Machine Learning Based User Retention and Channel Allocation: 6G Aspect

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Abstract

Future 6G wireless network will be focused on Artificial Intelligence (AI) based network selection, resource allocation and user satisfaction. A user has multiple options to switch one service provider to another service provider in case of network quality degradation. The new schemes/policies are required to retain their valuable users. This paper proposed supervised machine learning methods such as Decision Tree, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), etc., to classify and identify the loyal user. The decision tree algorithm has been identified as the best classification technique in order to identify the type of user (loyal, normal, and recent). A threshold-based algorithm is proposed to allocate the resource, particularly to loyal users. The performance of the algorithm is measured in terms of average waiting time (AWT), and the number of particular types of user's services dropped. Priority is given to the loyal user when only 10% network resource is available. The simulation environment is created by SimPy implemented in Python. The result of the simulation run represents that no loyal user' services have been interrupted during communication. Loyal users achieved less AWT as 32.51s compare to the normal user and recent user.

1. Introduction

The standard of the 5G communications is almost over and deployment has commenced globally. A new standard of the sixth-generation (6G) wireless network will have the full provision of AI and projected to be deployed between 2027 and 2030[1]. Furthermore, user satisfaction and network QoS will play a more vital role in 6G. 6G offer all the services intelligently and automatically. Coexistence of networks is the elementary requirements of telecom and IT Industry and creates an open competition between the service providers [2]. Telecom service providers are investing comprehensively to keep their prospective users, rather than obtaining the new users. Retaining the prospective or valuable user in their system is a great task, and requires various approaches, framework, models and business strategies to keep them [3]. It would also be important to explore that what would make a user walk away from the current service provider. The most straightforward and primary reason is poor network QoS, expensive service cost, absence of continuous services and unattended user. A customer would always prefer to associate to the always best connected network in a least service cost. The service providers must give the priority to their loyal users by offering better network services.

 Due to exponential growth in mobile user and restricted number of resources, there may be fair chances of network quality degradation experienced by some of the users. Users can switch from one service provider to other, if they are not better served. A quick decision is required in such scenario and AI based schemes are useful in this direction. The range of AI has grown extremely since the intelligence of machines with machine learning capabilities has formed intense impacts on Industry, business and society [4]. Only particular users are supposed to offer wireless network QoS in order to equilibrium the cost of offered services and estimated revenue generation. Machine learning based classifier such as K-Nearest Neighbour (KNN), Decision Tree (DT), Random Forest (RF); Support Vector Machine (SVM) etc. are used to classify the type of user [5].

The 5G system could not capture sensory inputs of Extended Reality (XR) because they could not deliver low latency for high capacity data rates. The emergence of drones, underwater communications and autonomous cars is a field where 5G could not meet the rate-reliability-latency ratio and spectrum requirements. . The spectrum is restricted due to technological advancement, operating cost, specified standard and well defined with spectrum and devices. The channel assignment strategies allow efficient utilization of spectrums. Telecom service providers must plan about efficient channel assignment strategies based on emerging technology in order to retain their valuable users.

The objective of this paper is to build a model/framework that can make effective resource utilization by serving valuable user at the time when there may be strong chances of dropping. The proposed framework relies on machine learning technique to identify valuable users and then prioritized them by allocating best resource (channel).

2. Related Work

The current wireless network is fast, heterogeneous, autonomous and intelligent. Heterogeneous means where a mobile user/device will be able to join seamlessly and switch to many wireless networks such as WLAN, Cellular, WMAN, and WPAN [6]. By the year 2025, there will be 75.44 billion connected devices that utilize network services according to Statistics Portal (2017). This will definitely increase the number of user/devices exponentially. Due to a limited number of resources (channel), there may be situations when the system has to select the user from the list of waiting queues. Conventional method mostly utilized profile based channel assignment strategies [7-8]. There must need a smart and intelligent system that can take decision automatically in case of resource assignment with better QoS for their valuable user. C.5 and Naïve Bayes for the segmentation of telecommunication users was proposed for dynamic segmentation rely on their billing and socio-demographic features of telecommunication users according to their billing and socio-demographic features [9]. Reference [10] proposed utility function to compute type of user. However, for the exponential growth in mobile user, utility function based techniques was obsolete. The Machine learning method is known as one of the significant tools to analyze combination of multi attributes. Machine learning developers use Python and related libraries for model building and analysis.

The resource (channel) distribution related to user mobility proposed in a cellular wireless network [11-12] to associate the best spectrum set of frequency/time while allowing for the user's mobility. Each mobile user has arrived at some rate for services and stay in a waiting queue. Various texts have been reported for queuing analysis of wireless 5G network. An M/M/1 queue with service interruption from primary users was measured and an evaluating policy was used to charge each secondary user that arrives on a queue [13-14]. Reference [15] suggested a queuing model for optimum resource allocation to achieve a greater overall capacity based on user category.

The major challenges of such 5G wireless systems are the quality of service (QoS) and efficient resource utilization, seamless handoff, intelligent network selection and user satisfaction [16]. Telecommunication

sectors also suffered the problem of customer churning due to poor network QoS [17]. Hence, new scheme and strategies will be required to sustain their valuable user. A churn prediction model was proposed in telecommunication industry based on random forest [18]. KNN based approach was also proposed to maximize the user expectations in heterogeneous wireless network based on a machine learning classification approach of KNN [2].

IoT, AI and Blockchain has already proven its potential in Healthcare and Agriculture [19] and Telecommunication is not an exception in this line. Emerging technology such as IoT and Machine Learning has potential to design smart and intelligent environment that can serve a maximum number of users efficiently. Wireless network was trained via AI and ML techniques for dynamic processing of spectrum handovers by analyzing primary user (PU) and secondary user (SU) [20]. To enable wireless accesses of IoT networks, AI can play an important role. 6G and beyond will accomplish the necessities of an entirely connected domain and deliver pervasive wireless connectivity for all with the help of emerging technology [21]. To permit wireless accesses of such IoT networks, artificial intelligence (AI) can play an significant role [22-24].

