Neural Network Estimation of Waterway Lock Service Times

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Good service-time estimates at locks are essential for evaluating waterway performance, planning improvements, and controlling operations. Difficulties in estimation are due to great variations in lock characteristics, vessel characteristics, operating options, and environmental conditions. In this study several artificial neural network models for lock service-time estimation are developed and compared. Results show that simple artificial neural network models yield lower prediction errors than simple regression models, that systematic removal of outliers can reduce the number of artificial neural network prediction errors, and that combined service-time models for locks with dissimilar chambers can be obtained without unreasonably compromising accuracy.

Inland waterway transportation in the United States is used for shipping heavy or bulky commodities because it is inexpensive and energy efficient. There are 216 lock chambers at 167 lock sites operated in the United States. The lock structures (Figure 1) used to raise or lower vessels across dams constitute the major bottlenecks in the U.S. waterway network and generate extensive queues, which lead to costly delays.

Locks have one or two parallel chambers whose characteristics may differ greatly. A commercial tow typically consists of a tow boat and a number of barges. If a tow has more barges than the chamber can accommodate, it must be disassembled into several pieces (called cuts) to pass through the chamber, and must be reassembled later. The lock service time mainly depends on the chamber size and tow size. The number of barges, number of cuts, and tow direction also affect the lock service time.

PROBLEM STATEMENT

Good estimates of lock service times are essential for improving lock operations, either through long-term investments or short-term control. However, service times are quite complex and are influenced by numerous factors. Lock service time is defined as the sum of all times (approach time, entry time, chambering time, exit time, time between cuts, turn-back time, etc.) spent processing a given tow through a specific lock.

Several studies of lock service time have used traditional methods such as regression analysis (*1*) and simulation (*2*), and have obtained relatively inaccurate models. Dai and Schonfeld (*2*) had to use historical service-time distributions rather than estimated models in their simulation. In this paper, we explore the possibility of obtaining better service-time models using neural network methods. In the following sections we discuss candidate variables, neural network models, comparative regression model building, model results, and model validation.

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IDENTIFICATION OF CANDIDATE VARIABLES

For this work we used the data from the Corps of Engineers' performance monitoring system (PMS) 1988 data base, which provides comprehensive records of the arrival and processing times for all vessels using a lock. Lock 27 on the Mississippi River was selected. It has a large main chamber (33.55 m × 366 m) and a half-size auxiliary chamber (33.55 m × 183 m). From the PMS data base, 14 candidate variables were selected based on their high correlations with lock service time. From those 14 variables, 6 input variables (tow direction, index of same direction, number of cuts, number of barges, ratio between tow length and chamber length, and ratio between tow width and chamber width) and 1 output variable (service time) are defined. The service time is the sum of approach time, entry time, chambering time, and exit time. If the tow must be cut to get through the lock, the time between cuts and turn-back time are added to the service time.

Statistical Analysis of Service Time

It is difficult to define the specific distribution of service time due to its complexity and the great variation in causal factors. The service-time distribution can be checked by analyzing its statistical characteristics. During 1988, 8090 tows were observed through the main chamber and 3784 through the auxiliary chamber. Table 1 shows the summary statistics for the service times of the main and auxiliary chambers.

The mean service times for the main and auxiliary chambers are 44.218 min and 26.490 min, respectively. Histograms for both chambers in Figure 2 show that service-time distributions are skewed to the right. Very few tows have large service times. The maximum deviation of service time from the mean is 6.4 standard deviations (σ) for the main chamber and 11.2 σ for the auxiliary chamber.

Because data collection is performed by lock operating personnel, mistakes are sometimes made. Some data may be recorded incorrectly or illogically. Such flawed data compromise the accurate estimation of service time and must be removed from the input. The data collected during lock failure conditions are also excluded from the input in this study.

