Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Comparative Analysis of Queueing Model and Artificial Natural Networks for OPD Patients

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Abstract: In this paper, we examined multi-server under FCFS pattern using ANN with Poisson arrivals and Erlang service time. The object of this article is to reduce the waiting time of OPD (Outpatient Department) patients. We have computed several performance metrics for the system and patients. These metrics include the expected total service time, the anticipated count of phases in the system and the queue, the projected waiting time within the queue and across the server system, as well as the total number of patients within the system. We have used multilayer feed forward network along with supervised training methodology to analyze better outcome of the proposed article. These calculations were performed within the context of multi-server setups by varying various stages. Numerical example demonstrations the superior efficiency and effectiveness of the latter compared to the former.

Keywords: Artificial Natural Networks, Patient Waiting Time, Hospital Efficiency, OPD Scheduling, Optimization Techniques, Real-time Patient Tracking

1. Introduction

In the ever-evolving landscape of healthcare, optimizing operational efficiency is paramount. One critical aspect often under scrutiny is the patient queue in Outpatient Departments (OPD). As healthcare facilities strive to enhance patient experiences and reduce waiting time, the integration of advanced technologies become imperative. This study delves into the realm of improving patient queues, employing a comparative analysis between traditional queueing models and cutting-edge neural networks.

Traditional queueing models have been employed to manage patient flows, relying on mathematical algorithms to predict and streamline queues. However, the emergence of neural networks presents an intriguing alternative. Neural networks, inspired by the human brain's architecture, exhibit the capacity to adapt and learn from complex datasets.

By juxtaposing the strengths and limitations of established queueing models with the adaptive learning capabilities of neural networks, we seek to identify the most efficient approach for optimizing patient queues. The implications of such improvements extend beyond mere operational enhancement; they directly impact patient satisfaction, overall healthcare quality and resource utilization. This research not only contributes to the ongoing discourse on healthcare management but also provides actionable insights for healthcare administrators seeking to implement data-driven strategies in OPD settings. In navigating the delicate balance between traditional methodologies and innovative technologies, this study paves the way for a more streamlined and patient-centric approach to outpatient care. Finally, this paper we developed a new approach to queueing model called multi server in which channel have equal stages in series and parallel fashion. Poisson follows queueing system with arrival and Erlang service time and also follows two types of process first is traditional and second is ANNs- assessment, some case study with multi-server with 5 and 6 steps. The adept medical professional, utilizing artificial neural networks (ANNs) in the intervention cohort, conducted patient interviews. In contrast, the control group for following conventional methods, engaged in interviews facilitated by a human doctor. As per the queue management system regulations, in case a patient missed their turn who typically had to wait for the completion of two initial patients' consultations and an additional patient returning for a second round. Patients have to wait from both groups (conventional and ANN) for the test report and their turn have withdrawn doctor’s office and it would be noted as a proposal violation (PV). If a patient's condition deteriorated, the investigator would liaise with the medical staff to ensure prompt treatment, utilizing a Poisson arrival and Erlang service rate queueing model with multiple service channels during the queuing time.

