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Statistical Analysis of Vessel Waiting Time and Lockage Times on the Upper Mississippi River

Final Report

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16. Abstract

This project uses statistical methods to analyze traffic congestion of the upper Mississippi and the Illinois Rivers, in particular, locks 18, 20, 21, 22, 24, and 25 on the upper Mississippi and the Lagrange and Peoria locks on the Illinois River. The main purpose of this project is identifying and evaluating non-structural alternatives (those not requiring construction, but rather procedural or policy changes, for instance, congestion fee, excess lockage time charges, helper boats, switch boats, deck winches, and moorings) that might be employed to offer nearby congestion relief. The first objective of this study was to carry out statistical analysis on locking activity at each lock site for each locked vessel to gain insight on forces that affect congestion and to examine the possibilities for congestion mitigation through non-structural alternatives. The second objective was to measure the effect of inland waterway congestion on barge transportation rates as well as other costs associated with the predetermined lock chokepoints and develop methodology increasingly appropriate for such measures.

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STATISTICAL ANALYSIS OF VESSEL WAITING TIME AND LOCKAGE TIMES ON THE UPPER MISSISSIPPI RIVER

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Executive Summary

The Upper Mississippi River (UMR) is an important artery for transporting export-destined grains from the north central United States to lower Mississippi River ports. In the past decade, an aged lock and dam system on the UMR in combination with a substantial increase in traffic have generated concern about the efficiency of these transport arteries. One major concern is lock capacity in the lower portions of the UMR where comparatively high traffic congestion leads to extended delays for barges/tows.

In this study, we analyzed systematically the arrival, waiting, and lockage time of vessels at the locks of Upper Mississippi River. Particular attention is paid to model the abovementioned processes separately to isolate and identify important determining factors in each stage of the overall lockage process. Our key findings reveal important differences in the determination of these processes. In addition to the usually considered factors such as vessel characteristics and tow configurations, the real time traffic intensity at the locks plays a key role in determining the amount of time a vessel has to wait at the lock. On the other hand, the actual lockage time can be more systematically explained by vessel and lock specific attributes and the timing factor.

Our study makes three contributions. First, we constructed models of the lockage process and showed the importance of modeling the delay time and lockage time as two separate processes. Failure to do this masks important differences in the determinations of these processes. Second, we demonstrated that the real time traffic intensity, even after we control for systematic variations due to vessel and tow characteristics, time of year, day of week, and time of week. We showed that real time traffic intensities are the most statistically significant factors in explaining delays at the locks. Third, we proposed a nonparametric model of traffic intensity, which allowed us to use the proposed lockage model for prediction purposes.

1. Introduction

The UMR navigation system extends approximately 660 miles from the adjacent area of St. Louis, Missouri, to Minneapolis, Minnesota. It provides American's Midwest an important transportation highway. For example, approximately 73 million tons of cargos were transported on the UMR in 2004. Products are usually transported by barges, capable of carrying 1500 tons each, on the UMR. Large barges are linked together into tows powered by a towboat.

The UMR is an important artery for transporting export-destined grains from the north central United States to lower Mississippi River ports. In the past decade, an aged lock and dam system on the UMR in combination with a substantial increase in traffic have generated concern about the efficiency of these transport arteries. One major concern is lock capacity in the lower portions of the UMR where comparatively high traffic congestion generates extended delays for barges/tows.

The mix and congestion of vessel traffic vary substantially according to time factors and the category of vessels. For instance, starting from March, commercial tow traffic increases quickly, reaches the peak during the summer, and then decreases in December. The tow carrying agricultural products usually has 15 barges, whereas mineral and chemical products may be transmitted between terminals on a tow with a few barges.

Reliable navigation conditions are created in the UMR system by 29 lock and dam facilities. The dams create a series of level pools, and the locks allow vessels to pass through the dams. Each lock includes at least one chamber where the water level can be adjusted to match the elevations of the pools above or below the lock and dam. The lock chamber includes gates at both ends to allow vessels to pass through. A lockage operation includes a vessel entering the chamber, having the water level raised or lowered, and leaving the chamber. At each lock, vessels traveling upriver or downriver will make queues if another vessel is passing the chamber. There are different queues for the commercial vessels and other small vessels. Most of the original locks on the UMR were designed for chambers that are 600 ft long. However, many tows now have 1200 ft in length such that these tows are required to decouple into several cuts to meet the 600-ft lock. For example, if a tow with 12 barges is going to pass through a lock, 9 barges will be pushed into the chamber by the tow boat and then the tow boat will disconnect with these 9 barges to return to the remaining 3 barges. After the first cut of 9 barges passes through the chamber and is attached to the wall nearby the chamber, the remaining 3 barges and the tow boat in turn enter the chamber and pass through it. Finally the first and the second cut are reconnected, and the tow with these 12 barges proceeds to the next lock. The nearby areas and river conditions of each lock are different from one another such that the efficiency with which locks can proceed tows with barges is varied. Under normal conditions, vessels are processed with a first-come, first-serve policy but with some priority given to vessels without barges.

The increased traffic on the UMR system has led to increases in congestion, delays at locks, and increasing vessels proceeding time. In response to the increasing level of lock congestion, many studies investigate the source of traffic and propose lock scheduling rules. Fuller and Grant (1993) examined the effect of lock delay on the cost and efficiency of the North Central US's corn and soybean markets via the UMR and Illinois waterways and showed the lock delay on the UMR will redirect grain to other transportation methods. Martinelli and Schonfeld (1995) calculated the delays of a set of interdependent locks and establish a more extensive assessment of improvement by including interdependencies in benefit calculations of lock improvement. Perakis and Li (1999) visited with major US inland waterways and interviewed their staff such as engineers and managers.

Gervais et al. (2001) evaluate the short-term benefits of extending five 600-ft locks to 1200 ft on the UMR by a disaggregated linear programming model. Southworth (2002) assessed the accuracy and robustness of two models that estimate the lock transit time in the economic analysis of UMR. Bobcock and Lu (2002) forecasted Mississippi River Lock 27 grain tonnage by a time series model. Ronen et al. (2003) analyzed the issue of reduction in waiting time and apply analytical queuing models and intelligent scheduling mechanisms to the UMR. Nauss (2008) addressed a real-world scheduling problem for sequencing commercial tows and barges through a lock incorporating setup time that are dependent in a unique fashion and proposes linear and nonlinear integer programs for determining the optimal sequence for locking vessels at a lock.

The waterway-simulation models are encouraged in the recent research since straightforward lock scheduling rules may be better than a deterministic optimizing model that requires constant updating of data. Sweeney (2004) used a replicating simulation model to deal with the steady-state problem and to create interdependent lockage activities. Smith et al. (2007) described a discrete-event simulation model to investigate the impact of alternative decision rules for a congested system of the UMR. Campbell et al. (2007) developed decision support tools to help study alternative operating rules on the UMR. Smith et al. (2009) constructed a discrete-event simulation model that satisfies incorporating features in a simulation model for waterway navigation stressed in Smith et al. (2007). Even though the simulation-based model can provide transparent lock scheduling rules, conventional deterministic models are still needed to provide support of scheduling rules from simulations.

The current study focused on constructing and estimating systematically the determination of time used by vessels at the locks. Instead of modeling the total time required to pass a lock, we decomposed it into two components: the waiting time and the actual lockage time. We showed that these two components are nearly uncorrelated, which calls for separate modeling of the waiting process and lockage process. Our results suggest that these two processes have different sets of key determining factors; modeling these two processes as one runs the risk of masking some important determining factors to either process.

A second key finding of this study was the importance of controlling for the influence of real time traffic intensity. Although traffic intensity varies systematically with season, day of week, and time of day, we demonstrated that real time traffic intensity, which is subject to stochastic fluctuation and also determined by certain unobserved factors, plays an important role in determining how much time a vessel has to wait at the locks. Correspondingly, in addition to the usual control variables in the modeling of delay time, we constructed two measures of real time traffic intensity, one for each major type of lockages, and incorporated them into our regression models. Our results show that including these two variables improves the goodness-of-fit of our model substantially.