NEURAL NETWORK MODELS

Neural networks are biologically inspired. They are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neuron. These elements are then organized in a way that may be related to the anatomy of the brain (*3*). The neural networks are also called connective systems or par-

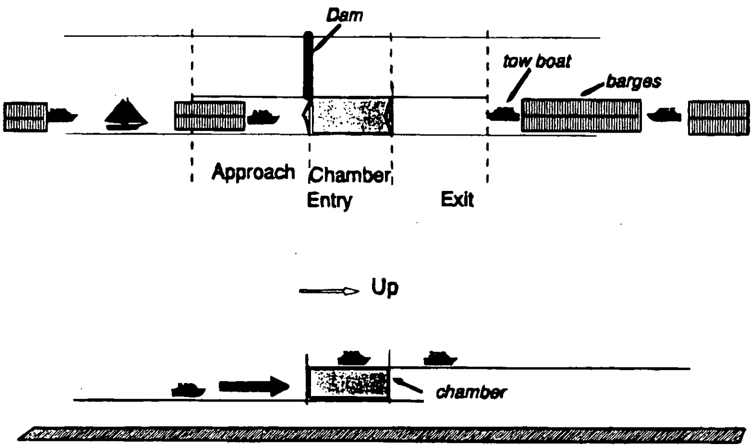


FIGURE 1 Lock system.

allel distributed processors. The many areas addressed by a neural network approach include data compression, recognition, prediction, classification, image processing, decision making, control, and optimization. For the estimation of service time, a backpropagation neural network model with three layers was constructed, as shown in Figure 3.

The neural network can also be defined as an interconnection of neurons such that neuron outputs are connected, through weights (e.g., W_{ij} and V_{ij}), to all other neurons including themselves. Both lag-free and delay connections are allowed (*4*). Figure 3 has one input layer of neurons, one output layer, and one hidden layer between the input and output layers. (This type of network may have more than one hidden layer.) Each of the neurons in a layer is connected to each of the neurons in the next layer. Table 2 defines the variables in Figure 3.

Normalization of Input Data

The weighted sums of inputs are compressed by the activation function into output values between 0 and 1. This study used the unipolar sigmoid activation function expressed in Equation 1 (*4*).

$$f(W'X) = \frac{1}{1 + \exp(-\lambda W'X)} \tag{1}$$

The normalization facilitates error convergence when the models are trained. The six input variables used here were normalized by dividing their actual values by their maximum values. Service times are normalized using the following equation:

$$Z_i' = \frac{Z_i - Z_{\min}}{Z_{\max} - Z_{\min}} \tag{2}$$

where Z_i' = normalized service time and Z_i = service time.

Training the Neural Network

A number of neural network models and training algorithms are currently available. Because of its reliability and its applicability to this study, the backpropagation algorithm that has been widely applied for prediction was chosen (*4*). The following backpropagation training procedure was used for n given training pairs:

Step 1: Select a learning constant (η) and initialize the weight vectors W and V using random numbers.

Step 2: Present the input data and compute the layers' output based on the unipolar activation function.

Step 3: Compute the error value: $E_{k+1} = (d_k - o_k)^2 + E_k$

Step 4: Compute the error signal for the output layer (δ_z) and hidden layer (δ_y):

$$\delta_z = (d_k - o_k)(1 - o_k)o_k \tag{3}$$

$$\delta_z = y_j(1 - y_j)\sum_{k=1}^{K} \delta_z w_{kj} \tag{4}$$

TABLE 1 Summary of Statistics of Tow Service Times at Mississippi Lock 27

Type of chamber	Mean	Standard deviation	Min/Max. service time	P_1†	P_{99}‡	No. of tows
Main chamber	44.218	14.857	8/140	14	82	8090
Auxiliary chamber	26.490	11.749	9/158	12	64.66	3784

† the service time which has 1% probability in the cumulative distribution.