Dimitriou and Langaris (2010) the study explores a single-server, repairable queueing model with two-phase service. Customers move from a queue to a retrial box after the initial service, with breakdowns, repairs, and numerical analysis conducted for system stability and performance. **Ekpenyong and Udon (2011)** improved the performance metrics of the Single-Server Single Queue System with Multiple Phases by introducing a novel Queuing System of Multi-Server with Multiple Phases. The analysis evaluates properties and measures for the Multi-Server with Multiple Phases model, drawing comparisons with the existing Single-Server with Multiple Phases model. **Bastani (2009)** study of population growth in British Columbia has led to heightened wait times and overcrowding in Emergency Departments, especially in units like the Intensive Care Unit (ICU) and Medical Unit (MU) to create a queueing network model for the emergency patient stream, concentrating on ICU and MU interactions. Through analytical methods simulation and determined optimal bed counts in these units to meet access standards. **Cho et al (2017)** applied the queueing theory; computed waiting times by excluding distorted digital data and factors like early arrival before hospital opening, common in the queueing system's initial stage. Analyzing pre- and post-EMR introduction and observed outpatient waiting times decreased by 44% to 78% in targeted public hospitals. **Felix (2007)** this study focuses on utilizing queuing theory for healthcare operations management, emphasizing factors influencing patient experiences and variations in healthcare resources between the University of Benin healthcare center and Faith Mediplex. The research highlights the impact of ownership, funding, and environmental factors on resource availability. The findings suggest that patient waiting times are a significant concern, and the study suggests developing techniques to reduce queues and enhance service efficiency in healthcare administration. **Green (2006)** described basic queueing models as well as some simple modifications and extensions that are particularly useful in the healthcare setting, and give examples of their use. **Green (2011)** analyzed is one of the most practical and effective tools for understanding and aiding decision-making in managing critical resources and should become as widely used in the healthcare community as it is in the other major service sectors. **Haghighinejad et al (2016)** study of the emergency department (ED) of the objective was to evaluate the response variables of waiting time, number waiting and utilization of each server and test the three scenarios to improve them. **Kalwar et al (2018)** analyzed the comfortable waiting times among various income groups reveals substantial differences. Aligning service with these preferences is key to sustaining patient satisfaction, given the crucial role of waiting time in customer contentment. **Hanumantha et al (2016)** obtained the various performance measures including mean system size for various states are obtained. Cost function is formulated and the effect of system parameters on the optimal threshold $N*$, mean queue size and minimum average cost are studied. **Khaskheli (2018)** Examined reception and OPD performance measures revealed the need to optimize the queuing system and people flow. Enhancing staffing with an additional assistant and doctor significantly reduced waiting costs. **Awowale (2017)** examined existing literature and conducted interviews to delineate roles and decisions across healthcare levels. This comprehensive understanding aids in analyzing administrative processes and developing tools for efficient decision-making in healthcare organizations. **Jiang et al. (2017)** study of AI's historical emergence, current applications in diagnostics and treatment, and envision a future emphasizing personalized medicine, predictive analytics, and ethical considerations in healthcare. **Bartosch-Harlid et al** (2008) explores the application of artificial neural networks in pancreatic disease, investigating their utility in diagnosis, prognosis, and treatment strategies. **Nolting (2006)** developed of a neural network model for healthcare, exploring its applications, challenges, and potential implications for improving healthcare systems and decision-making processes. **Kayri (2010)** examined the optimization using Multilayer Perceptron Neural Network and compares it with decision tree methodologies, exploring their effectiveness in pattern recognition and decision-making processes. **Kustrin and Beresford (2000)** provided the basic concepts of artificial neural network (ANN) modeling, emphasizing its application in pharmaceutical research for enhanced data analysis and prediction. **Silva et al. (2017)** conducted on the artificial neural network architectures and training processes, providing insights into the advancements and applications within the field of artificial neural networks. **Sharma and Chopra (2013)** explored applications of artificial neural networks in management, offering a comprehensive literature review on how these networks are employed for decision-making, forecasting, and optimizing processes in various management domains. **Chin et al (2013)** provided modeling daily patient arrivals at the Emergency Department, utilizing artificial neural networks to assess the relative importance of contributing variables for enhanced decision support systems. **Süt and Senocak (2007)**

conducted an assessing the performance of multilayer perceptron neural networks, recurrent neural networks, and statistical methods in diagnosing coronary artery disease. **Kudyba and Gregorio (2010)** identified the some factors influencing patient length of stay metrics for healthcare providers and to explore the application of advanced analytics in understanding and optimizing these crucial healthcare performance indicators. **Eswaran and Logeswaran (2012)** discussed on a dual hybrid forecasting model, exploring its applications in supporting decision-making within healthcare management. The review highlights the model's effectiveness in enhancing decision support in healthcare contexts. **Hornik (1990)** analyzed the capabilities of multilayer feed forward networks, exploring the mathematical foundations and limitations of these neural networks in approximating complex functions. **Gutierrez and Martinez (2011)** discussed on hybrid artificial neural networks, delving into models, algorithms, and data integration and explores advancements in hybrid approaches, offering insights into their applications and effectiveness in various domains.

2. Patient Visiting Procedures: Conventional vs Artificial Neural Networks

According to the figure1, we study the patient visiting process varies between conventional and ANN (Artificial Neural Networks) methods, denoted as A and B. In the conventional process (A), patients commence with registration, filling out forms manually. Subsequently, they wait in line for consultation, interacting with human staff. Diagnosis involves traditional methods, and treatment decisions rely on the doctor's expertise. Following this, patients move to billing and finally depart after completing paperwork. Conversely, in the ANN-enhanced process (B), registration is streamlined through digital interfaces. Patient interviews involve AI-assisted technology, optimizing data analysis for diagnosis. Treatment decisions may incorporate machine learning insights. Billing and paperwork processes are expedited, offering a potentially more efficient and technology-integrated healthcare experience.

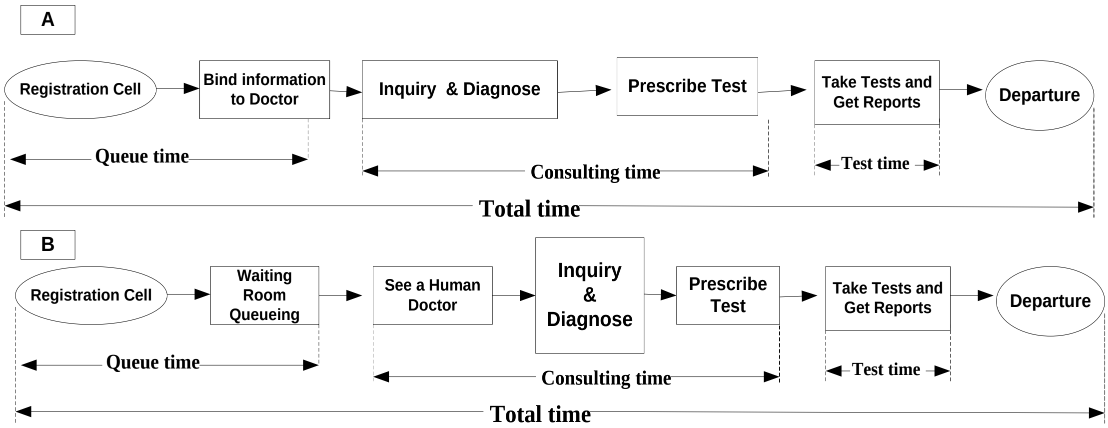

Fig. 1.Patient visiting process for conventional and ANN (A & B) process (Registration to Departure)