To ensure positive predicted time usage, and to suppress the substantial right skew of the delay time distribution, we took the logarithm transformation of the delay time in our regression. We considered an alternative modeling strategy, treating the waiting time as a survival process. Our exploratory model specification analysis indicated that a Weibull model with accelerated hazard rate was suitable for the delay time process in question. We therefore modeled vessels' delay time using a maximum likelihood estimator under the assumption of the Weibull distribution. The results turned out to be similar to those obtained on the linear model of log of delay time.

We modeled the actual lockage time using similar strategies. In addition to the typical set of season and time factors, some key vessel characteristics, such as number of barges and total tonnages carried by the vessel, play an important role in the determination of lockage time. This is different from the delay time process, which is greatly affected by the real time traffic intensity at the lock. More than 70 percent of the variations in lockage time can be explained by our model.

The proposed models perform well in terms of explaining vessels' delay and actual lockage time at the locks based on observed vessel characteristics and tow configuration, and real time traffic intensity. For the purpose of future delay and lockage time, however, there exists a complication—the traffic intensity is not available. In order to employ the proposed model for forecasting purpose, we needed a satisfactory model for traffic intensity as well. We therefore constructed a nonparametric estimator of real time traffic intensity for two major types of vessel lockages based on given vessel characteristics, tow configurations, time of year, day of week, and time of day. We utilized the recent advance in nonparametric estimations by Li and Racine (2007) that allows both continuous and discrete covariates in smoothing regression. It turns out that this method outperforms linear predictors considerably and provides a highly reliable prediction for traffic intensity. To assess the impact of using predicted instead of actual traffic intensity, we re-calculated our regression, this time replacing the actual traffic intensities with their nonparametric predictions. As expected, the overall significance of the model is lower than the original one (using observed traffic intensity), but it still performs considerably better than a baseline model that does not account for the effect of real time traffic intensity.

In summary, our study makes three contributions. First, we showed the importance of modeling the delay time and lockage time as two separate processes. Failure to do so masks important differences in the determinations of these processes. Second, we demonstrated that the real time traffic intensity, even after we control for the systematic variation due to vessel and tow characteristics, time of year, day of week, and time of week, still plays a most important role in our analyses. As a matter of fact, we showed that real time traffic intensities are the most statistically significant factors in explaining delays at the locks. Third, we further proposed a nonparametric model of traffic intensity, which allows predictions of future lockage time based on our proposed models, with actual real time traffic intensities replaced by their estimates.

The rest of the paper is organized as follows. Section 2 gives a detailed descriptive analysis of the data used in this study and notes some important patterns of vessels' arrival, delay, and lockage times at the lock. The findings of this section provide valuable guidance of our model construction. Section 3 constructs separate models for vessels' delay and lockage times, discusses various estimation strategies, and presents the regression results. Section 4 provides a model for traffic intensity at the locks, the results of which can then be used in predictions of future lockage time. The last section concludes.

2. Descriptive Analysis

In this study we mainly investigated the relationships between the waiting and lockage time of vessels and some possible influencing factors, such as the type of vessel, the type of lockage and the type of mechanical assists, as well as time factors such as months and days of week. All data are provided by US Army Corps of Engineers (USACE). We first provided some definitions of variables used in this study. In our study, the delay time and the lockage time are used as dependent variables. The delay time is the time elapsed from the arrival of a vessel at a lock to the start of locking through the chamber, and the lockage time is evaluated from the start of locking through the chamber of a vessel to the end of its lockage. The precise definition of times is included in Table 1. To capture the influence of lockage- and vessel- specific characteristics, we used several indicator variables, including a dummy for lockage type C, a dummy for vessel type T, and a dummy for mechanical assist type J, as a part of explanatory variables in our model. The dummy variable for lockage type C takes the value one if the type of lockage that a vessel passes through is C, which stands for consecutive lockages (a tow is cut into two or more lockages to pass through the chamber), and takes zero otherwise. Similarly, the dummy for vessel type T takes the value one if the vessel is T, which stands for commercial tow boats, and takes zero otherwise. Finally, the dummy for mechanical assist J takes the value one if the type of the mechanical aid to a vessel is J and takes zero otherwise. Tables 2, 3, and 4 list the definitions of lockage type, vessel type, and mechanical assist. In addition to the aforementioned variables, we also included dummies for months and dummies for days of week to capture potential time-specific effects. For example, the dummy for Monday takes the values one if the vessel in question arrives on a Monday and takes zero otherwise.

Table 1. Definition of the Event Associated with Times.

Event Code	Description
ARR	The datetime that the vessel arrived and is ready to lock through.
SOL	The datetime that the vessel started locking through the chamber. This occurs when the lock and vessel are ready to lock. It is the earliest of the stern of the outbound vessel being next to either the bow of the incoming vessel or the designated arrival point. In the case of a lock stoppage, the datetime is the time the lock stoppage started.
BOS	The time when the bow of the entering vessel is abreast of the lock gates and it is in a position parallel to the guide wall to enter the chamber.
EOE	Earliest of these two times: 1) The time when the entering vessel is secured within the lock and the gates are clear; 2) The closing of the gates has been initiated.
SOE	The time when the exit gates are fully in their recesses, and the horn has been sounded. If the vessel starts its exit prior to the gates being fully opened, the Start of Exit Time is when the bow of the exiting vessel crosses the gate sill.
EOL	The datetime that the vessel ended its lockage. When a lock has completed serving a vessel and can be dedicated to serving another vessel or when the stern of the vessel is next to the arrival point. In the case of a lock stoppage, the datetime is the time the lock stoppage ended.
Delay	The time elapsed from ARR to SOL.
Lockage	The time elapsed from SOL to EOL.

Source: US Army Corps of Engineers

Table 2. Definition of Lockage Types.

Event Code	Description
O	O – open pass – The vessel traverses the lock with no lock hardware operation/chambering. The vessel goes straight through the chamber with both sets of gates open. This may occur at tidal locks.
F	F – fast double (Multi-chamber) – The towboat and possibly some of its barges are separated from the remaining barges and are locked through a different chamber from the remaining barges.
J	J – jack knife – The tow is rearranged, usually from two barges wide to three, by breaking the face coupling on at least one barge and knockout of the tow (and the towboat is moved alongside the barges).
K	K – knockout – The towboat alone is separated from its barges and moved alongside the barges for lockage.
N	N – navigable pass – The vessel traverses the dam instead of the lock. The vessel actually navigates outside the lock walls.
S	S – straight – The tow and/or its barges are not broken up for lockage.
T	T – barge transfer – Barges are placed in the lock chamber by one towboat, removed and continued on their journey with another towboat.
V	V – set over – The towboat and one or more of its barges are separated as a unit from the remaining barges to be “set over” for service. Tow and barges are moved alongside the barges for lockage.
Z	Z – other (remarks) – Any type of lockage not defined by one of the above.

Source: US Army Corps of Engineers

Table 3. Definition of Vessel Types.

Vessel Type	Vessel Code	Description
Commercial	C	C - Dry Cargo Vessel [self-propelled] - A self-propelled vessel carrying dry cargo.
Other	J	J - Dredge Vessel [self-propelled] - A self-propelled vessel designed to remove material from a dredge site.
Commercial	E	E - Liquid Cargo Vessel (i.e., Tanker) [self-propelled] - A self-propelled vessel carrying liquid cargo.
Other	K	K - Crewboat (does not include boat crew) [self-propelled] - A self-propelled vessel used primarily for transporting commodities and/or personnel, excluding people required to operate the crewboat (supply boats/utility vessels).
Other	M	M - Commercial Non-cargo Vessel - Vessel owned and/or operated by commercial industry, but does not carry cargo or passengers for a fee, i.e., vessel owned/used by business only for business purposes.
Other	N	N - Non-federal Government Vessel (i.e., state or local govt) - Any government vessel, other than a federal government vessel, i.e., state, local, etc.
Commercial	F	F - Fishing Vessel (commercial) - Boats that catch and carry fish for subsequent sale.
Other	G	G - Federal Government Vessel.
Other	L	L - Lightboat - tow/tug boat with no barge(s).
Commercial	P	P - Passenger Boats & Ferry (commercial).
Recreation	R	R - Recreational Vessel.
Commercial	T	T - Towboats or Tugboats (Commercial).
Other	U	U - Federal Government Contractor Vessel - a vessel operated under contract for the United States Government.
	X	X - Lock Stoppage - This code can be used for a nonvessel that is locking through the lock. Also, this code is used when the lock is down and unable to service boats.
Other	Z	Z - Other (Remarks).