6G aimed with key features like energy efficiency, spectral efficiency, security, customization, and user satisfaction with AI [25]. AI and Machine learning based approaches are able to take an explicit decision of the network as well as user selections in a heterogeneous environment. Machine Learning classification methods, for example ZeroR, Naive Bayes, DT, RF, SVM, KNN, and Logistic Regression etc., were used to analyze the efficiency of several machine learning classification models for calculating personalized usage employing entity's phone log data [26]. This Personalized information about the user will be useful to categorize the valuable user in the proposed model. Each user expects their connection to be fast, easy to link and flexible as far as possible. On one side there is growing number of devices and users, other side there is limitation of available resources. Taking this into cognizance there is always a need for a techniques / schemes for efficient resource utilization. This motivates the author to design a framework that can take a smart decision on user selection when only few resources are left. Proposed work contributes to the literature by following ways:

- User classification based on supervised machine learning methods such as Decision Tree, SVM, KNN etc.).
- Channel allocation mechanism to only valuable user after a certain threshold.

3. Proposed Model

The objective of this paper is to recommend a machine learning based model to prioritize the user at the time of channel assignment strategies on the foundation of their loyalty. The overall model of the proposed work is depicted by figure 1. There are two main parts of proposed work:

a) Identification of loyal user

b) Channel Assignment Strategy

User first arrives in request queue and the user type is computed by using supervised machine learning techniques. The user are categorize in loyal user, normal user and recent user based on labeled data set. The data set has parameters like U, T, R and Npv has taken for the computation of user type. All the parameters/symbols used in this paper has represented in table 1. The dataset is used for training and testing of the model with supervised learning techniques as given in [2]. After computation the C_u, the next step is to assign channel according to their type and threshold criteria in order to provide best services to loyal user/valuable user.

Table 1: Parameters/Symbol Definitions

S. No.	Notation	Definition
1.	U	Usage (U) is fundamentally data usage that user consumes for each traffic class and also measured in GB.
2.	T	Time duration (T) is the time that a user is linked with the service provider..
3.	R	Revenue (R) is the money that's how much user is paying to the service provider in term of service charges.
4.	N_{pv}	Net Promoted Value (N_{pv})is computed on the basis of how likely user suggests his service providers to other user, friend, society etc.
5.	C_u	Denoted as Computed User (C_u) type such as 'Loayl','Normal', and 'Recent'
6.	t	User is generated with roughly every x time interval in a queue and generate by expovariate ($1/x$) function defined in simPy. x=10sec is assumed in the proposed work.
7.	s	s is a service time, required to process user requests and generate by expovariate ($1/y$) function defined in simPy. y is mean time a user busy with network for the service. y=4sec is assumed in the proposed work.
8.	AWT	Average waiting time of all the user in the system
9.	AST	Average service time of all the user in the system

3.1 Identification of Valuable User based on Machine Learning

Present environment is bit centric towards the user. The service providers are accumulating various types of evidence about the user behavior and designs to analyze these data to obtain information to hold their users. Net Promoter Value (N_{pv}) which defines how likely user suggests his service providers to other user [27]. There may be numerous groupings of features/attributes with diverse possible values such as usage, duration, revenue, and N_{pv} can utilize in the computation of type of user, as given below:

- If $U \geq 0.7$ and $T \geq 0.7$ && $R \geq 0.7$ and $N_{pv} \geq 0.7$ then $C_u = 'L_u'$

- If U is between (0.7 to 0.5) and T is between (0.7 to 0.5) and R (0.7 to 0.5) and N_{pv} is between (0.7 to 0.5) then C_u = 'N_u'
- If U < 0.5 and T < 0.5 and R < 0.5 && N_{pv} < 0.5 then C_u = 'R_u'

It is very challenging to identify user type, according to the attributes U, T R, and N_{pv} only. There may be various amalgamations of attributes with diverse possible values to compute the user type (C_u). The selection of attributes may vary according to the choice of service providers. Utility based model could be more complex to predict and identify (C_u) due to exponential growth of user devices, multiple providers and choice of multiple attribute in the type of user computation. It is significant to compute quick prediction of valuable user. Current technological development in machine learning has vision to learn the system without being explicitly programmed. Service providers can simply add/delete/modify their choice of attributes in data sets. A supervised learning is applied to the dataset that maps an input pattern to a target output based on a given data set. There are 150 records in the dataset. 70% of data is used for training purpose and 30 % of data is used for testing purposes. Target output class is computed on following given assumption to classify the category of user. There are three types of user – Loyal user (L_u), Normal User (N_u) and Recent user (R_u). L_u is a valuable user for the service providers as it contributing in businesses in terms of Return on Investment (RoI). Hence, retention of L_u becomes important for the business or service providers. Loyal user is also referred as a valuable user in throughout the text. KNN, Decision tree, SVM techniques are applied to classify the user type. Algorithm steps and classifier function has implemented in Python [6]. Table 2 represents the performance metrics of selected classifier. Table 2 represents that decision tree has best accuracy, precision, recall and F1-Support parameter of user type prediction.

Table 2 : Accuracy of Classifier

S. No.	Algorithm	Accuracy	Precision	Recall	F1-Support
1.	SVM	0.9111	0.93	0.91	0.91
2.	KNN	0.9777	0.98	0.98	0.98
3.	DT	1	1	1	1

Arrival of the user in any network system is quiet random. It is very complex to predict that how many users will be linking the network system. Distribution schemes and pattern generation are actually a valuable idea to study and identification of L_u when there is high traffic. For the simulation, we have generated different pattern of $U, T, R,$ and N_{pv} by using uniform, random, triangular and gamma variate etc.. Figure 2, figure 3, figure 4, and figure 5 are representing the input pattern of attributes $U, T, R,$ and N_{pv} of 50 users which is produced by uniform distribution normalized between 0 to 1.

Table 3 represents the average number of loyal users by using different distribution and multiple run.

Table 3: L_u generated in numerous distributions

S. No.	Distribution Name	Number of L_u
1.	Gamma Variate	2
2.	Random	15
3.	Triangular	13
4.	Uniform	17

From the table 3, it is obvious that maximum numbers of L_u are produced by the uniform distribution.

