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Stochastic Analysis of Single Server Queuing System with Recurrent Customer Arrival in a Banking System Using Machine Learning

Kiran Vivrekar[1], Dr. Rakesh Pandit[2]

[1]Research Scholar, Department of Computer Science and Engineering, Medi-Caps University, Indore, Madhya Pradesh, India, kiran.vivrekar@medicaps.ac.in
[2]Assistant Professor, Department of Computer Science and Engineering, Medi-Caps University, Indore, Madhya Pradesh, India, rakesh.pandit@medicaps.ac.in

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ABSTRACT
Uncertain waiting times in banking client lines may negatively impact customer satisfaction. Although the formula for waiting time provided by Little's Law in queue theory is general, it cannot be directly used to offer finite wait time estimate in practice. Examining potential predictors of waiting time is the primary goal of this research. The paper's implementation of the Artificial Neural Networks approach makes use of the Fast-Artificial Neural Network engine. Artificial Neural Networks were trained using Resilient Propagation. The input neurone was compared using both a time-series and a structural method. It was suggested that structural variables such as Queue Length and Head of Line length estimator variables be enhanced by averaging the length from prior intervals and the number of servers. We utilized an experimental approach to find the optimal configuration for the number of neurons in the input and hidden layers. This research found that compared to the time-series technique, the structural approach yielded more accurate estimates. The outcome is also improved when the combination of updated helper variables is used.

1. INTRODUCTION

Queues are encountered on a daily basis. Bank branches will see lengthy lines as a result of inefficient handling of consumer enquiries. The creation of lengthy lineups is also influenced by the random distribution of arrivals. Estimating how long people will wait in line may be challenging, despite the necessity of queue management. Despite the fact that "Principle 4: Uncertain Waits are Longer than Known, Finite Waits." [1] states in the psychology of waiting, known finite waits are nevertheless difficult to accomplish. Some research began to predict waiting times in an effort to find limited wait times and improve the line experience for customers. Financial institutions are among the many that utilize automated queue management systems. Unfortunately, waiting-time estimate capabilities are lacking in the majority of these queue management systems. One of the computerized queue management systems utilized in Indonesian banks, the Mattel Queuing System (MQS) data log, is used in this research. The Queuing theory is a necessary reference for estimating queue wait times. Directly putting queuing theory into practice is challenging. The queue management system does not provide the arrival rate or service rate. We need to use simulation to create variables for wait-time estimate in this research. Wait times in the actual world may be estimated using those factors. Wait times as a function of service quality were the subject of research by [2]. The likelihood of an overflow of customers was determined using Little's Law. The topic of wait-time estimate was the subject of a notable publication [3]. They used statistical time-series forecasting as their technique. They did not gather data that was homogeneous or evenly spaced, unlike most time-series data. Hence, they must take an average value every ten minutes and use regression to fill in the blanks when data is lacking. Their service's mean absolute error dropped to under two or three minutes, according to their studies. In order to estimate wait-time using time-varying little's law (TVLL) [4], Kim and Whitt conducted another investigation. Their predisposition towards Little's Law was diminished. To forecast customer service, wait times, Ibrahim and Whitt performed a comparable research. A combination of queue length (QL) and the amount of time a customer has to wait at the head of the queue (HoL) was used as a predictor by the authors [5]. They derived a formula to forecast wait-time, which is a parametric technique in their work. So, we tried out a bunch of other adjusted predictors that relied on those two. The use of Artificial Neural Networks (ANN) for time-series data estimation and prediction has been the subject of several research. By combining ANN with expert systems, Guresen suggests modelling time-series data, especially stock market data [6]. The lack of traditional formulae and its ability to respond to market fluctuations make this strategy one of the greatest methods to simulate the stock market, according to him. A related research that used ANN to forecast stock prices got the job done, successfully predicting the closing price by observing its patterns of behavior and propensity [7]. When compared to statistical methods, Neural Networks provide better forecasts [8]. Yet another effort to simulate how well an ANN using the enhanced conventional Back Propagation algorithm (RPROP) and QUICKPROP performs in time-series forecasting. The research shown that the method is applicable to real-world issues and has good generalizability [9]. Studies like these demonstrate how artificial neural networks (ANNs) may be used to predict waiting times in banking queues using series data. Relatedly, [10] used a variety of learning algorithms to forecast how long customers would have to wait in line to see a bank teller. Using the formula from Queuing Theory, GBM, Random Forest, and Deep Learning (DL), the authors created and evaluated four prediction models. The GBM model outperformed the other three models with a 97% accuracy rate and a 75% F1 measure. For reasons of both familiarity and practicality, ANN is used to forecast waiting time in this research. Based on the results of the research, we are aware that there are a variety of approaches to developing data-driven prediction models. But this research isn't about comparing the efficacy and accuracy of various prediction systems; it's about using RPROP Neural Networks to look at major drivers of waiting time.