Source: US Army Corps of Engineers

Table 4. Definition of the Mechanical Assist.

Event Code	Description
0	0 - No assist.
I	I - Tow equipped with bow thrusters.
J	J - Barge only assisted by tow haulage equipment such as a winch or kevel.
K	K - Hydraulic assist was used to assist the vessel. This consists of opening the lock valves to assist a downbound tow. Only used where authorized.
L	L - Extra personnel were used to assist the vessel. These may either be lock operators or vessel personnel who would not ordinarily be assisting the vessel.
N	N - Tow and barge assisted by tow haulage equipment such as a winch or kevel.
Z	Z - Other (Remarks).

Source: US Army Corps of Engineers

In this section, we undertook a systematic analysis of lock traffic congestion. Our data consist of a complete record of all vessels passing through locks 20 and 24 on Upper Mississippi River in the year 2008. Both are 600-ft locks; the vessel logs indicate frequent delays at the locks. As is discussed above, the activities of a vessel at a certain lock can be broken into three processes: arrival, waiting, and lockage. Below we look at each process for the two locks in question. We have 1,798 and 1,853 observations, respectively, for locks 20 and 24.

Figure 1 reports the monthly vessel arrival frequency. As expected, the waterway traffic on the upper Mississippi picks up in the spring and peaks in the summer. It then declines steadily into the fall as the harvest season closes until the winter, when the waterway traffic is limited by ice conditions on the river.

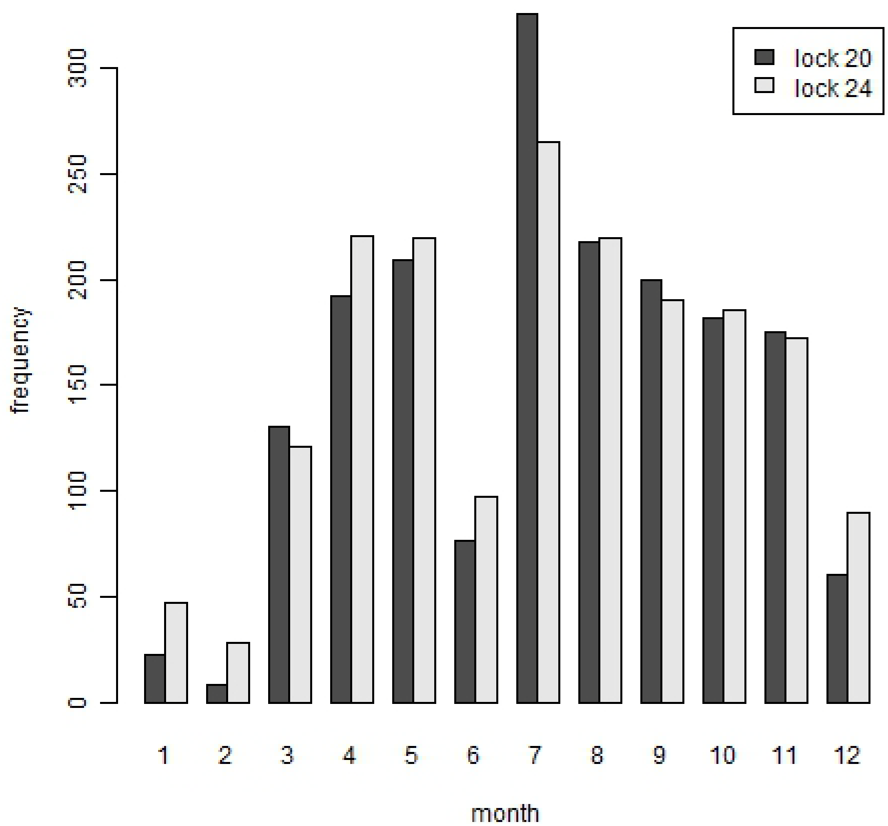

Figure 1. Vessel Frequency per Month.

Figures 2 and 3 summarize the corresponding arrival frequencies by day of the week and hour of the day. Unlike the seasonable pattern, there does not exist pronounced weekday or hourly effects.

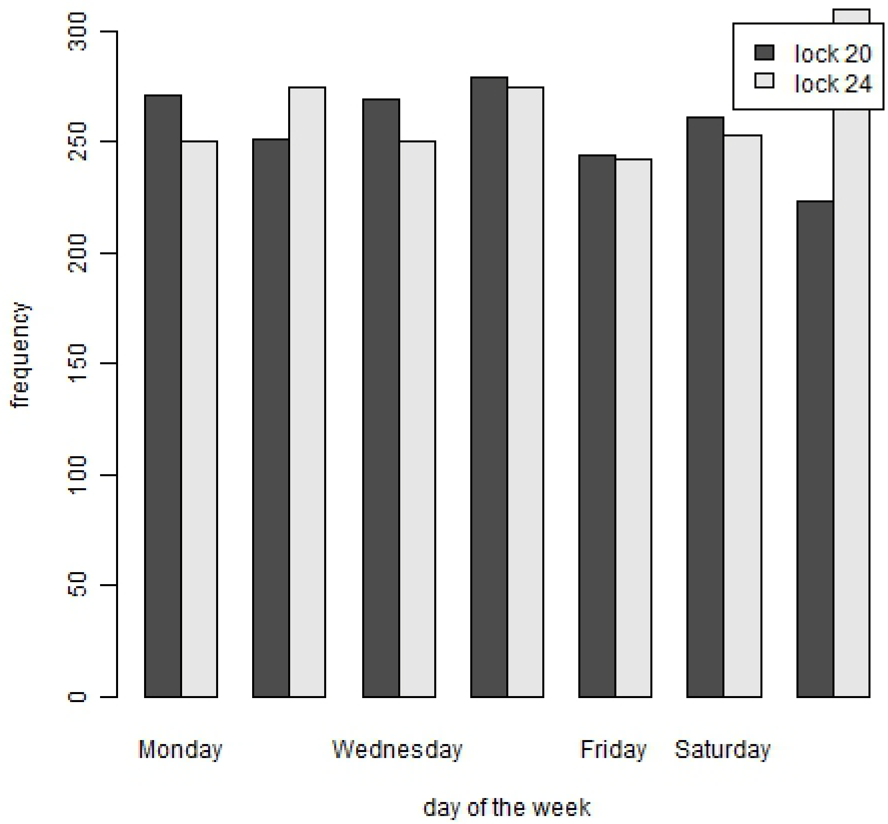

Figure 2. Vessels per Day of the Week.