3.2 Channel Assignment Techniques

Channel capacity can be maximized by applying different assignment techniques [28]. The channel allocation strategies are mainly categorized into a fixed channel assignment (FCA), dynamic channel assignment (DCA) and Hybrid channel assignment (HCA). In FCA, each place is assigned a fixed set of channel permanently. FCA is simple and easy to implement. In DCA, channels are not permanently assigned; channel is distributed as per the demand of the user. Proposed work follows DCA to assign the channel as per user demand. In any strategy, one can serve only a fixed number of users at a particular instance and the maximum size is corresponding to the total number of channels exist within the network. A user demand is directly served if a channel is free otherwise services has been dropped. There must be required new techniques to employ the resource proficiently. Furthermore, there may be chances that many loyal users can miss the service due to the fixed number of channels and loyal user' requirements are either dropped or postponed in the network service.

The proposed system assigns the channel according to algorithm 1, which give priority to the valuable user when the number of channels is less than the threshold value. The channel assignment mechanism is usually based on threshold values. In this paper, channel is reserved for valuable user (loyal user) services.

3.3 Model Assumption

1. Total number of channels that a network can serve is $n=45$ and number of user $=50$.

2. Generate new users roughly every second is x, arrival time pattern is generated by

   expovariate($1/x$) function, $x=10$ sec is assumed for simulation.

3. Time to use network service (s) is also generated by expovariate($1/y$) for each arrived user, y is

   mean time a user busy with network for the service. y=4 min. is assumed for simulation.

4. Total number of channel reserve for loyal user is 10% of n.

5. User type is classified by the decision tree classifier.

The proposed model is implemented by using Python based on algorithm 1. Algorithm 1 is implemented with SimPy- A process based discrete-event simulation framework based on standard Python. Algorithm 1 is executed in multiple runs, and three distinct values are obtained for *AWT* and *AST* and the number of drops for each specific type of user. Results are shown in Table 4.

Algorithm 1: Computation of AWT and AST for specific user type

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1. Mobile user is generated with each x time interval, by using:
   t = random.expovariate(1.0 / x)

2. User pattern is generated by using uniform distribution.
   U = random.uniform(0.1, 1)
   R = random.uniform(0.1, 1)
   T = random.uniform(0.1, 1)
   N_{pv} = random.uniform(0.1, 1)

3. Create a sample of user by using:
   sample= np.array([[U,T,R, N_{pv}]])

4. Predict/ Compute Type of user by DT Classifier
   from sklearn.tree import DecisionTreeClassifier
   dt = DecisionTreeClassifier()
   dt.fit(X_train, y_train)
   #Predict the response for generated sample
   dt.predict(sample)

5. if channel >= 5 then
      Channel Allocated and compute wait time and service time
   else if (C_u== 'L_u')
      Channel Allocated and compute wait time
   else
      User request for channel is dropped
6. Service time is also generated by expovariate distribution:
   s=random.expovariate (1.0 / y)

7.   Compute no. of L_u, N_u, R_u, *AWT*, and *AST*.

Table 4: Result of Algorithm 1

No. of Run	Type	Total No.	AWT(sec)	AST(min.)	No. of user Drop
1.	Loyal	19	30.01	11.33	0
	Normal	17	43.87	14.35	1
	Recent	14	43.87	19.57	4
2.	Loyal	17	32.74	11.56	0
	Normal	22	34.79	12.28	6
	Recent	11	50.60	17.86	0
3.	Loyal	17	34.79	11.56	0
	Normal	16	37.11	14.03	2
	Recent	17	42.82	15.11	4

4. Results And Discussion

Proposed work, analysis number of valuable user generated by the system. From the table 3, It has been observed that 34% valuable user is generated by the uniform distribution. Taking this into cognizance there must have a scheme or policy that the system can retain valuable users. User retention is possible only when service provider offers them better network QoS. Proposed work represented that number of loyal type user has dropped by proposed work based on threshold and also compare the same without threshold as shown in table 5. The result represented that a very less number of loyal user services has been dropped.

Table 5: Comparison of No. of User Drop with and without threshold

From table 4 it is clear that the average waiting time of loyal users is much less than normal and recent type user. From table 4, AWT of L_u is 32.51s, N_u is 38.59s, and R_u is 46.76s. Also, fewer number of L_u type user dropped by the proposed model as shown in table 5. The proposed model leads the satisfaction level of valuable user and hence increase the chances of retention with the associated service provider. The proposed work introduced benefits to both users and service providers. User can enjoy with best network services, and service provider can have a gain in revenue and retention of the valuable user since adding a new user in the system are more costly compared to holding old user.

5. Conclusion

The proposed work focuses on the QoS aspect of 6G, where user satisfaction and intelligent network system are preferred. The intelligent network environment can be created by using machine learning. In this paper, we proposed a machine learning based approach to compute the type of users such as 'Loyal', 'Normal', and 'recent' type. KNN, DT, SVM classification algorithm has been applied to compare the

No. of Run	Type	Total No.	Type of user Drop (With Threshold)	Type of user Drop (Without Threshold)
1.	Loyal	19	0	2
	Normal	17	1	0
	Recent	14	4	3
2.	Loyal	17	0	2
	Normal	22	6	4
	Recent	11	0	0
3.	Loyal	16	0	2
	Normal	17	2	0
	Recent	17	4	4

accuracy of the algorithm for the computation of the type of user. The decision tree has been identified as best classifier with 100%.   Loyal user has given preference to allocate the channel when only 10% of the channel has left. Further, a simulation environment is created for the suitability of the proposed algorithm by using SimPy implemented in Python. Simulation results indicated that no loyal user services are dropped, and even they have less *AWT* compare to the normal and recent type of user. Loyal users achieved less *AWT* as 32.51s compare to the normal user (AWT=38.59s) and recent user (AWT=45.76s).