2. APPROACH TO RESEARCH

In this research, a tool named Wait-Time Estimator is built to examine the utilization of artificial neural networks (ANNs) in wait-time estimation. The error! diagram shows the general design of the wait-time estimator. Could not locate the referenced source. The FANN [11] engine is the backbone of this tool's ANN implementation. Utilizing the AIR Application, Wait-Time Estimator manages the user interface and front-end data flow. Once the tools are in place, it will be much simpler to apply this research to a real-world queuing system in the future. Through ANE (AIR Native Extensions), the AIR application is able to talk to FANN and access the queue data warehouse.

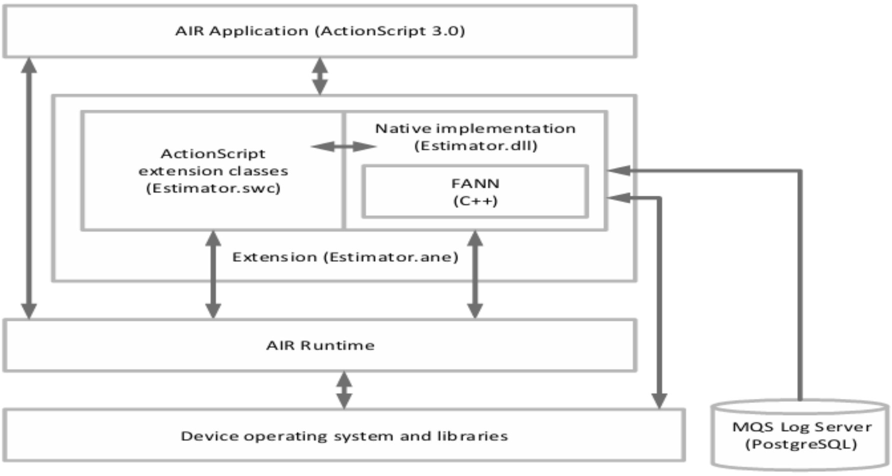

Fig. 1 Tool architecture for wait estimation

2.1. FANN and ANN

The research here makes use of Resilient Propagation (RPROP), a refined version of the widely-used back-propagation training technique [11]. The RPROP algorithm's main benefit stems from the ANN training procedure, which updates the ANN weights by using just the sign of the error function gradient, rather than the error value itself [12]. During training, the ANN weights were adjusted [12]. Fast Artificial Neural Network Library (FANN) is used to implement RPROP in this research. FANN is a free and open-source neural network library that supports fully connected and sparsely connected networks, and it constructs multilayer artificial neural networks in C [11]. The libraries of FANN have been available since 2003 and have seen extensive usage in both academic and industry contexts, which led to their selection. Here, every ANN makes use of the sigmoid activation function with an activation steepness of half. An input layer, a hidden layer, and an output layer make up a multilayer network. With varying numbers of hidden neurones, a single hidden layer is used. The input neurone that will be examined in the experiment will be a time series method, which uses prior consecutive time-series data.

2.2. Collecting Data

The study's data comes from actual industry sources, namely one of Indonesia's major banks. Mattel Queuing System is the name of the queue management system that the bank has installed. We gathered log data that included wait times at various tellers. The 22.082 data points collected are split as follows: 65% for training and 35% for testing. Two methods are contrasted in this research: the structural method and the time-series technique 3. The environmental condition variable of the queue dictated the input layer in the structural method.