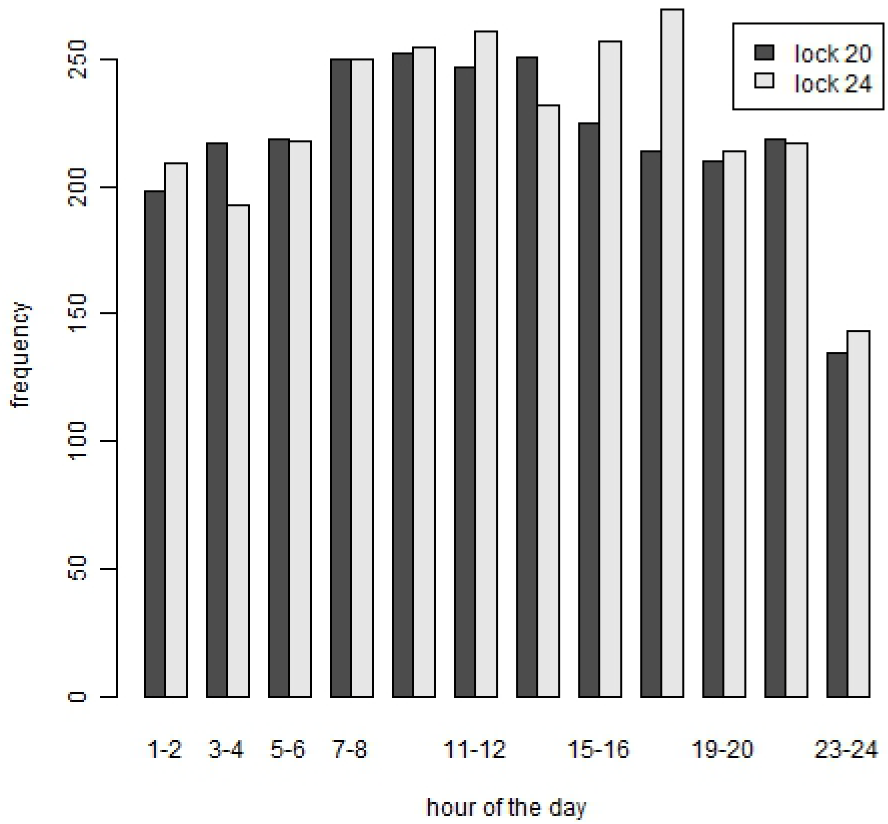

Figure 3. Vessels per Hour of the Day.

A histogram is a graphic display of tabular frequencies and is used to plot density of data. In our study, we report the histograms of overall lockage and delay times of locks 20 and 24 in Figures 4–7. In Figures 4 and 5, the distributions of lockage time of locks 20 and 24 are rather similar, whereas the distributions of delay time of locks 20 and 24 are somewhat varied, as shown in Figures 6 and 7. The similarity of lockage distributions may result from similar geographic factors and similar types of transiting vessels. However, the difference of delay time between locks 20 and 24 indicates that the lock 24 may be more congested than lock 20.

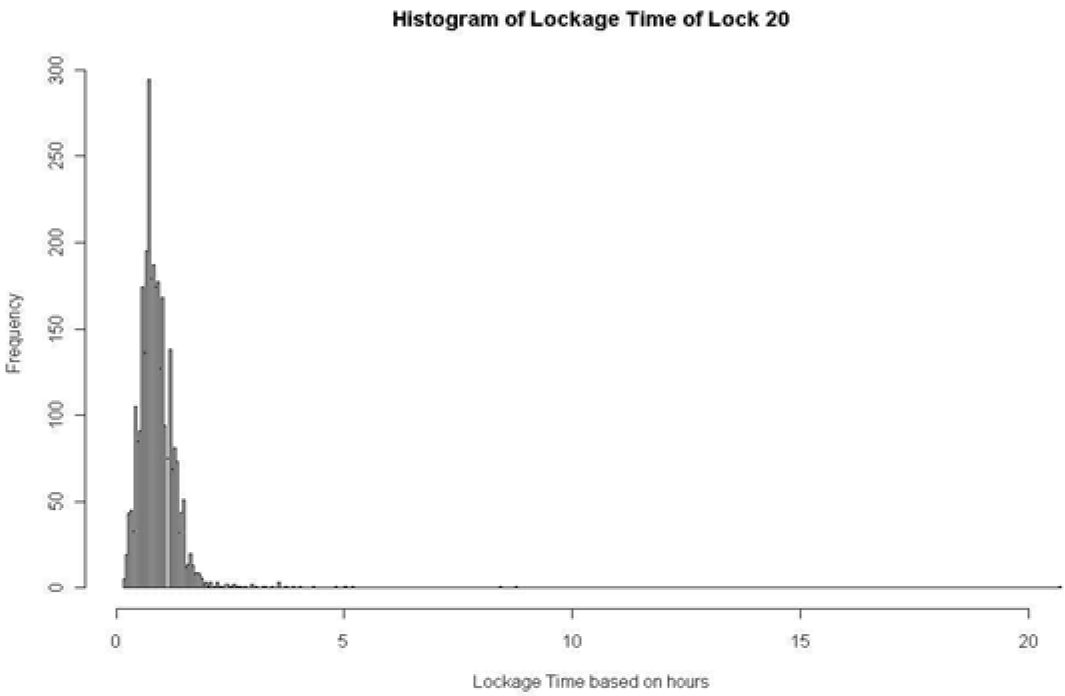

Figure 4. Histogram of Lockage Time of Lock 20.

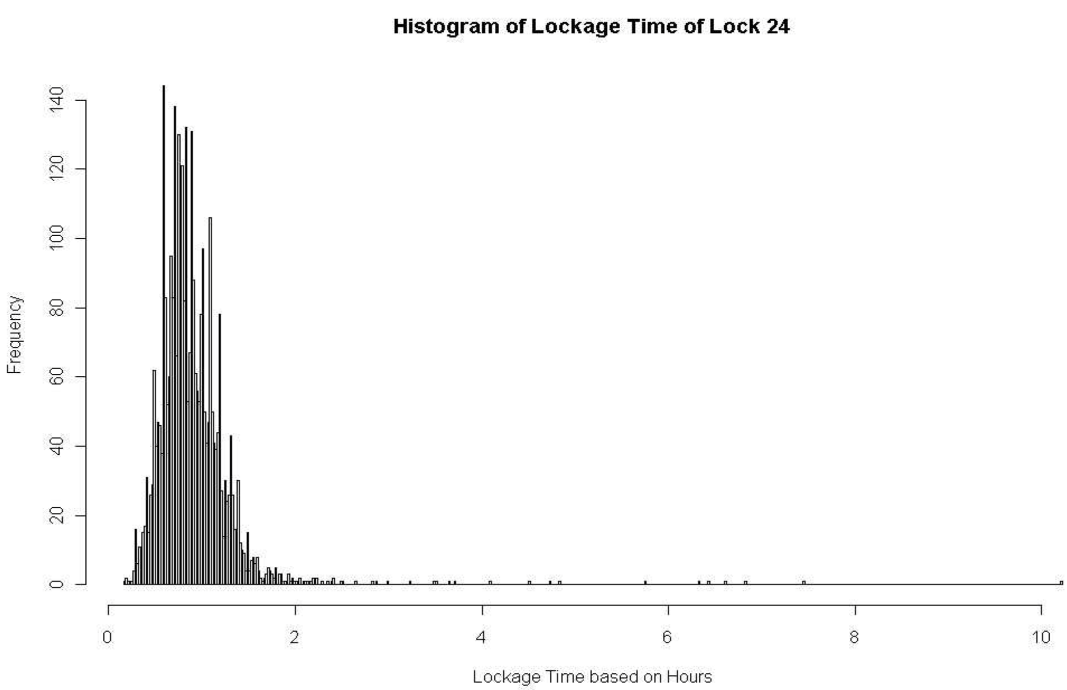

Figure 5. Histogram of Lockage Time of Lock 24.

