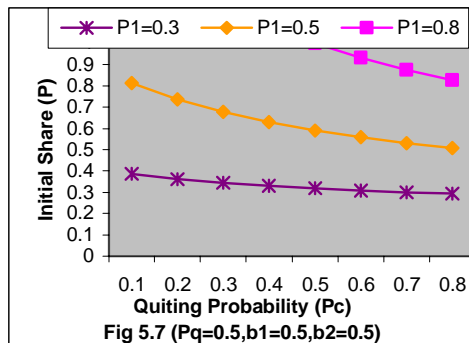
The *Pc* which is quitting probability of from attempt process has adverse effect on initial traffic share. With the increase of *Pc* browser sharing proportion of user falls down. Moreover if a browser owner company keeps final user proportion high, then with increasing *Pc* probability, the fall in initial share proportion user is very high.

VII. CONCLUDING REMARK:

The browser failure probability affects to the user proportion in the market and having inversely proportional relation. However, between two the other competeting browser failure rate increases the user proportion of the earlier. If the quitting probability Pc is high then fall in proportion of browser user rate is also high. If the browser owner company wants to maintain a certain standard of user share proportion then company has to maintain a certain level of initial proportion. More and more user's will opt that browser having the lower failure rate. The quitting probability Pc affects the proportions of initial browser share, and with the increase of Pc this proportion falls down.

It is recommended for browser owner competitors to reduce their quitting probability Pc as much as possible in order to maintain their customer proportion. However companies are advised to have a watch on browser failure rate of other competeting companies.

If a rate of a company is lowest in terms of browser failure and lowest in terms of quitting probability Pc then the company can enjoy relatively a large number of browser user proportion in the market.

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Author's Biography

Dr. Diwakar Shukla is working as an Associate Professor in the Department of Mathematics and Statistics, Sagar University, Sagar, M.P. and having over 21 years experience of teaching to U.G. and P.G. classes. He obtained M.Sc.(Stat.) Ph.D.(Stat.), degrees from Banaras Hindu University, Varanasi and served the Devi Ahilya University, Indore, M.P. as a Lecturer over nine years obtained the degree of M. Tech. (Computer Science) from there. During Ph.D., he was junior and senior research fellow of CSIR, New Delhi qualifying through Fellowship Examination (NET) of 1983. Till now, he has published more than 80 research papers in national and international journals and participated in more than 35 seminars / conferences at national level. He also worked as a selected Professor to the Lucknow University, Lucknow, U.P., for one year and visited abroad to Sydney (Australia) and Shanghai (China) for conference participation. He has supervised eleven Ph.D. theses in Statistics and Computer Science both; and six students are presently enrolled for their doctoral degree under his supervision. He is member of 10 learned bodies of Statistics and Computer Science both at national level. The area of research he works for are Sampling Theory, Graph Theory, Stochastic Modelling, Computer Network and Operating Systems.

Mr. Rahul Singhai has obtained M.C.A. degree from H.S. Gour University, Sagar, MP, in 2001 and obtained M.Phil degree in Computer Science from Madurai Kamaraj University, Madurai, Tamilnadu in 2008.. He is a parmanenet faculty member in IIPS, Devi Ahilya University, Indore. Presently he is pursuing Ph.D in Computer Science from H.S. Gour University, Sagar. His research interest includes Computer Network, Data mining, operating System & Software Testing. He has authored and co-authored 12 research papers in international and national journals and proceeding. Currently, he is working on to develop new probability based methods for data preprocessing in data mining.