Declarations

'Funding' and/or 'Conflicts of interests'/'Competing interests'

- No funds, grants, or other support was received.
- The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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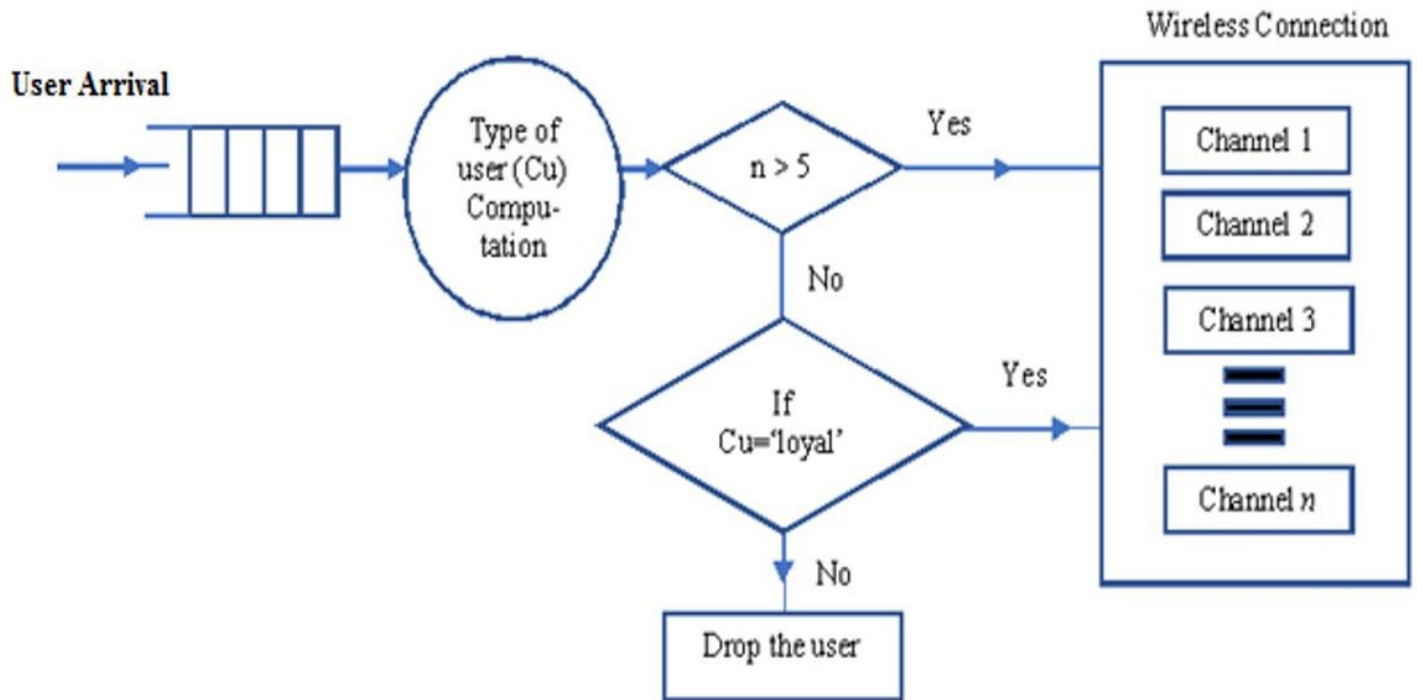
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Figures