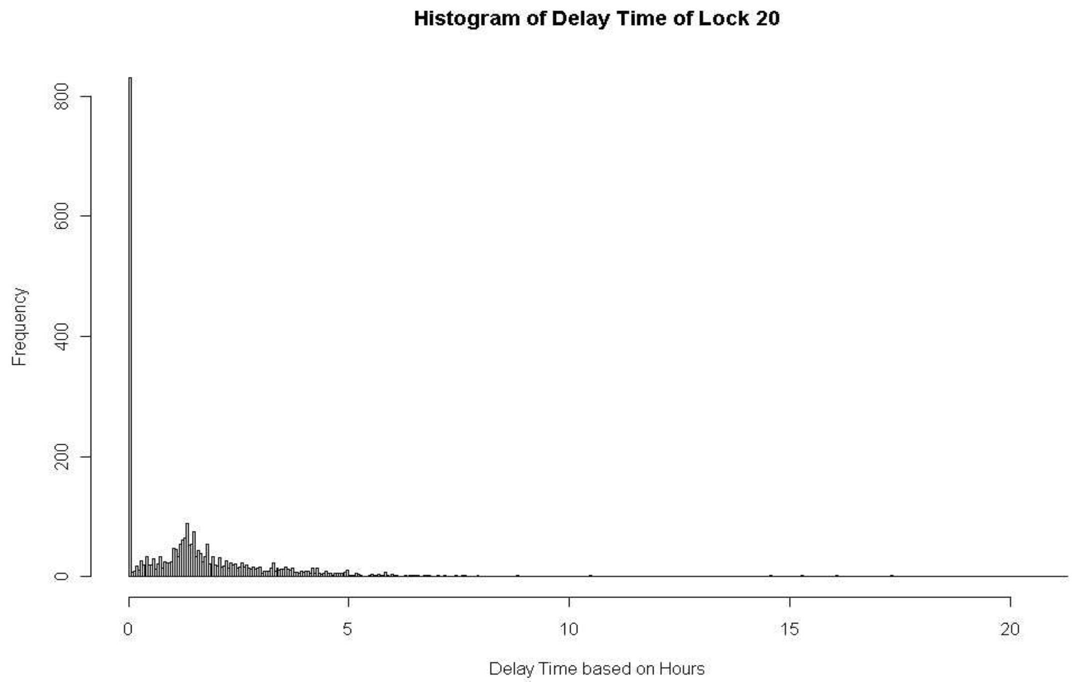

Figure 6. Histogram of Delay Time of Lock 20.

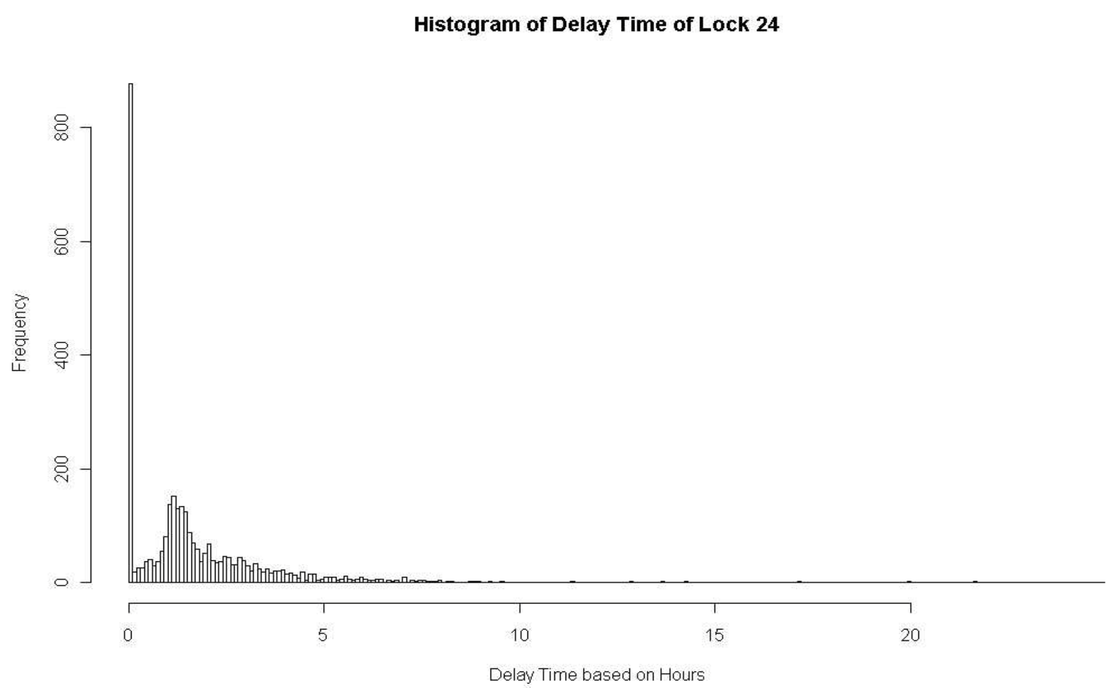

Figure 7. Histogram of Delay Time of Lock 24.

We next considered the distribution of lockage delay time. Since the general patterns of lockage delay and passage times are rather similar between locks 20 and 24, we report only results for lock 20 below for the rest of this section. In Figures 8, 9, and 10, we report the box plots of delay time for lock 20. The box plot is an effective way of presenting distributional information. For each plot, the bold horizontal bar denotes the median, the two hinges correspond to the first and third quartiles, and the two outer whiskers bound roughly the 95 percent asymptotic confidence interval under the assumption of normality. Outliers beyond this confidence interval of the median are plotted individually. In addition, variable box width is used to reflect the frequency of the categories being plotted.

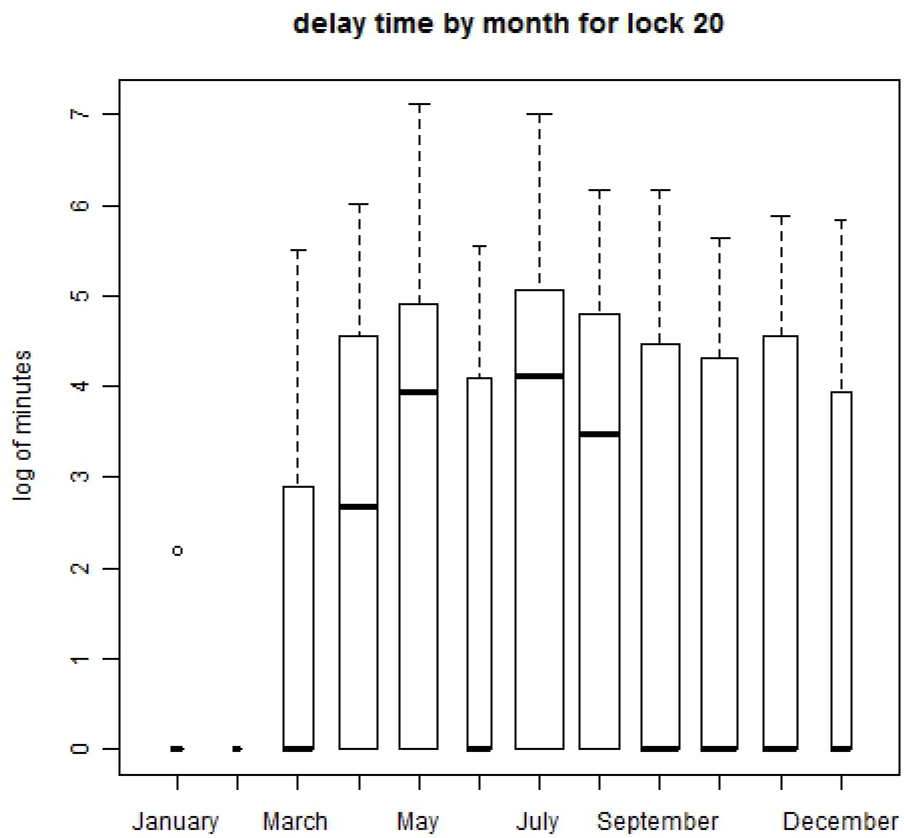

Figure 8. Delay Time by Month, Lock 20.