3. Description of Queueing Model

In this section, we discussed a multi-server queue model is a mathematical representation used to analyze and understand the dynamics of queues in systems with multiple servers. This model entity often representing patients or tasks, arrive at a queue and await service from one of several available servers. The key parameters include the arrival rate of entities, the service rate of each server, and the number of servers.

The performance of such systems is characterized by metrics like the average queue length, system utilization, and patient waiting time. Multi-server queue models are applied in diverse fields from telecommunications networks to patient systems and service industries, optimize resource allocation and enhance overall system efficiency. By studying the interplay between arrivals, service rates, and server availability, these models provide insights into the performance and scalability of complex systems with multiple service points.

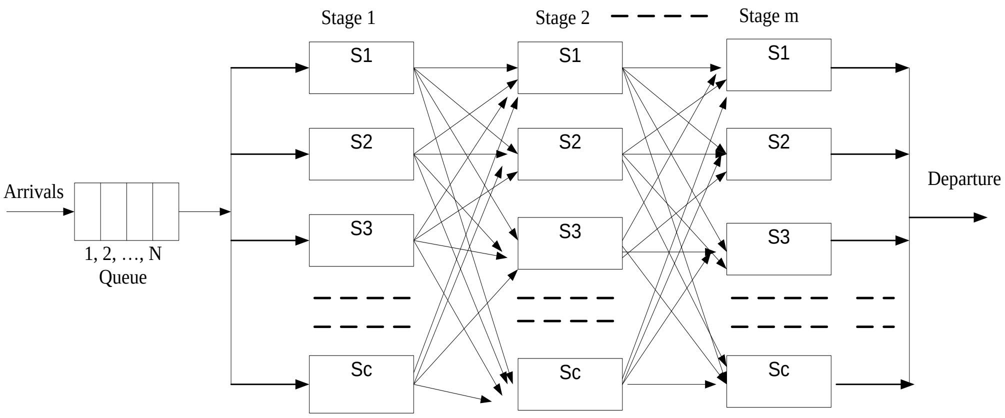

Fig.2.Model of single queue and multi-servers with m- stages

4. Description of Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's neural structure. Comprising interconnected nodes, or artificial neurons, organized in layers, ANNs excel in learning patterns and making predictions. The input layer receives data, which progresses through hidden layers via weighted connections. These weights adjust during training, optimizing the network's ability to recognize intricate patterns in diverse datasets. The output layer produces the network's prediction and ANNs are integral to machine learning, powering tasks like image recognition, natural language processing, and decision-making. Their adaptability and capacity for complex tasks make them a cornerstone in modern artificial intelligence, contributing to advancements in various fields, from healthcare diagnostics to autonomous vehicles.

A queueing model, integrated with Artificial Neural Networks (ANNs) serves as a sophisticated solution for minimizing OPD patient waiting time. In this model, patient arrivals and service time are meticulously analysed and optimized using ANNs, which predict and adapt to varying patient flow patterns. By incorporating real-time data and historical information, the system forecasts demand, enabling efficient allocation of resources and staff. The queueing model, enhanced by ANNs, not only streamlines the patient flow but also ensures that OPD patients receive prompt and personalized care. This innovative approach revolutionizes the healthcare operations, elevating patient satisfaction and overall hospital efficiency.

5. Mathematical Model

We operated under the premise that specific mathematical symbols denote particular concepts. For example, we utilized "nμ" to signify the quantity of patients served per unit time, consequently denoting "mcμ" as the number of phases served within the same timeframe. The probability density function linked with the Erlang distribution can be elucidated as follows:

λ = arrival rate

μ = service rate

m = number of phases

c = number of multi- servers

The system of difference equations in a steady- state is derived as follows:

$-(\lambda + m.c.\mu)P_n + mc\mu\, P_{n+1} + \lambda\, P_{n-1} = 0; \quad n > 0$

(3.1)

$-\lambda P_0 + mc\mu\, P_1 = 0; \quad n = 0$

(3.2)

Let $\rho = \frac{\lambda}{mc\mu}$ and dividing (3.1) and (3.2) by mcμ, we get

$(1+\rho)P_n = \rho\, P_{n-m} + P_{n+1} = 0; \quad n \geq 1$

(3.3)

$P_1 = \rho P_0, \quad n = 0$

(3.4)