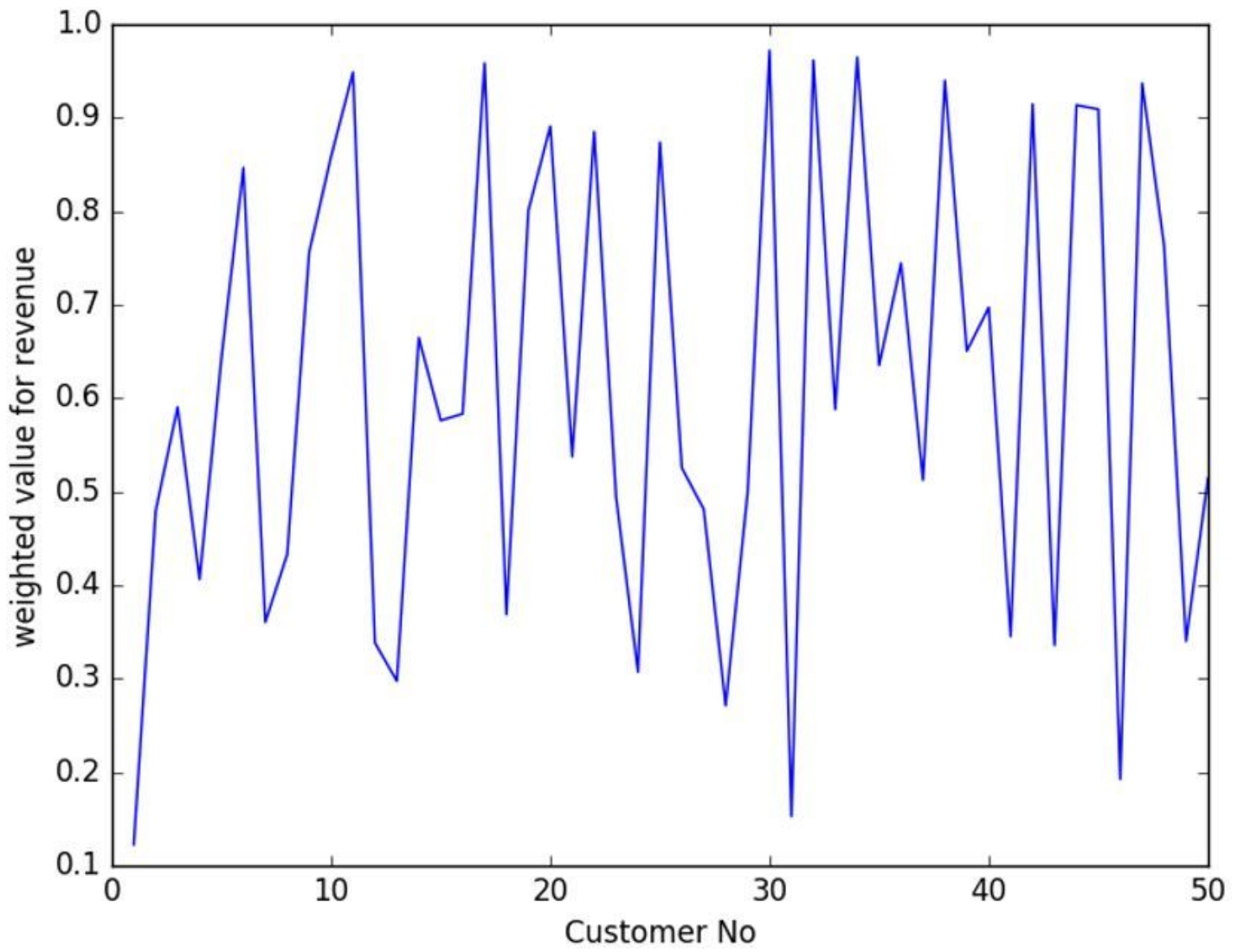**Figure 1**

Model of the proposed work

Figure 2

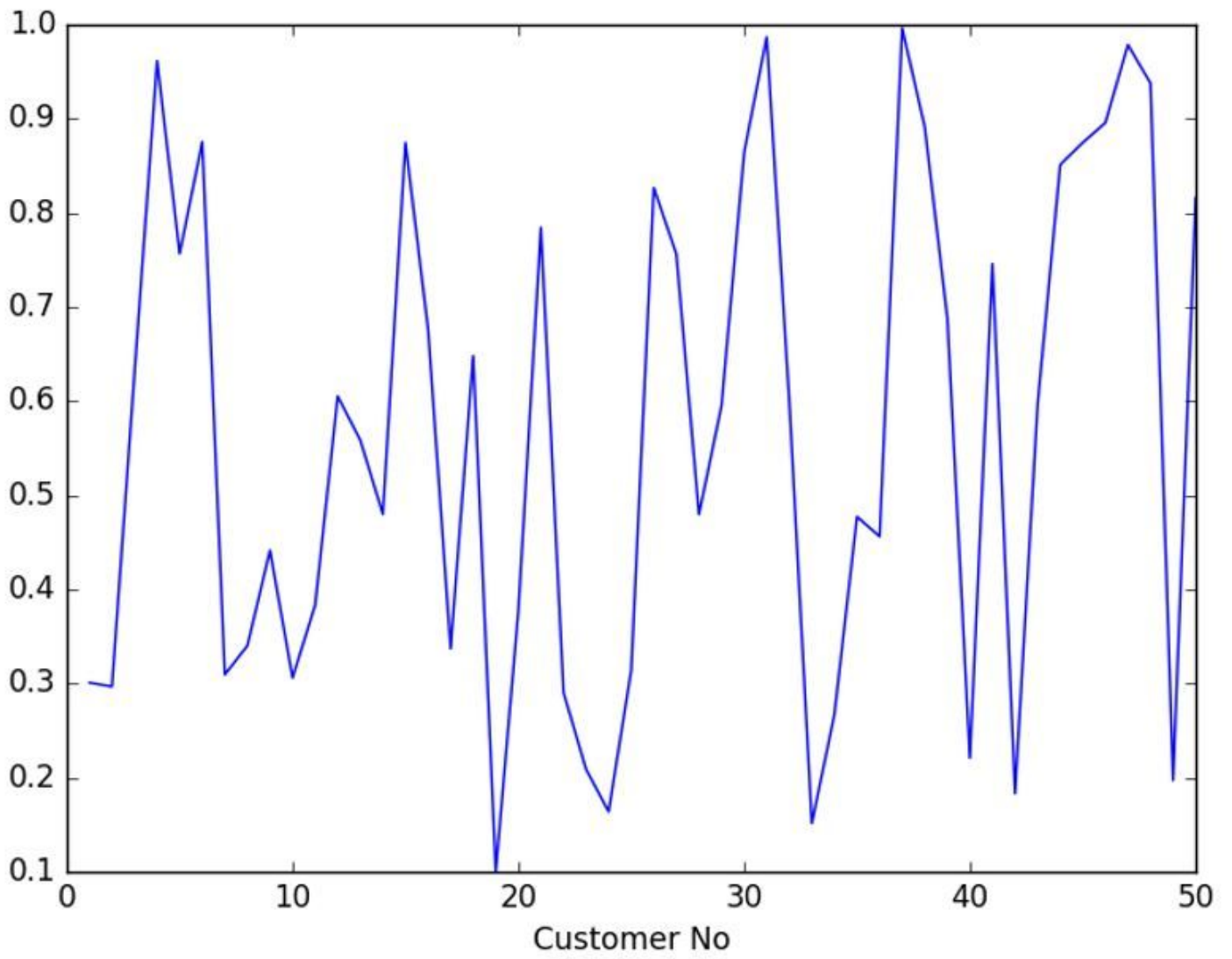Sample Pattern Usage

Figure 3