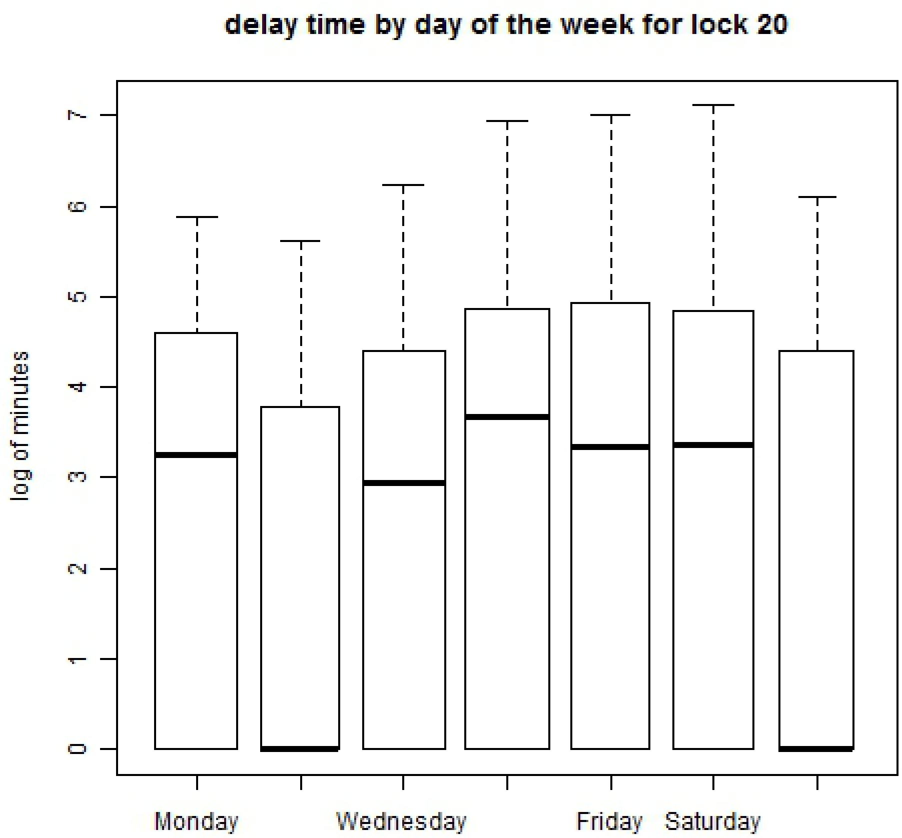

Figure 9. Delay Time by Day of the Week, Lock 20.

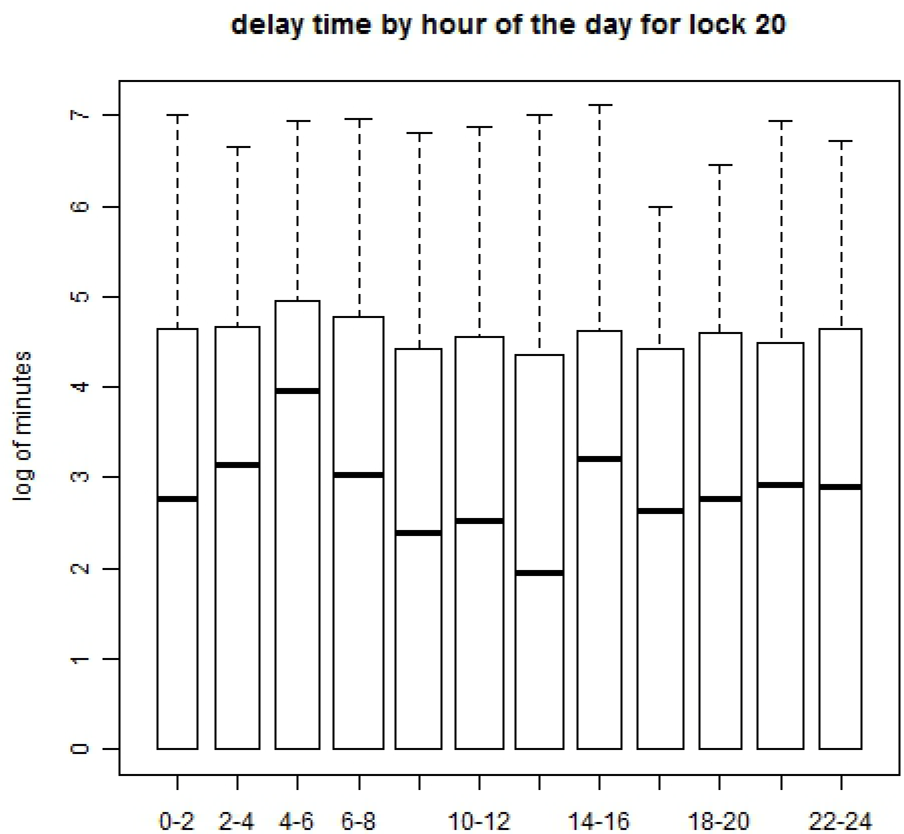

Figure 10. Delay Time by Hour of the Day, Lock 20.

We used a logarithmical transformation on the delay time to reduce the substantial right skewness in its distribution. (This transformation is also used in our regression analysis). Figure 8 reports its distribution by month. Due to the small number of vessels in January and February, the distributions seemed to be degenerated into a number of mass points, depending on the ice conditions of the river. Other than that, after the transformation, the distribution is still markedly rightward skewed; the medians of the distributions are clearly closer to the right end of the distributions, while only whiskers of the right tails are reported (this is because of a large number of vessels reported near zero waiting time). There are also substantial seasonal variations in terms of delay time distributions. During the peak season, especially in May, July, and August, the median delay time and its dispersion reach their highest levels. Clearly, the length of delay is associated with the traffic at the lock. Figure 9 and 10 report the distribution of delay time by day of the week and hour of the day (every two hours), respectively. These distributions are also right skewed, while the degree of variation is considerably smaller compared to the monthly distribution.

We then investigated the distribution of log lockage time in a similar manner, reported in Figures 11, 12, and 13. In terms of seasonal pattern, compared to the delay time distribution, lockage time distribution is more compact and symmetric. (Note the difference in vertical scale between the two sets of plots.) Excluding January and February, the median lockage time appears to be relatively stable for the rest of the year. Again, there is smaller intra-week and intra-day variation, and the median lockage time changes little across different categories in the Figures 12 and 13.

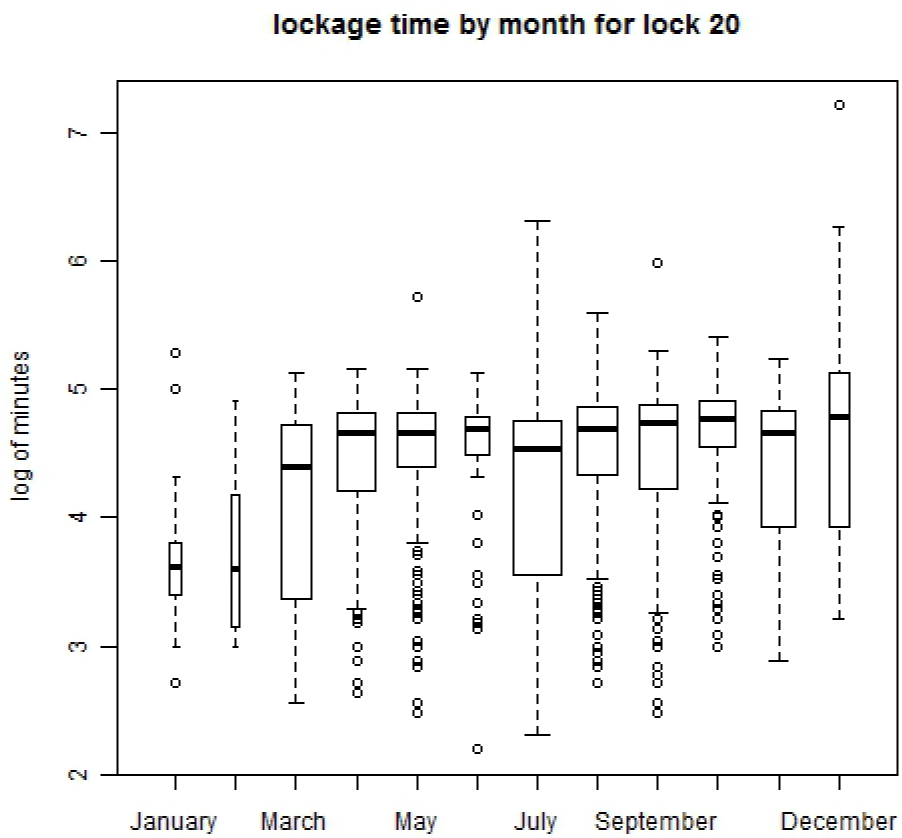

Figure 11. Lockage Time by Month, Lock 20.