‡ the service time which has 99 % probability in the cumulative distribution

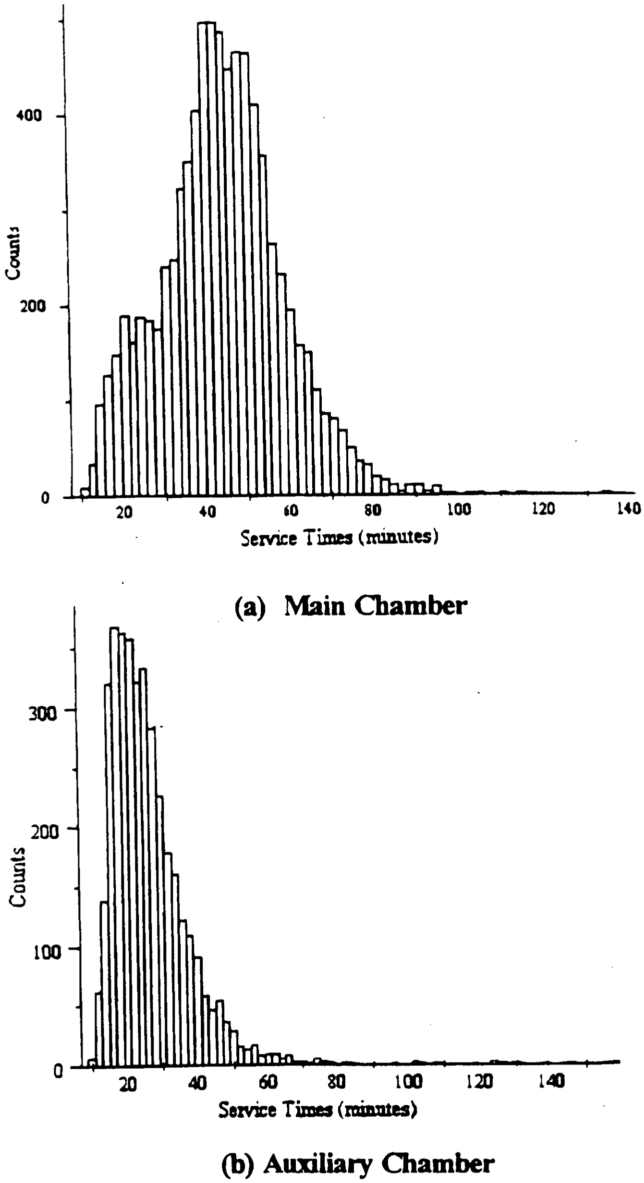


FIGURE 2 Histograms of service times before removing outliers.

Step 5: Adjust output layer weights ($W_{kj} = \eta\delta_z Y$) and hidden layer weights ($V_{ji} = \eta\delta_y Z$) to minimize the error signal.

Step 6: If n pairs of data are all trained, go to Step 7. Otherwise, go to Step 2.

Step 7: If the stopping rule is satisfied, terminate. Otherwise, go to Step 2.

In order to control the learning speed, the algorithm was run using different learning constants (η). The effectiveness and convergence of the error backpropagation learning algorithm depended on the value of learning constant η. In general, however, the optimum value of η depends on the problem being solved. The purpose of the momentum (M) method was to accelerate the convergence of the error backpropagation algorithm (*3*). For best results, different input parameter values were used to train the neural network:

- The number of hidden nodes (H): 3, 4, 5;
- The value of the learning constant (η): 0.4, 0.45, 0.5; and
- The value of momentum (M): 0.2, 0.3, 0.4.

To run the program, the input data were divided into two groups of training data and test data (4090 training data and 4000 testing data for the main chamber, and 1984 training data and 1800 testing data for the auxiliary chamber).

Performance Evaluation

The test data sets, 4000 pairs for the main chamber and 1800 pairs for the auxiliary chamber, were used to verify the trained neural network. Each test data set was evaluated after training the neural network through 50 iterations. The following three types of prediction errors were considered in assessing the neural network model performance:

- Maximum error between actual service time and estimated service time
- Average error between actual service time and estimated service time
- Mean absolute percent error (MAPE):

$$\text{MAPE} = \frac{1}{n}\left(\sum_{i=1}^{n} \frac{|A_i - E_i|}{A_i} * 100\right) \qquad (5)$$

where

A_i = actual service time of testing data,
E_i = estimated service time from neural network model, and
n = number of testing data set.

Here, MAPE was mainly used to assess the model's prediction accuracy.