To solve (3.3) and (3.4), the method of generating function is used
Let $G(z) = \sum_{n=0}^{\infty} P_n . Z^n$; $|Z| \leq 1$
(3.5)
Multiplying (3.3) by Z^n and summing over the range, we obtain
$(1+\rho)\sum_{n=1}^{\infty} P_n . Z^n = \rho\sum_{n=1}^{\infty} P_{n-m} . Z^n + \sum_{n=1}^{\infty} P_{n+1} . Z^n$
(3.6)
An addition of ρP_n to LHS of (3.6) and $P_1 = \rho P_0$ to RHS of (3.6), yields
$(1+\rho)\sum_{n=1}^{\infty} P_n . Z^n + \rho P_0 = P_1 + \rho\sum_{n=1}^{\infty} P_{n-m} . Z^n + \sum_{n=1}^{\infty} P_{n+1} . Z^n$
(3.7)

$$\Rightarrow (1+\rho)\left[P_0 + \sum_{n=1}^{\infty} P_n . Z^n\right] - P_0 = \rho\sum_{n=1}^{\infty} P_{n-m} . Z^n + \left[P_1 + \sum_{n=1}^{\infty} P_{n+1} . Z^n\right]$$
$$\Rightarrow (1+\rho)\left[P_0 + \sum_{n=1}^{\infty} P_n . Z^n\right] - P_0 = \rho\sum_{n=1}^{\infty} P_{n-m} . Z^n + \left[P_1 + \sum_{n=1}^{\infty} P_{n+1} . Z^n\right]$$
$$\Rightarrow (1+\rho)\sum_{n=0}^{\infty} P_n . Z^n - P_0 = \rho\sum_{n=k}^{\infty} P_{n-m} . Z^n + \frac{1}{P}\sum_{n=1}^{\infty} P_{n+1} . Z^{n+1}$$

Since $P_{n-m} \neq 0$ for n – m = 0, we have
$(1+\rho)\sum_{n=0}^{\infty} P_n . Z^n - P_0 = \rho\sum_{m=0}^{\infty} P_m . Z^{n+m} + \frac{1}{P}\sum_{i=1}^{\infty} P_i . Z^i$, n - m =M; n + 1 =i

$$= \rho Z^m \sum_{m=0}^{\infty} P_M . Z^M + \frac{1}{P}\left[\sum_{i=1}^{\infty} P_i . Z^i - P_0\right]$$

or $(1+\rho)\, G(z) - P_0 = \rho Z^m\, G(z) + \frac{1}{P}[G(z) - P_0]$
or $(1+\rho)\, G(z) - P_0 \frac{Z_0(1-P)}{(1-P)-\rho\, P\,(1-P^m)} = Z_0\left[1 - \rho\, P\left\{\frac{1-P^m}{1-P}\right\}\right]^{-1}$ $|Z| \leq 1$
$= Z_0\sum_{n=0}^{\infty}(P\rho)^n\left[\left\{\frac{1-P^m}{1-P}\right\}\right]^n$
(3.8)
Therefore,

$$G(z) = P_0\sum_{n=0}^{\infty}(P\rho)^n\,(1 + z + z^2 + \cdots . + z^{m-1})^n$$

$G\,(z) = P_0\sum_{n=0}^{\infty}(\rho)^n\,(z + z^2 + \cdots . + z^m)^n$
(3.9)
Putting z= 1 in (3.9), we get
$G\,(1) = P_0\sum_{n=0}^{\infty}(\rho)^n\, m^n = P_0\left(\frac{1}{1-k\rho}\right)$
Since $\sum_{n=1}^{m}(1)^n = m$
(3.10)
For z=1, (3.5) gives $G\,(1) = \sum_{n=0}^{\infty} P_n = 1$
(3.11)
$\sum_{n=0}^{\infty} P_n = 1 = P_0\left(\frac{1}{1-m\rho}\right)$ or $P_0 = 1 - m\rho$
(3.12)
Substituting the value of P_0 into equation (3.8), we acquire:

$$G(z) = (1-m\rho)\sum_{n=0}^{\infty}(z\rho)^n\,(1 - z^m)^n(1-z)^{-n}G(z)$$
$$= (1-m\rho)\sum_{n=0}^{\infty}(z\rho)^n\left\{\left[\sum_{\gamma=0}^{\infty}(-1)^{\gamma}\, n_{C_\gamma} y^{\gamma m}\right]\left[\sum_{\gamma=0}^{\infty} n+i-1_{C_I}\, y^I\right]\right\}; \quad (-1)^{2I} = 1.$$

$\sum_{n=0}^{\infty} P_0 z^n = (1-m\rho)\sum_{n=0}^{\infty}(z\rho)^n \left[\sum_{\gamma=0}^{\infty}\sum_{\gamma=0}^{\infty}(-1)^{\gamma} n_{C_\gamma}\, n+i-1_{C_I} y^{I+\gamma m+N}\right]$

(3.13)

Upon comparing the coefficient of z^n on both sides of equation (3.13), we obtain:

$P_0 = (1-m\rho)\sum_{n,\gamma,i}\rho^n(-1)^{\gamma}\, n_{C_\gamma} n+i-1_{C_I}$

(3.14)