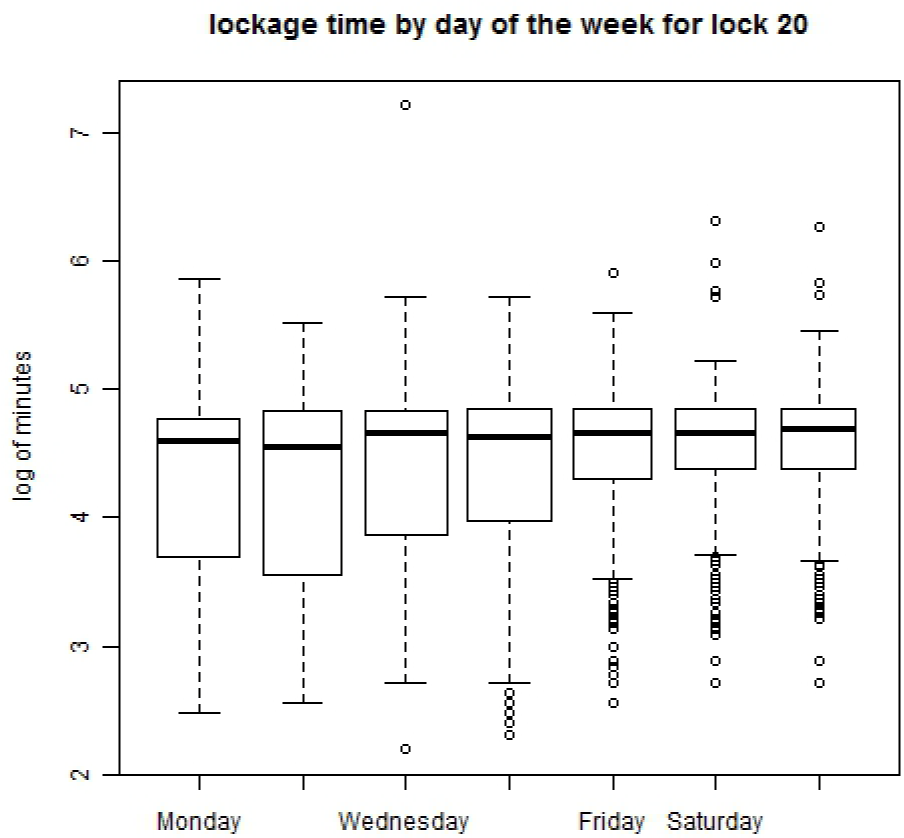

Figure 12. Lockage Time by Day of the Week, Lock 20.

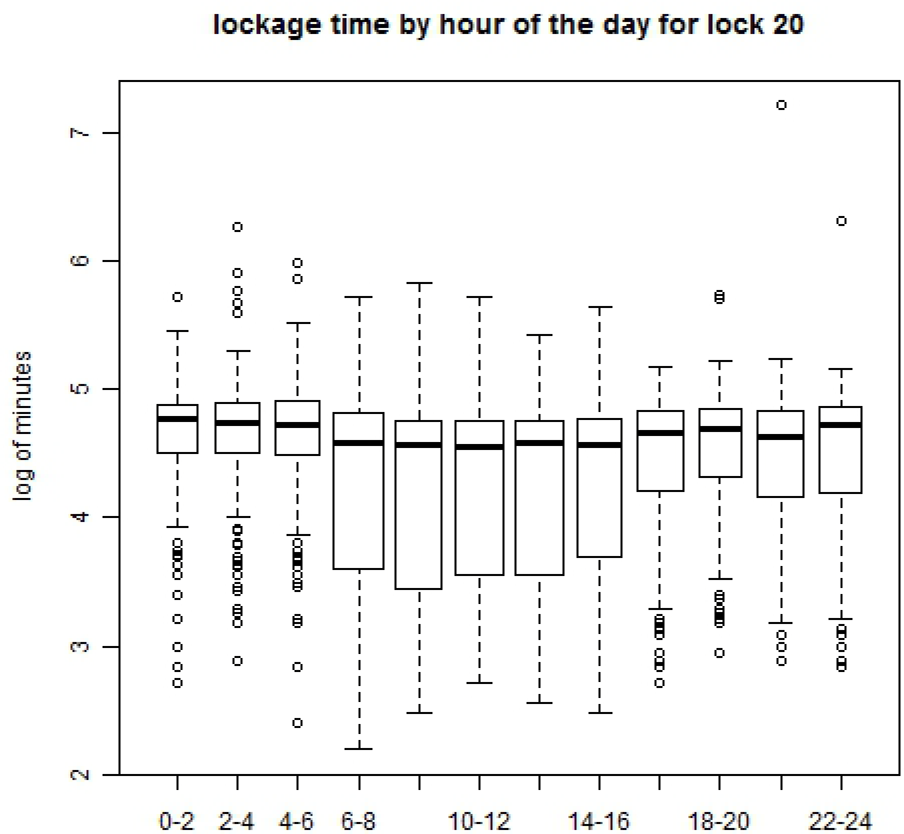

Figure 13. Lockage Time by Hours, Lock 20.

Last, we observed that there is little correlation between the delay time and lockage time. For lock 20, the correlation is as small as 0.03, which motivates our decision to model these two processes separately in our regression analysis.

The main factor behind the variation in vessels' delay and lockage time is the tow configuration. A lockage type is termed 'consecutive' if it needs to be broken into more than one cut transit in sequence. The majority of vessels that utilized the locks are commercial tow boats that require consecutive lockages. For example in our sample, 68 percent and 75 percent of vessels used consecutive lockages for locks 20 and 24, respectively. Figure 14 plots the distribution of delay and lockage time for lock 20. The time usage patterns for these two types are markedly different. On average, consecutive lockages experienced a substantially longer delay; their lockage times were also longer, but the difference is much smaller.

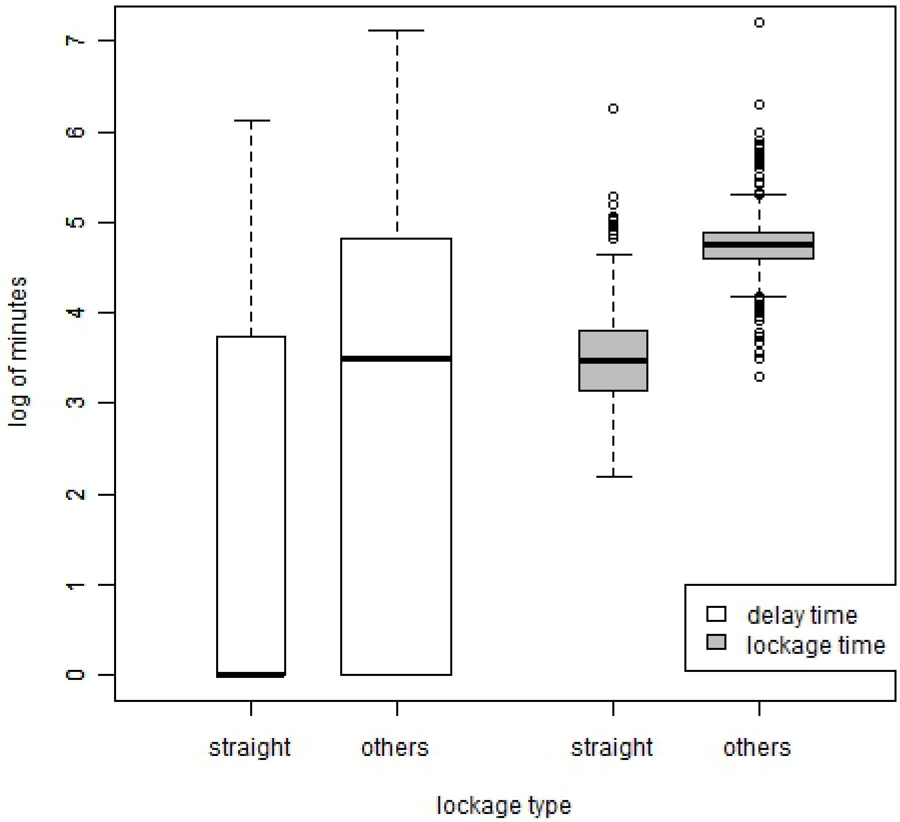

Figure 14. Lockage Time and Delay Time by Lockage Type, Lock 20.