IMPLEMENTATION AND RESULTS

To estimate the lock service time, the neural network model developed in the previous section was applied. The backpropagation algorithm was encoded in the C language, and run on the Unix system. The PMS data were divided into two groups of training data

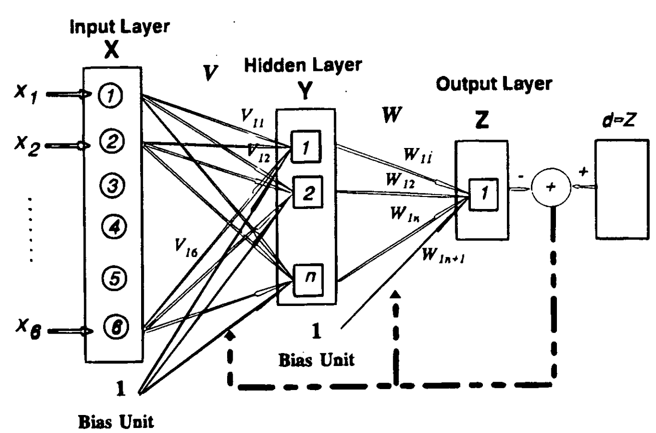


FIGURE 3 Backpropagation neural network.

TABLE 2 Input and Output Variables

Variables	Definition	Ranges
X_1	Tow direction	1 or 2
X_2	Index of tow with same direction (0) or opposite direction (1) from the previous one	0 or 1
X_3	Number of cuts in a tow	1 - 3 cut
X_4	Number of barges in a tow	0† - 23 barges
X_5	Ratio between tow length and chamber length	0† - 3‡
X_6	Ratio between tow width and chamber width	0† - 2‡
Y_i	Hidden layer output	-
V_{ij}	Weight matrix for hidden layer	-
W_{ij}	Weight matrix for output layer	-
Z	Service time, output layer	8 - 158 min

† Recreational boats have zero values.
‡ If X_5 or X_6 are greater than 1.0, tow must be divided into cuts to fit into lock chambers.

and test data. The neural networks were trained with 4090 input data for the main chamber and 1984 input data for the auxiliary chamber at each iteration. All experiments were limited to a maximum of 1000 iterations. At every 50 iterations, the service time was estimated with testing data based on the trained neural network models. The experiments were performed for every combination of parameter values, for a total of 27 experiments (3 types of hidden node × 3 learning rate values × 3 momentum values). The test solution with the best MAPE was saved from these experiments. The estimation results obtained with neural network models show that the MAPE of training data usually converges to one value. However, in some experiments the MAPE fluctuates. A possible reason is the inappropriate choice of values for such parameters as learning rate (η) or momentum (M). Table 3 shows the initial best MAPE solution in the specific experiments.

Data Manipulation

As described previously, some data might have been recorded incorrectly or illogically, since data were collected by humans. These data hinder accurate estimation of service time and should be removed if they can be properly detected. Barnett and Lewis (*5*) define an outlier as "an observation which appears to be inconsistent with the remainder of that set of data" and explain the relationships between the extreme observations, outliers, and contaminants. An outlier can also be defined as an extreme observation that has errors that are considerably larger in absolute value than the others, about 3 or 4 standard deviations from the mean (*6*). In order to detect outliers, the deviations between actual and estimated service times were computed. These deviations and the outliers with deviations beyond 3 σ (3 standard deviations) are summarized in Table 4.

The summary shows that the mean values of deviations for both chambers are negative (-2.03 and -0.56), which means that service times are slightly overestimated. Bell-shaped histograms of deviations between actual and estimated service times for both chambers are shown in Figure 4. The error analysis detected 81 outliers for the main chamber and 59 for the auxiliary chamber. Histograms of service times for both chambers after removing outliers are shown in Figure 5. The service time for the cleaned data sets was then reestimated with same procedure initially used in service-time estimation. The results are shown in Table 5.