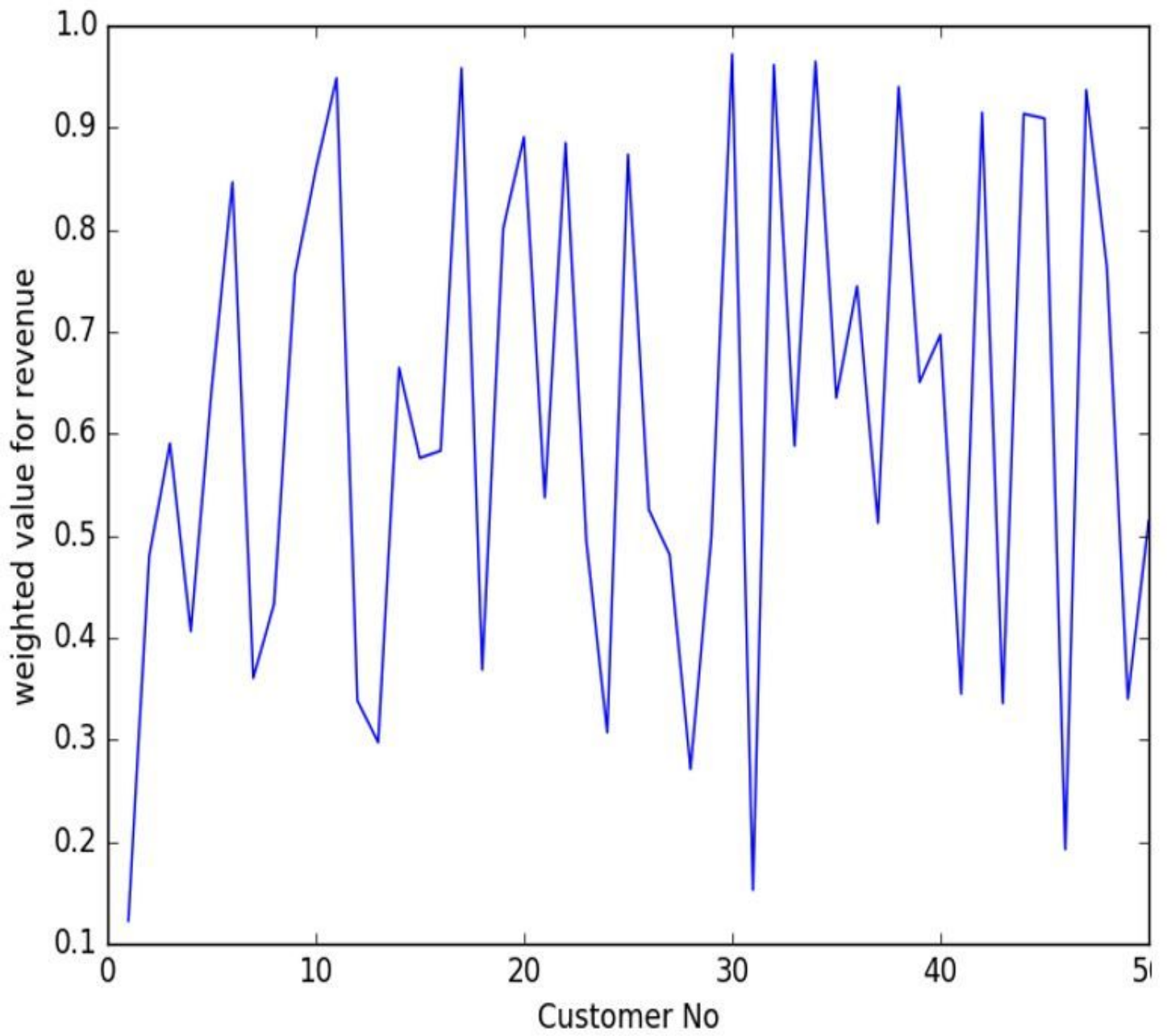Sample Pattern Duration

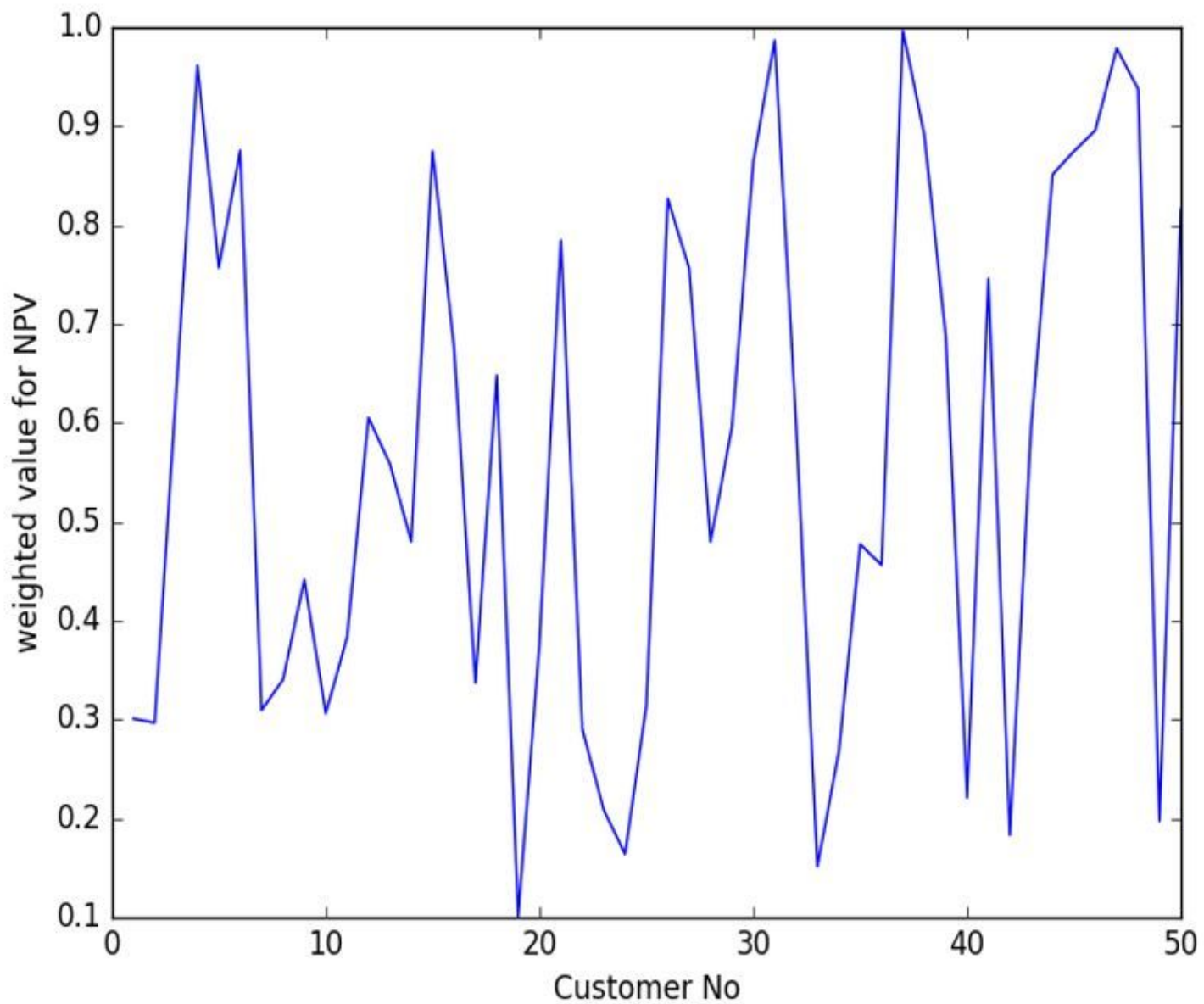**Figure 4**

Sample Pattern for revenue
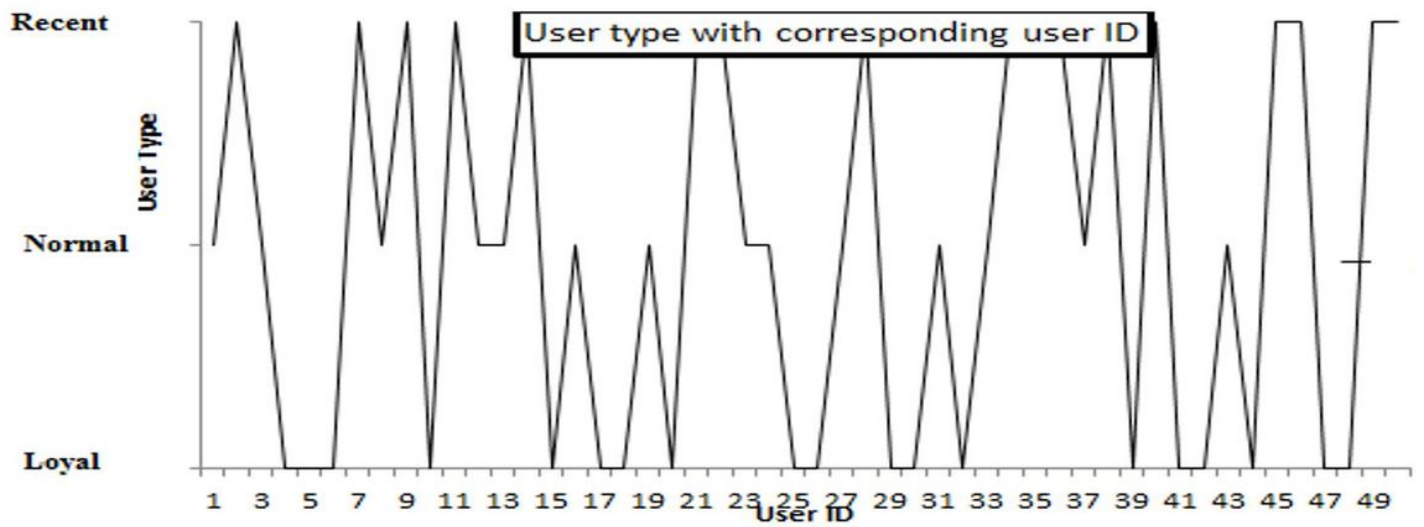