6. Performance Measures

In this section, we derive the mean number of phases present in both the system and queue. Additionally, we calculate the mean number of patients within the queue and the entire system. Furthermore, we determine the mean waiting time experienced by patients in the system, and we also assess the mean number of patients within the system across various phases in the queuing model. Finally, we extract the expected total service time. We examine a specific equation and calculate the average number of phases within the system, under specific conditions; we utilize the following formula for this purpose:

$$L_s(m) = \sum_{n=0}^{\infty} n\, P_0$$

$$(1+\rho)P_0 = \rho\, P_{n-m} + P_{n+1}; \qquad n \geq 1.$$

Now, when we multiply both sides by n^2 and then sum the result, we obtain:

$$(1+\rho)\sum_{n=1}^{\infty} n^2 P_n = \rho \sum_{n=1}^{\infty} n^2\, P_{n-m} + \sum_{n=1}^{\infty} n^2\, P_{n+1}$$

$$(1+\rho)\sum_{n=1}^{\infty} n^2 P_n = \rho \sum_{n=k}^{\infty} n^2\, P_{n-m} + \sum_{n=1}^{\infty} n^2\, P_{n+1}$$

If we have n – m = n and n +1 = n, then the right-hand side (RHS) simplifies to:

$$(1+\rho)\sum_{n=1}^{\infty} n^2 P_n = \rho \sum_{n=0}^{\infty}(n+m)^2\, P_n + \sum_{n=1}^{\infty}(n-1)^2\, P_n$$

$$= \rho \sum_{n=0}^{\infty}(n+m)^2\, P_n + \left\{\sum_{n=0}^{\infty}(n-1)^2\, P_n - P_0\right\}$$

$$= \sum_{n=0}^{\infty}[\rho\,(n^2 + m^2 + 2nm) + (n^2 + 1 - 2n)]P_n - P_0$$

$$= (1+\rho)\sum_{n=0}^{\infty} n^2 P_n - 2\,(1-m\rho)\sum_{n=0}^{\infty} n\, P_n + 2\,(1+\rho m^2)\sum_{n=0}^{\infty} P_n - P_0$$

Hence, $\sum_{n=0}^{\infty} n\, P_n = \frac{\rho m^2+1-P_0}{2\,(1-m\rho)}$

$$L_s(m) = \sum_{n=0}^{\infty} n\, P_n = \frac{\rho m^2 + 1 - P_0}{2\,(1-m\rho)} = \frac{\rho m^2 + 1 - (1-\rho m)}{2\,(1-m\rho)}$$

$$\therefore \quad L_s(m) = \frac{\rho m^2 + 1 - (1-\rho m)}{2\,(1-m\rho)} = \frac{\rho m\,(m+1)}{2\,(1-m\rho)} = \frac{m\,(m+1)}{2} \cdot \frac{\rho}{(1-\rho m)}$$

$L_s(m) = \frac{m\,(m+1)}{2} \cdot \left(\frac{\lambda}{m\,n\,\mu}\right)\left(\frac{n\mu}{n\mu-\lambda}\right)$ [Since $\rho = \frac{\lambda}{m.n.\mu}$, $\lambda < n\mu$ and $\rho.m < 1$]

$$L_s(k) = \frac{m\,(m+1)}{2}\left\{\frac{\lambda}{n\mu-\lambda}\right\} \qquad (4.15)$$

(4.1) Utilization factor:

$\rho = \frac{\lambda}{m.n.\mu}$;

Here "λ" is arrival rate of patient, "μ" is service rate, "n" is number of server and "m" is different phase for patients.

(4.2) Mean Number of Phases in the Queue:

$$L_p = \frac{L_S(m)}{n\mu} = \frac{(1+m)}{2}\left\{\frac{\lambda^2}{n\mu\,(n\mu-\lambda)}\right\}$$

(4.3) Mean Number of Patients in the Queue:

$$L_q = \frac{L_S(m) - Average\ Number\ of\ Phases\ in\ Service}{k} = \frac{(1+m)}{2m}\left\{\frac{\lambda^2}{n\mu\,(n\mu-\lambda)}\right\}$$

(4.4) Mean Waiting time in the Queue:

$$W_q = \frac{L_q}{\lambda} = \left(\frac{1+m}{2m}\right)\left\{\frac{\lambda}{n\mu\,(n\mu-\lambda)}\right\}$$

(4.5) Mean Waiting time of a Patients in the System:

$$W_s = W_q + \frac{1}{n\mu} = \left(\frac{1+n}{2n}\right)\left\{\frac{\lambda}{n\mu\,(n\mu-\lambda)}\right\} + \frac{1}{n\mu}$$

(4.6) Mean Number of Patients in the System:

$$L_s = L_q + \frac{\lambda}{n\mu} = \left(\frac{1+m}{2m}\right)\left\{\frac{\lambda}{n\mu\,(n\mu-\lambda)}\right\} + \frac{\lambda}{n\mu}$$