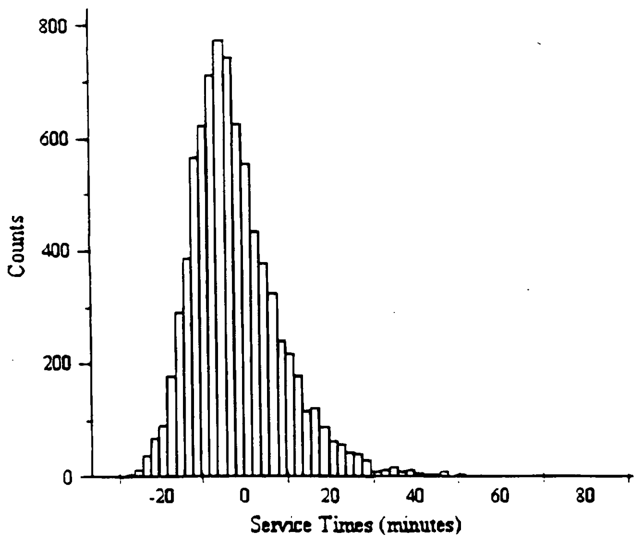
Without outliers, the new MAPEs for the main chamber are about 16.8 percent lower and for the auxiliary chamber about 16.1 percent lower than those in Table 3. The main chamber and auxiliary chamber have their best solutions when the numbers of hidden nodes are 5 and 4, learning rates are 0.4 and 0.5, and momentum values are 0.3 and 0.4, respectively. The auxiliary chamber shows a higher MAPE, largely because the service times at the auxiliary chamber are more variable than at the main chamber.

TABLE 3 Performance Value of Neural Network Without Removing Outlier Data

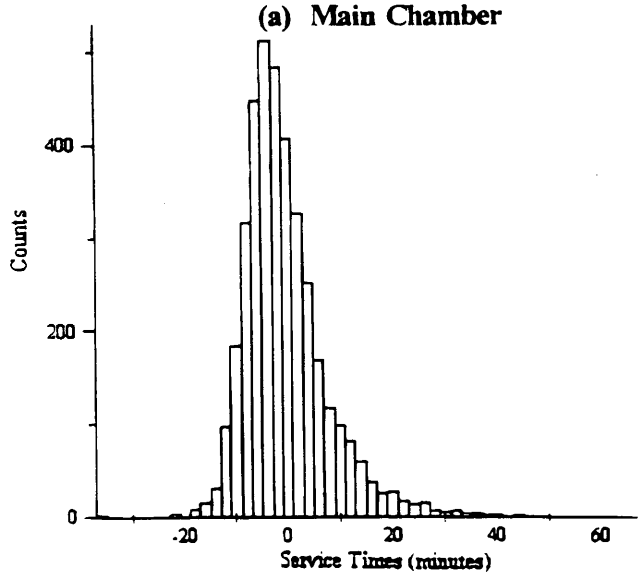
	Maximum absolute error (minutes)	Average absolute or (minutes)	MAPE (%)
Main chamber	61.996	7.855	21.049
Auxiliary chamber	77.696	5.872	23.461

TABLE 4 Summary Statistics of Deviation

	Mean	Standard Deviation (SD)	Total number of data	Number of outliers
Main Chamber	-2.031	10.928	8090	81
Auxiliary chamber	-0.556	8.109	3784	59