Figure 5

Sample Pattern for NPV

Figure 6

User ID with specific type
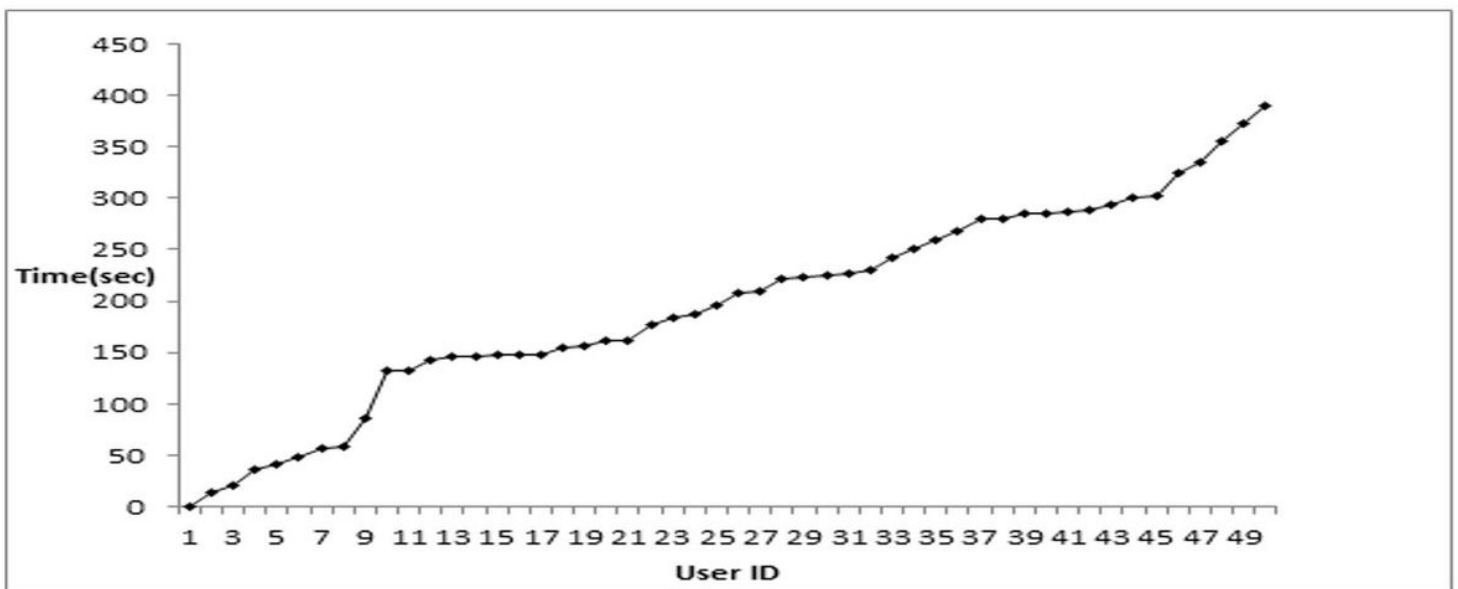
Figure 7

Arrival pattern of user generation in a network

Figure 8