2.3. Using time-series data

Customer data arrays tagged with arrival time and wait-time duration (D) make up bank customer queuing data. The arrival times of each consumer were completely at random. Consequently, the waiting time of a queue cannot be used directly as a time series variable. Unlike stock data, which allows us to extract a value at a certain instant in time, this data does not. A wait-time is a flow time series that requires a summary of its operations over a certain time frame. This is similar to adding up all the new cars sold every day of the month to get the total number of new car sales for the month. Based on [3], we've settled on a 10-minute period. The waiting time of past customers cannot be used as input data for a time-series technique for estimating the waiting time of new customers. It seems that the system may not have logged the waiting time of previous customers, as shown in the error message. The new client comes while they are still in wait, hence the reference source could not be retrieved. This may be resolved by first estimating the waiting time from the preceding interval using Wait-Time Estimator.

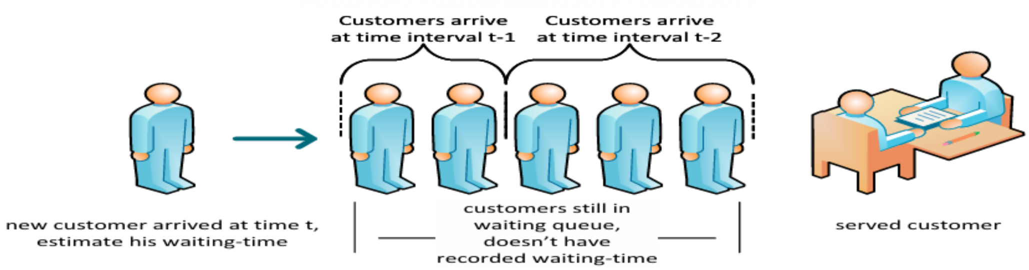

Fig. 2 Data for unrecorded series

Iterative ANN [13] may be used to accommodate this answer, as shown in the Error! I was unable to locate the necessary reference material. must be met. Another estimate will use this function's result as input. This means that the same estimating procedure will be used recursively to fill in any unrecorded intervals with the results of the corresponding preceding intervals.

2.4. Method based on structures

In waiting-time estimates, the structural technique is simpler to implement than the time series approach. The recorded value serves as an input neurone in the structural method. Our log data only records a customer's arrival time and waiting time, thus we only have limited access to the needed recorded numbers in this research. There is no documentation of the queue length (QL) or the number of servers (c). Hence, we need to simulate the generation of QL data and the number of servers before using this strategy. By using all consumer data that has been captured, this simulation will attempt to replicate the queue flow. This means that for each client who arrives in the virtual queues, Wait-Time Estimator may keep track of QL and c. Each customer's arrival time is recorded in the queue length (QL) variable in order to get QL data. At the end of each day in the experiment, this variable will contain the current QL and will be reset to 0. Error! shows how this works.

Server Number (c): Since our research focused on the M/M/c queuing model, we fed the estimator the number of servers in our service. The study's simulation method for generating the number of servers is comparable to the QL procedure. One key distinction is that the Waiting-Time Estimator program keeps track of the server pool for each client who has arrived. After then, Wait-Time Estimator gets the current count of servers in this pool for each client that arrives. Nevertheless, servers that are not actively servicing any customers will be removed from the server pool list prior to this counting. Servers that aren't actively used will be marked down. Fig. 4(b) shows the process in action.

The elapsed waiting time of the consumer at the head of the queue (HoL) is used in this research, drawing upon Ibrahim's study [5]. In Figure 3, we can see HoL in action inside a client line. There is no HoL data in the study's log data, just as there is no QL data. Hence, we ran a comparable simulation to get the necessary data.

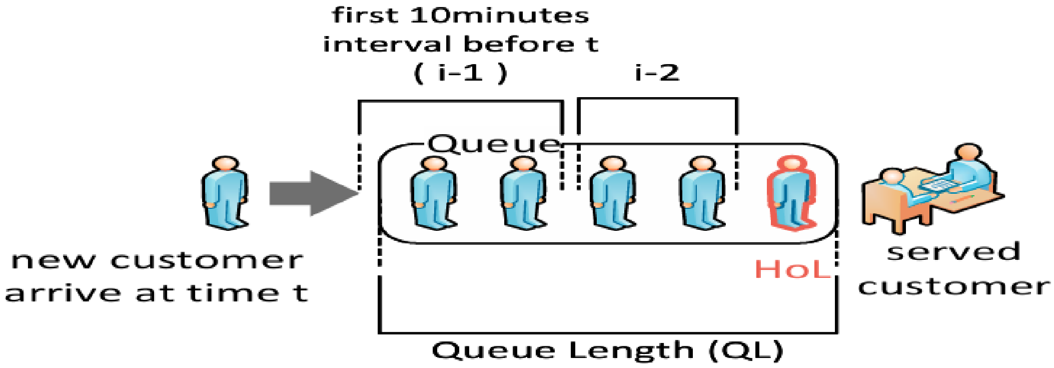

Fig. 3 Data for recorded series

Figure 3 shows that all we need is QL to get HoL from the customer's arrival time t. This customer t's mean HoL data is the arrival time of customer t minus the arrival time of customer t-QL.