(4.7) Determination of Expected Total Service Time:

$$E(T) = \frac{1}{n\mu}$$

7. Algorithm of ANN for Queueing Model

Step 1: Generates the dataset for the queueing model by calculating various metrics (Utilization factor, Queue Length in queue, waiting time in queue, etc.) Based on the given data (arrival rate, service rate, number of channels and number of servers).
Step 2: It uses the formulae provided in the original question to compute the metrics and combines the inputs and outputs into a single dataset.
Step 3: loads the pre-processed dataset generated in the previous step.
Step 4: creates a feed forward neural network model using MATLAB's Neural Network Toolbox (`fitnet`).
Step 5: The model is configured with a specified hidden layer size (hidden_layer_size) and the 'trainlm' training algorithm (gradient descent).
Step 6: sets the activation function for the hidden layers to 'poslin' (positive linear) and for the output layer to purelin' (linear) for regression tasks.
Step 7: The model is then trained using the training data.
Step 8: Finally, the trained neural network model, along with the extracted weights and biases, is saved for later use in prediction.
Step 9: loads the trained neural network model and the extracted weights and biases for E (T) and Wq predictions.
Step 10: defines a new set of inputs (`new_data`) for prediction, representing arrival rate, service rate, number of channels, and number of servers.
Step 11: Using the trained model, makes predictions on the new data and calculates the Expected Total Time (E(T)) and Waiting Time in Queue (Wq) based on the provided inputs.
Step 12: Display the predicted values for E (T) and Wq.

8. Numerical Illustration

We have obtained various performance measures using the above queueing model as multiple servers with various phases, i.e. Utilization factor, average number of phases in the queue, average number of patients in the queue, average waiting time in the queue, average waiting time of a patients in the system, average number of patients in the system with various performances. In this paper, we study some cases regarding to numbers of patients and using the channels with various phases and taking some parameters and obtained performance analysis above the same.

In this paper, we have analysed the data of the patients of a private hospital for three months, from Monday to Saturday and from 9 am to 6 pm, in which we have used the queue model and artificial neural network to predict the occurrences in patients. By detecting the diseases and treating them at the right time, we have also analysed the performance of the system.