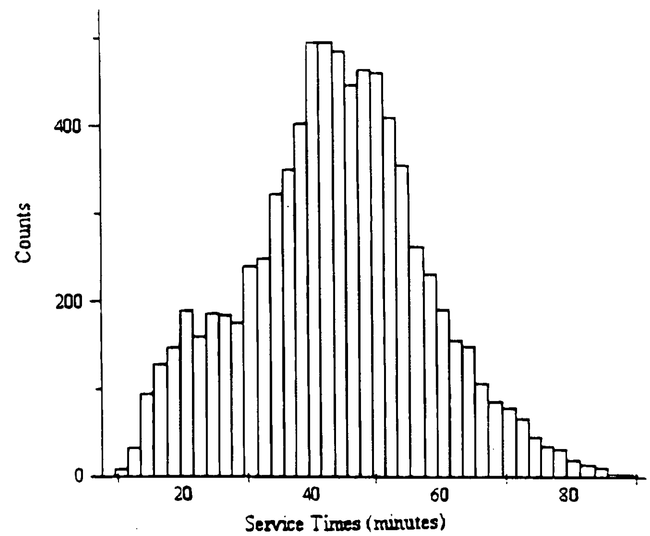


(a) Main Chamber

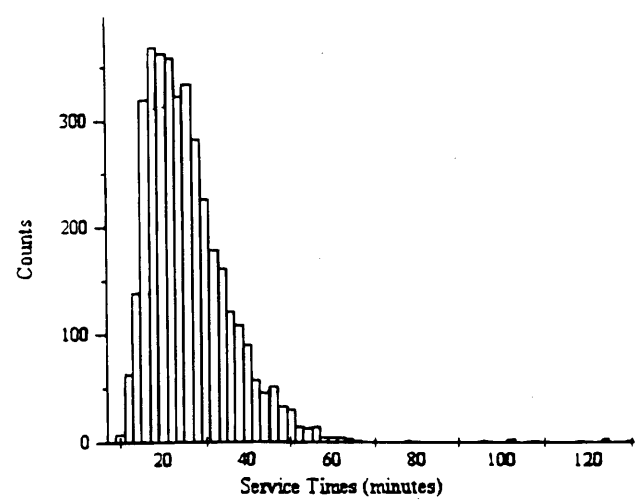


(b) Auxiliary Chamber

FIGURE 4 Histograms of deviations between actual and estimated service times.



(a) Main Chamber



(b) Auxiliary Chamber

FIGURE 5 Histograms of service times after removing outliers.

TABLE 5 Performance Value of Neural Network After Removing Outlier Data

	Maximum absolute error (minutes)	Average absolute error (minutes)	MAPE (%)	% MAPE improvement (%)
Main chamber	37.059	7.846	17.516	16.8
Auxiliary chamber	27.003	5.502	19.683	16.1

Multiple Regression Model

For a comparative assessment of prediction accuracy, multiple regression models of service times were also developed. Model I is a linear function and Model II is a nonlinear function that can be transformed to linear form by taking the logarithms of both sides.

- Model I:

$$Y = b_0 + b_1x_l + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6$$

- Model II:

$$Y = a^*\exp\,(b_1X_l + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6)$$

Table 6 shows the results of multiple regression analysis based on the same training data sets. Both Model I and Model II have lower R-squared values. Because the R-squared values are related to linear models, they were not used as performance measures. Instead, the MAPE was used for a comparative assessment.

Overall, MAPEs are considerably lower (by up to 30.9 percent) for the neural network models than for the regression models. A possible reason for the superior neural network performance is the ability to search for any linear or nonlinear relation without explicitly defining that relation or specifying its properties.

ESTIMATION OF COMBINED SERVICE TIME FOR TWO-CHAMBER LOCK

In earlier sections, separate neural network models were developed to separately estimate the service times for main and auxiliary chambers. There are, however, some practical applications in which it is not known in advance which tows will use which chamber. To allow such applications, a combined service-time model was developed for a two-chamber lock (Mississippi Lock 27).

Combined Input Data

Previously, six variables were used as inputs. The combined service-time estimation models used the same variables except for the ratio between tow and chamber length, which was replaced by tow length. (That ratio is not known until a chamber is selected.) Thus, the six input variables were tow direction, index of same direction, number of cuts, number of barges, tow length, and ratio between tow width and chamber width. The two separate data files for the chambers were combined into one input file with 12,160 tows based on 1988 PMS data at Mississippi Lock 27.

Figure 6 shows the cumulative distribution and histogram of actual combined service times. The mean actual combined service time is 38.93 min and the standard deviation is 16.39. The combined input data were trained using Neuroshell 2 software (*7*).

Training the Neural Network

Backpropagation networks are known for their ability to generalize well on a wide variety of prediction problems. Backpropagation networks are a supervised type of network, that is, trained with both inputs and outputs. Three different types of backpropagation networks, standard connection, jump connection, and recurrent, were used to train the input and output data. To find the best combined service-time estimation model, the following neural network models were selected for training the input and output.