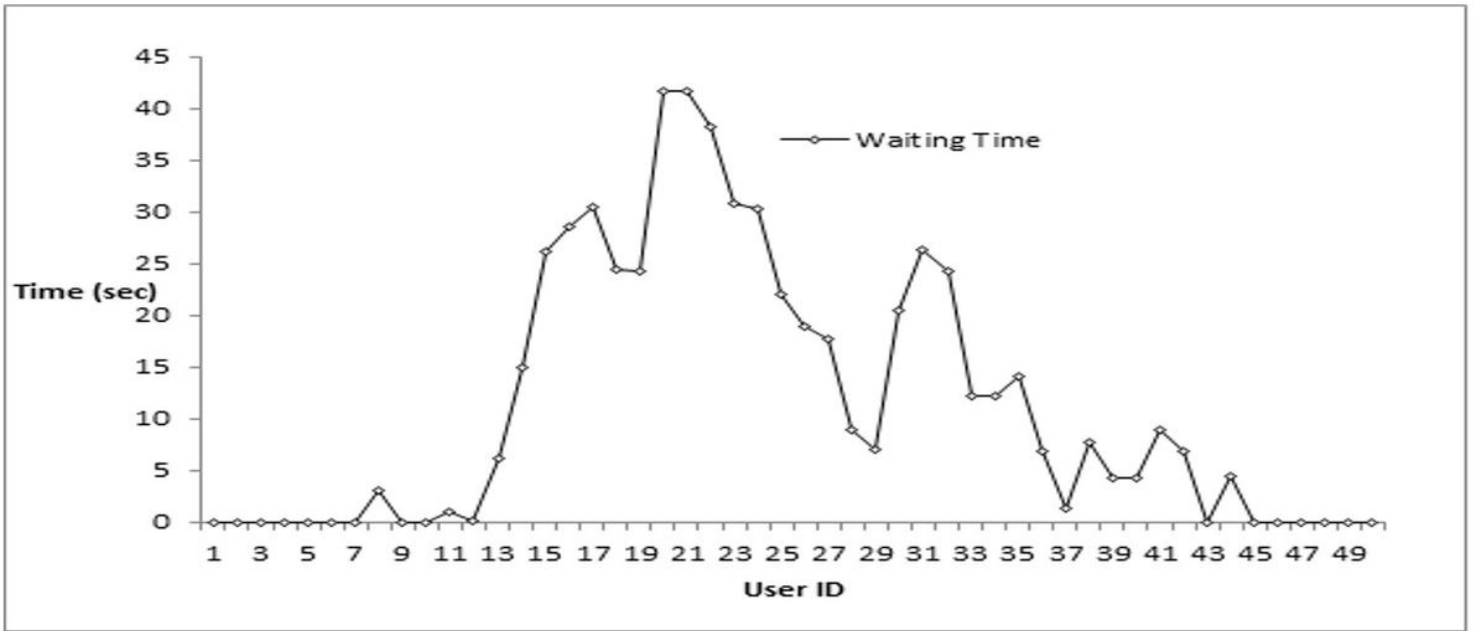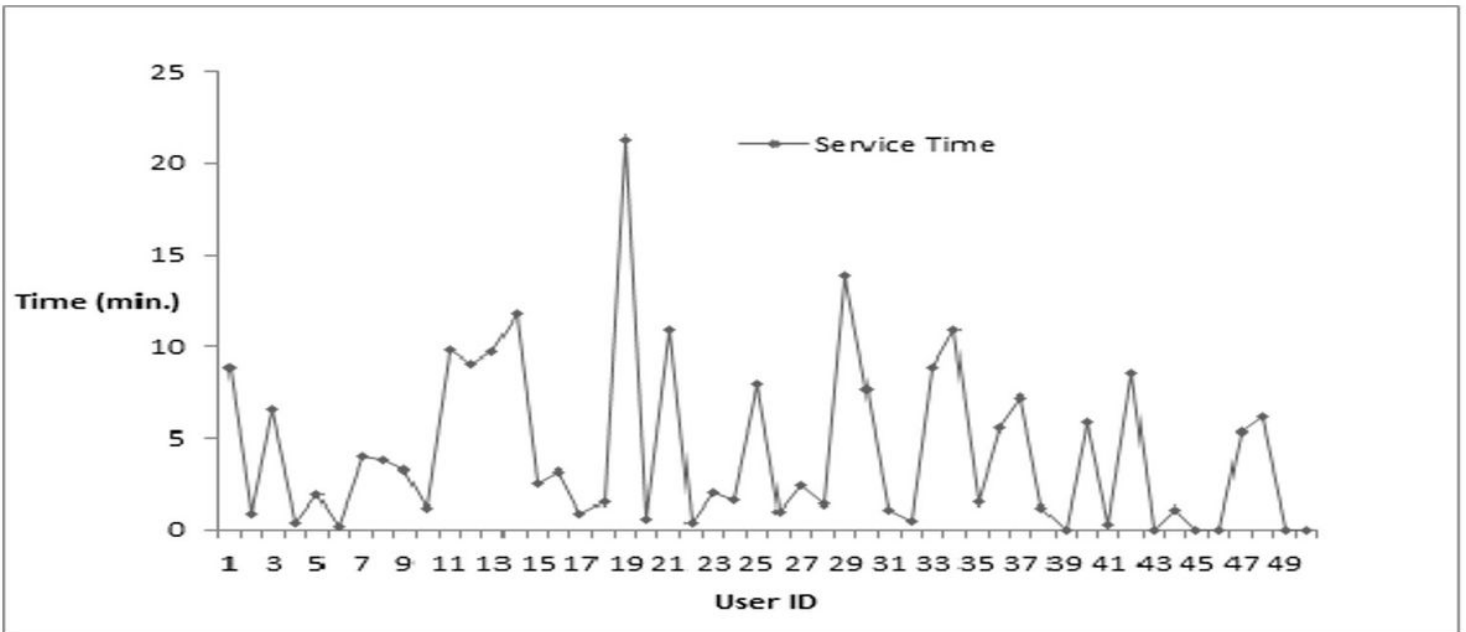
Average waiting Time for generated user ID

Figure 9

Average service time of generated user ID