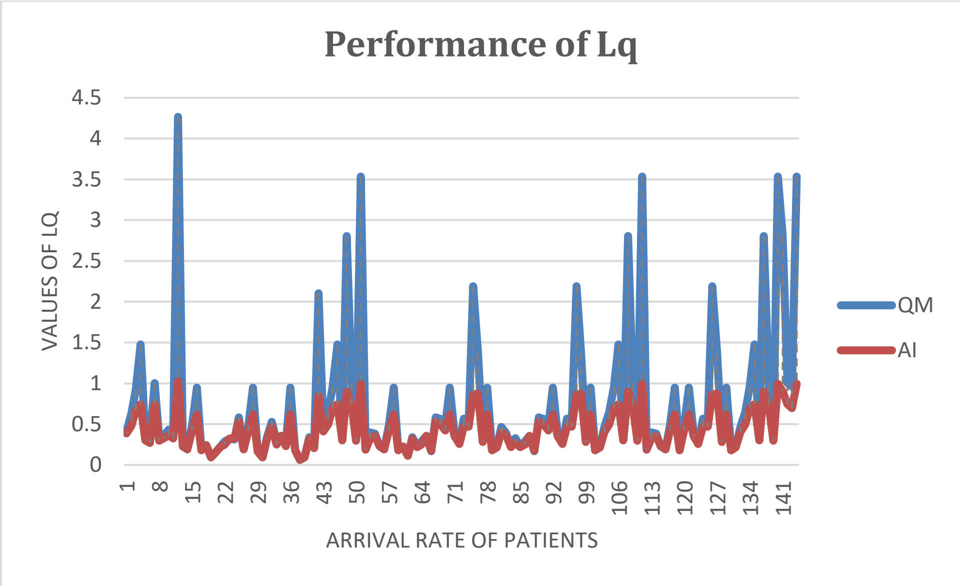

Fig. 3: Conventional mode vs ANNs for Lq

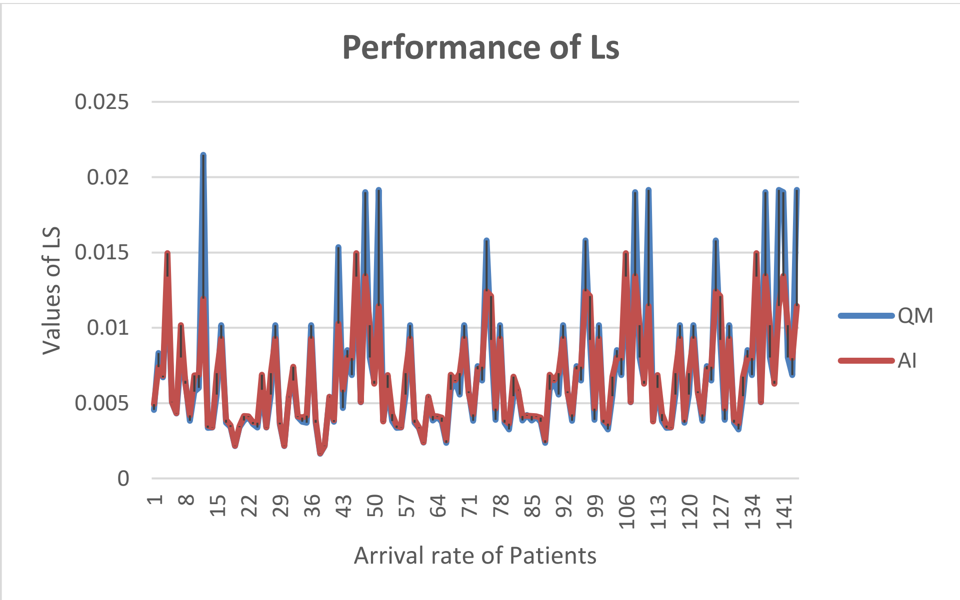

Fig. 4: Conventional mode vs ANNs for Ls

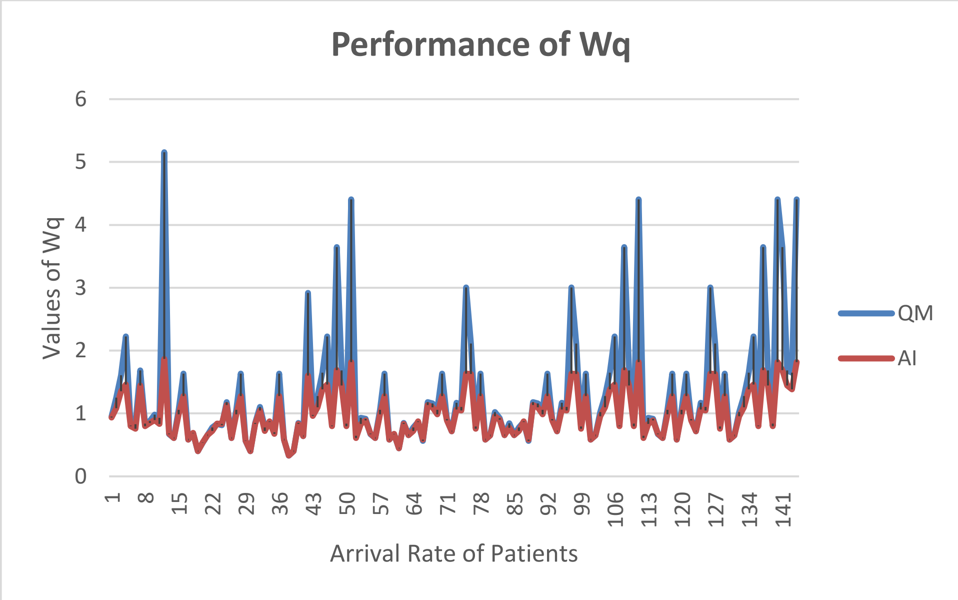

Fig. 5: Conventional mode vs ANNs for Wq

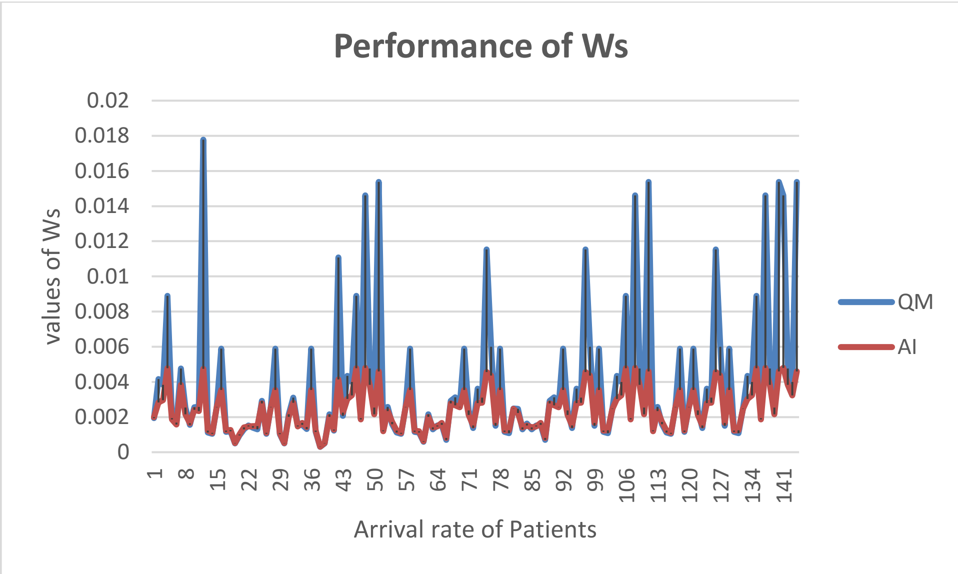

Fig. 6: Conventional mode vs ANNs for Ws

9. Result Discussion

We study of OPD patients by using multi-server queue model with multi phases and obtained waiting time in queue and system, expected total service time with utilization factor. Here, we follow two processes, one is conventional and second is artificial neural networks (ANNs) with various types of parameters and it's found some numerical values. Our findings indicate that artificial neural networks (ANNs) surpass MATLAB and other tools in terms of efficiency; leading to both time and cost savings. It seems that the artificial neural networks (ANNs) technique provided more effective and utilization results than conventional technique.