3. RESULTS AND DISCUSSION

We evaluate the structural method and the time-series approach side by side in this section. Finding the optimal setup for the time-series method is a prerequisite. We need to specify the number of hidden neurons before we can search for the optimal configuration of input neurons. Following the best-case scenario, we start with 17 hidden neurons [14]. In addition to the most popular rule-of-thumb, other parameters will be considered when deciding on the optimal number of hidden neurons [15]. With n being the number of inputs, we also use n+1 as a criterion. The input and output layer sizes should be within the range of the hidden neurone number. The optimal number of hidden neurons is two-thirds of the size of the input layer plus the size of the output layer. The buried neurone count shouldn't exceed twice the size of the input layer. To determine the optimal amount of input neurons, this research used experimental methodologies. For the 1, 2, 3, 4, and 5 anticipated series, we began using the closest interval. To test the effect of a greater number of inputs neurons, we increased the number by 10, 20, and 30. Spot on! It was unable to locate the necessary reference material. illustrates the outcome, which approximately proves that a bigger number of inputs neurons would produce a higher inaccuracy. Mean Squared Error (MSE) quantifies the squared mean difference between the actual waiting time and the expected waiting time; it is used to evaluate the forecast error rate. Since MSE is not negative, it is preferable for values to be closer to zero. It should be noted that the values of MSE are units; values measured in seconds will be shown by the square root of the SME test (RMSE).