- COM271: three-layer standard connection backpropagation network; that is, every layer is connected or linked to the previous layer.
- COM272: four-layer standard connection backpropagation network.
- COM273: five-layer standard connection backpropagation network.
- COM274: three-layer jump connection backpropagation network; that is, every layer is connected or linked to every previous layer.

TABLE 6 Results of Multiple Regression

		R-square	MAPE
Model I	Main chamber	0.4801	25.34 %
	Auxiliary chamber	0.4151	26.01 %
Model II	Main chamber	0.5811	24.75 %
	Auxiliary chamber	0.4071	27.86 %

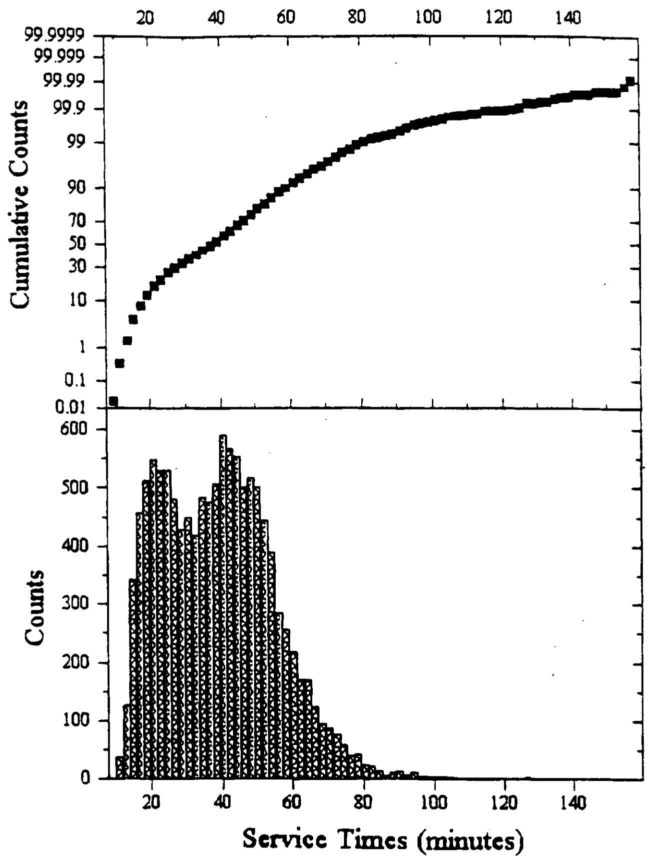


FIGURE 6 Cumulative probability distribution and histogram of actual service times for combined chambers.

- COM275: four-layer jump connection backpropagation network.
- COM276: three-layer recurrent backpropagation network with dampened feedback.
- COM277: General regression neural networks (GRNNs). There are no training parameters such as learning rate and momentum for these networks, but a smoothing factor determines how tightly the network matches its predictions to the data in the training patterns.

It should be noted that a three-layer network has one hidden layer and a four-layer network has two hidden layers.

Results for Combined Service-Time Models

Each model was trained until stopping rules were satisfied. Training stopped when either the average error was below a predefined level, or when 50,000 events occurred without improvement in the minimum average error. The values of the learning constant and momentum were updated from 0.1 to 0.5 by 0.1 increments at every iteration. The weight vectors were also updated to minimize the error between actual values and estimated values. The best test set was saved every time it reached a new minimum average error. Combined service times were estimated for each model at Mississippi Lock 27 based on the saved best test set. Table 7 shows the summary of statistics for combined estimation models.

The means and standard deviations were calculated from the best test set. As shown in the table, the COM277 (GRNN) model has the lowest MAPE. Figure 7 shows the cumulative probability distribution and histogram of service times estimated by the COM277 model, which has a tendency to estimate the service time as two values of 22 min and 48 min.

SUMMARY AND CONCLUSIONS

This study has statistically analyzed lock service times, developed neural network models for service-time estimation, and comparatively assessed neural network models and regression models. First, the statistical analysis of lock service times shows that the main chamber has a mean service time of 44.218 min and a standard deviation of 14.857 min. The auxiliary chamber has a mean service time of 26.490 min and a standard deviation of 11.749 min. Both distributions are skewed to the left. The maximum deviations of service times from the mean are 6.4 σ for the main chamber and 11.2 σ for the auxiliary chamber.