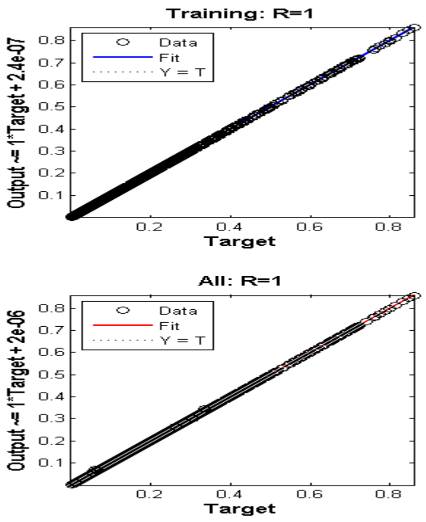

Fig. 7: Regression lines with Training and Testing data

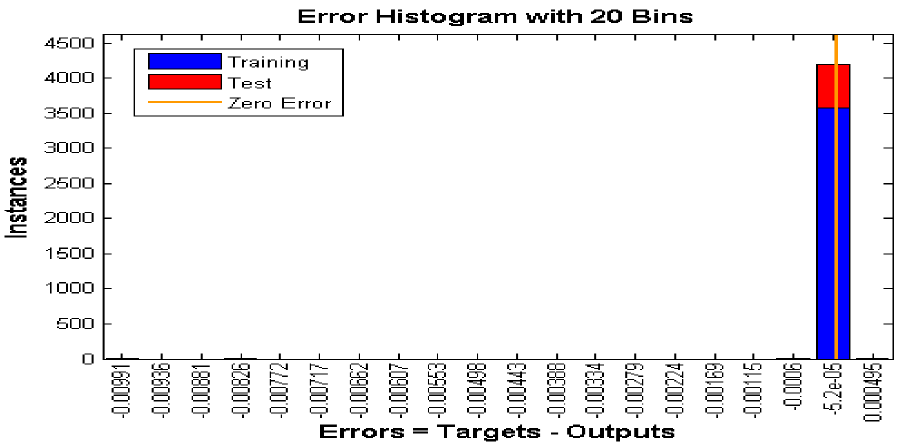

Fig. 8: Represent Errors from Original and Neural Network

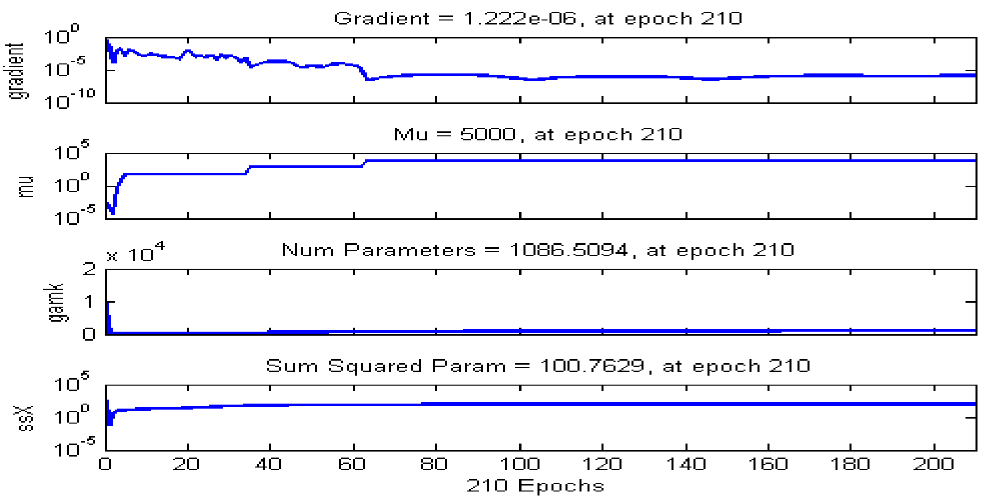

Fig. 9: Training Data with Epochs

10. Validation of Data:

In this section, we have validated our data using MATLAB and Artificial Neural Networks and we observed the ANNs is better technology to MATLAB. Our model has reduced the waiting time according to the purpose of the paper. Figures 7, 8 & 9 shows that our data is absolutely correct and also we desired from the training data test with epochs, error target output and lines of regression.

11. Conclusion

We investigated with a multi-phased queue model, and its performance metrics are derived through two distinct approaches: the traditional method and artificial neural networks (ANNs). ANNs utilize the queue model to address congestion issues, particularly during peak periods, thereby contributing to the maintenance of patient well-being with positive reputation of healthcare services. Various queueing models have been developed to address overcrowding and queuing challenges. By applying this model, we can assess industrial production quality and proactively identify potential severe diseases. The model facilitates timely intervention and appropriate treatment for patients, potentially saving lives. The outcomes of model are obtained through both queueing models and Artificial Neural Networks (ANNs) under conditions of exceptionally high patient influx, considering specific average service times and a range of parameters. Results and graphical representations demonstrate a reduction in waiting time and expected total service time when compared with the traditional queue model. The efficiency and effectiveness of the ANNs in OPD is much better performance of the traditional model.

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