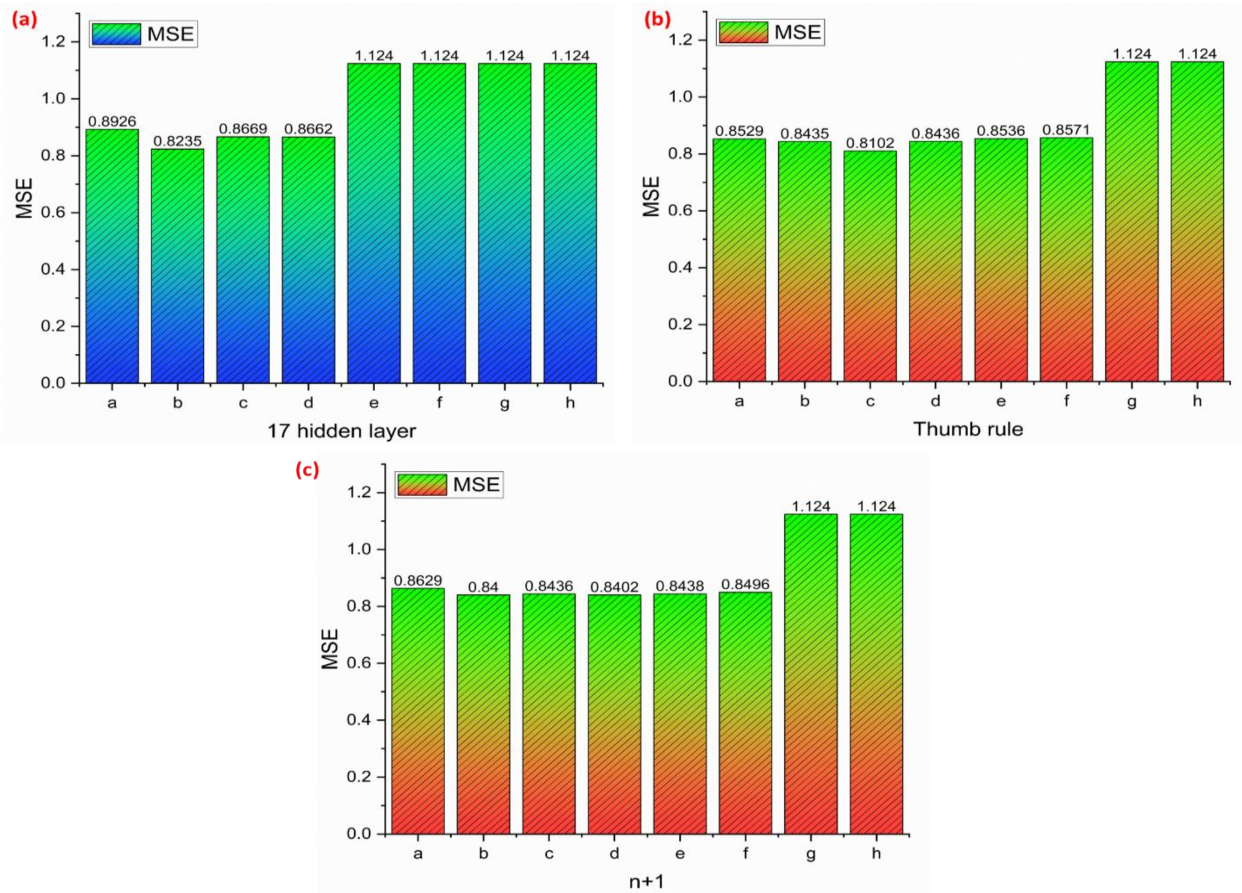

Fig. 4 MSE comparative chart for time series

You can see the difference between the lower groups and a higher MSE group in Figure 5. The findings demonstrate that the lowest among the inputs are three with rule-of-thumb, two with n+1 hidden, and four with n+1 hidden. We will compare these top findings to the predictor factors of another Wait-Time Estimator, such QL and HoL.

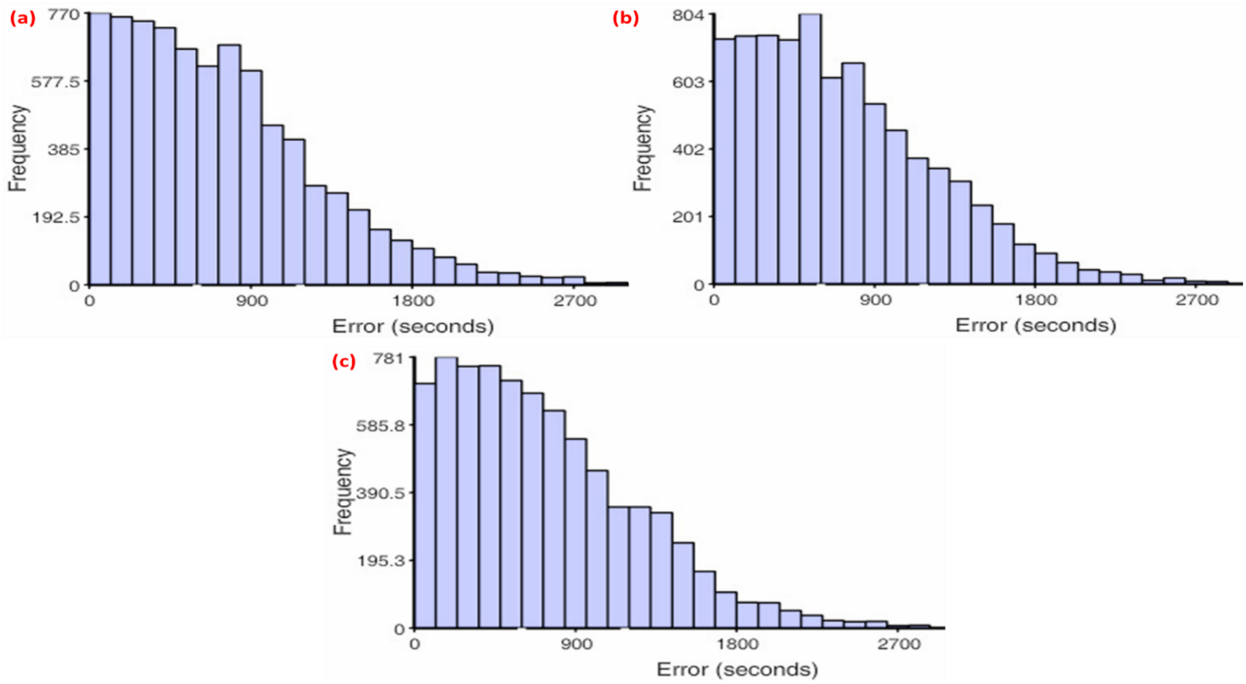

Fig. 5 MSE histogram for optmized approach (a) time-series (b) structural (c) structural approach with helper (Di-7, QL, c, and HoL)

We provide the distribution error in histograms in Figure 5 for the purpose of comparing the time-series technique with the structural approach. Results show that both methods achieve a greater density with a smaller margin of error. In comparison to the series technique, which had an MSE of 0.8400 (2 input, n+1 concealed), the structural approach achieved an MSE of 0.8129 (QL, c, HoL). With an MSE of 0.8118, however, our hybrid method (Di-7, QL, c, and HoL) produces somewhat superior results.