Second, neural network models for estimating service times were developed separately for the main and auxiliary chambers at Mississippi Lock 27. The estimation was performed with six input variables and one output variable based on 1988 PMS data. The MAPEs are 21.05 percent for the main chamber and 23.46 percent for the auxiliary chamber. After removing the outliers (beyond 3 σ), the MAPEs decreased by 17.52 percent for the main chamber and 19.68 percent for the auxiliary chamber. For a comparative assessment of prediction accuracy, two multiple regression models were developed and the lock service times were estimated. The MAPEs of regression models range from 24.75 percent to 27.86 percent. Comparisons between these neural network models and regression mod-

TABLE 7 Summary of Estimation Statistics

ANN network types	Mean (min)	Standard deviation	MAPE(%)
Actual service time	38.93	16.39	
COM271	38.925	12.580	21.354
COM272	44.424	21.784	30.036
COM273	38.864	12.492	21.280
COM274	39.672	12.217	22.519
COM275	39.498	17.411	26.018
COM276	39.121	11.361	22.915
COM277	38.915	12.680	21.040

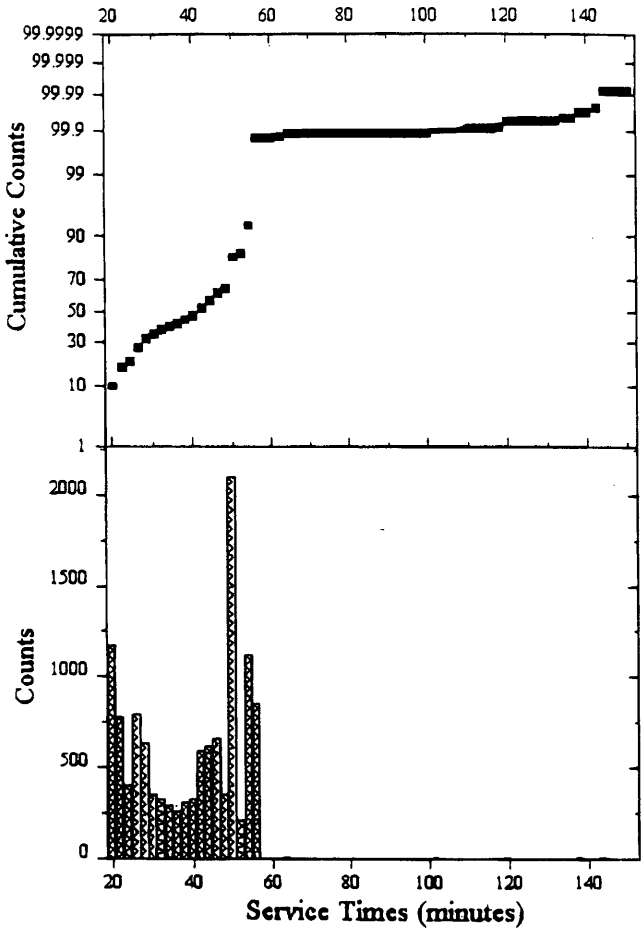


FIGURE 7 Cumulative probability distribution and histogram of estimated service times for combined chambers.

els show that the MAPEs are considerably lower (by about 24.3 percent for the main chamber and 29.2 percent for the auxiliary chamber) for the neural network models.

Third, combined service-time models for locks with dissimilar chambers were developed based on six input variables and one output variable. The results show that the combined actual service times have a mean of 38.932 min and a standard deviation of 16.389. The best combined service-time estimation model (COM277) has a mean of 38.915 min and a standard deviation of 12.680. The MAPE of the best set is 21.039 percent. This combined service-time estimation model can estimate the lock service time without unreasonably compromising accuracy, even before knowing which tows will use which chamber.

Based on these results, the prediction accuracy of neural network models is considerably better than for the regression models considered. Neural network models clearly have considerable potential for improving lock service-time estimation.

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