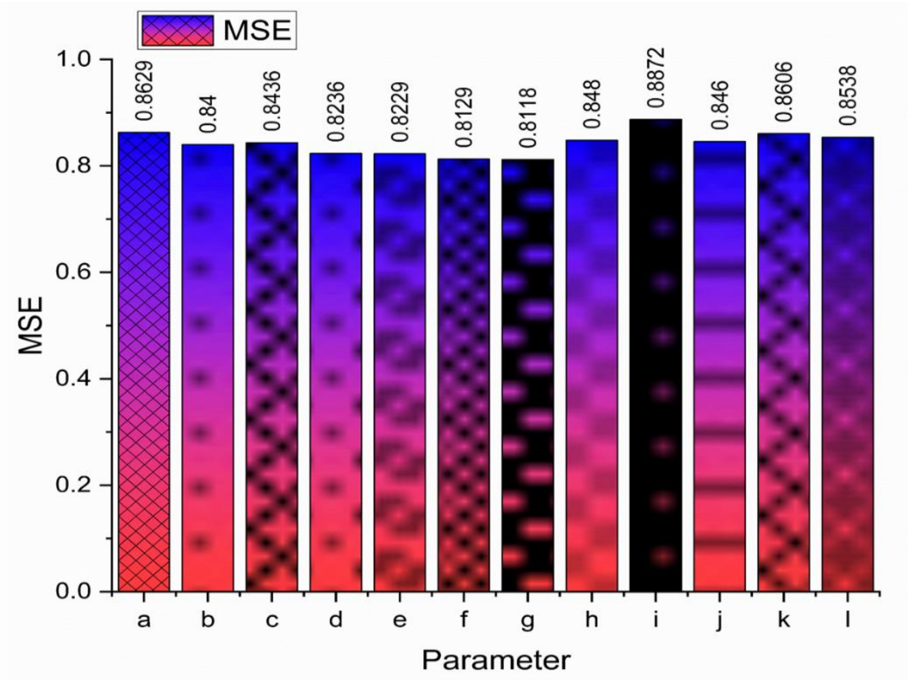

Fig. 6 MSE comparison chart

Figure 6 displays a comparison of all MSE results for all combinations. The results from the structural method are better than those from the time-series technique, which is modest. After including time-series imitative variables, the structural method achieved the best possible outcome. As an input layer for Wait-Time Estimator, Di-7, QL, c, and HoL demonstrate this optimal outcome. Artificial neural networks (ANNs) are able to carry out estimates more easily due to their general knowledge of environmental variables. More factors need to be addressed for complicated queues, however. An estimate's precision may be enhanced with little assistance from historical wait-time factors, such as Dd-7.

4. CONCLUSION

Authors estimated the client queue wait-time at a bank by using a time-series technique from a prior study by Bulut et al. [3] To transform queue data into time-series data, we use the same procedure. To assess various predictor factors, Artificial Neural Networks are used. Training takes less time using Resilient Propagation NN. This estimate's results demonstrate that the time-series method is effective in identifying the wait-time pattern. Additionally, we evaluate the outcome in comparison to a structural method that utilizes HOL, c, and QL as predictors. For the sake of this analysis, a helper variable (Dd-7) was also included. Results from the structural method (QL, c, HoL) are better than those from the time-series technique in this research. Even better is the outcome when the imitative time-series approach variable (Dd-7) is used. The enhanced outcome is a consequence of enhanced prediction capabilities after the inclusion of wait-time in the previous week's data. When it comes to banking client queues with complicated causal factors, further study is required, while both the time-series and structural approaches offer strong pattern recognition for wait-time estimates. For this reason, it is important to record the elements such as queue length, number of servers, and head of queue. Furthermore, while estimating the service rate variable in queue theory, it is important to consider the kind of services.

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