3. Regression Analysis

In this section, we report regression analysis of the delay and lockage time observed in our data sets. As is discussed above, there is little correlation between the delay and lockage times. We therefore opted to model these two processes separately. Although the general time patterns at the two locks exhibited a high degree of similarity, there existed systematic differences between them due to their respectively unique terrain and river conditions that affect the efficiency with which they can process commercial barge tows.

The delay time of a vessel at a lock is influenced by various lockage and vessel characteristics, and seasonal and timing factors, including lockage type, vessel type, the presence of 'helper boats,' total tonnage, time of year, day of week, and time of day. Some of the systematic traffic lock conditions, albeit unobserved, can be captured partially by the month, day of week, and time of day dummy variables. These dummy variables, however, do not capture *stochastic* variations in real time traffic intensity at the locks.

Our baseline model is specified as follows:

$$DelayTime_t = \alpha_0 + \alpha_1\, Double_t + \alpha_2\, Other_t + \alpha_3\, TowBoat_t + \alpha_4\, Helper_t + \sum_{j=2}^{12} \gamma_j Month_{t,j} +$$

$$\sum_{j=1}^{6} \eta_j Day_{t,j} + \varepsilon_t \cdots (1)$$

where ε is an independently and identically distributed disturbance, and the right-hand-side variables are defined as:

- Double: double lockage vessel.
- Other: vessel type other than double or straight.
- Tow Boat: commercial tow boat.
- Helper: helper boat for lockage.
- Month: monthly dummies for February through December.
- Day: day of week dummies for Monday through Saturday.

To account for the effects of traffic intensity, we constructed measures of real time traffic intensity for each vessel arriving at a lock. In particular, for a given vessel arrival time *t*, we identified a three-hour window, $[t-2, t+1]$, as the period within which arrivals of other vessels are likely to affect the lockage of the vessel in question. Due to the variation in delay and lockage time across vessel types, we calculated two measures of traffic intensity within the constructed window:

- $S_{t,d}$ = number of vessels requiring double lockages.
- $S_{t,o}$ = number of other types of vessels.

After including these two traffic intensity measures, we found that the coefficients for hourly dummies are statistically insignificant in all our model specifications. This is not unexpected as we discussed above that there is little systematic variations across hours of day. We therefore removed this factor from our model. Our second model specification, with the traffic conditions included, is given by:

$$DelayTime_t = \alpha_0 + \alpha_1\, Double_t + \alpha_2\, Other_t + \alpha_3\, TowBoat_t + \alpha_4\, Helper_t + \alpha_5\, S_{t,d} + \alpha_6\, S_{t,o} +$$

$$\sum_{j=2}^{12} \gamma_j Month_{t,j} + \sum_{j=1}^{6} \eta_j Day_{t,j} + \varepsilon_t \cdots (2)$$

By construction of the indicator variables in the model, the case left out in our model is vessels with straight lockages that are not commercial tow boats.

The second column of Table 5 reports results from our baseline model (1) without the two traffic intensity measures. The third column reports results from model (2). The general results from these two models are rather similar. Vessels with double lockages and other types of lockages rather than straight passage require considerably longer delay time compared with straight lockages. After controlling for lockage types, commercial tow boats still log longer delay time than other vessel types, although the effects are shown to be smaller than those of lockage types. The presence of helper boats reduces delay time. The seasonal variations are evident, as are the effects of day of week.

Table 5. Single Robust Regression on Lock 20.

Parameter estimates (Standard errors in parentheses)				
	Regression on Delay Time	Regression with Traffic Effect	Survival Regression on Delay Time	Regression on Lockage Time
Constant	-7.462 (0.489)***	-7.608 (0.428)***	-7.468 (0.390)***	-3.589 (0.069)***
Lockage_C	0.744 (0.170)***	0.663 (0.148)***	0.726 (0.134)***	0.922 (0.039)***
Lockage_NC &NS	1.288 (0.288)***	1.072 (0.251)***	0.905 (0.230)***	0.751 (0.041)***
Vessel_T	0.325 (0.243)	0.430 (0.213)**	0.464 (0.200)***	0.164 (0.034)***
Assistant_J	-0.190 (0.157)	-0.203 (0.136)	-0.237 (0.124)**	0.061 (0.022)***
Num_brg	___	___	___	0.014 (0.003)***
Tonnage	___	___	___	0.008 (0.001)***
February	-0.341 (0.900)	-0.006 (0.785)	-0.188 (0.717)	0.017 (0.127)
March	0.412 (0.514)	0.025 (0.448)	0.665 (0.412)	-0.320 (0.072)***
April	1.323 (0.515)**	0.657 (0.449)	1.571 (0.417)***	-0.351 (0.072)***
May	2.120 (0.514)***	1.020 (0.450)**	2.093 (0.418)***	-0.382 (0.072)***
June	1.095 (0.551)**	0.518 (0.481)	1.377 (0.442)***	-0.343 (0.077)***
July	2.456 (0.502)***	1.254 (0.440)***	2.279 (0.408)***	-0.450 (0.070)***
August	1.847 (0.510)***	1.075 (0.445)***	1.901 (0.413)***	-0.331 (0.071)***
September	1.261 (0.511)**	0.562 (0.446)	1.501 (0.413)***	-0.288 (0.071)***
October	1.013 (0.516)**	0.573 (0.450)	1.357 (0.418)***	-0.242 (0.072)***
November	1.107 (0.516)**	0.625 (0.450)	1.609 (0.414)***	-0.240 (0.072)***

December	0.637 (0.566)	0.617 (0.493)	1.752 (0.457)***	0.151 (0.079)*
Monday	0.445 (0.198)**	0.212 (0.173)	0.281 (0.161)**	-0.096 (0.028)***
Tuesday	-0.308 (0.203)	-0.208 (0.177)	-0.319 (0.163)**	-0.038 (0.028)
Wednesday	0.270 (0.198)	0.103 (0.173)	0.148 (0.159)	-0.067 (0.028)**
Thursday	0.651 (0.197)***	0.284 (0.173)	0.442 (0.160)***	-0.065 (0.028)**
Friday	0.461 (0.202)**	0.268 (0.176)	0.332 (0.163)**	-0.042 (0.028)
Saturday	0.579 (0.199)***	0.322 (0.174)*	0.454 (0.160)***	0.015 (0.028)
Traffic_1	___	0.444 (0.082)***	0.318 (0.075)***	___
Traffic_2	___	1.353 (0.058)***	1.086 (0.057)***	___
Log(Scale)	___	___	0.549 (0.018)***	___

Note: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Examine the effects of including two real time traffic intensity measures. The coefficients of these two variables are both statistically significant beyond a 1 percent confidence level. These two variables are the most statistically significant variables in our estimations, even more than those of lockage and vessel types. Moreover, the impacts of double lockages are more than three times of those of other types. As a result of accounting for these two key variables, the overall significance of other variables generally decline, especially coefficients for month and day of week dummies. One notable exception is the effect of helper boat, whose coefficient increases in both (absolute) magnitude and statistical significance. The most drastic change is in terms of the adjusted R-square, which increases from 0.125 to 0.337, clearly suggesting the importance of these two variables in explaining the variation in delay time at the locks.

In the above models, we have employed the least squares estimation convention, assuming that error term of our model, after log-transformation of the dependent variable, follows asymptotically a normal distribution. The log-transformation is undertaken for two reasons: (i) to ensure positive predicted dependent variable; and (ii) to reduce the degree of right skew and potential heteroskedasticity. However, due to the nature of the dependent variable, i.e., a waiting time, an alternative modeling strategy is to employ duration or survival analysis. Additional benefits can be obtained under the maximum likelihood estimation of duration models. For example, the maximum likelihood estimation is asymptotically efficient; and in our case, survival analysis makes available readily accessible toolsets for in depth analysis of the delay process.

A common point of departure for duration analysis is the exponential duration model, where the waiting time is modeled as a conditional mean of an exponential distribution. This model implicitly assumes that the hazard rate of the duration is proportional or memory less, in the sense that the probability an event (in our case, lockage) happens is independent of the elapsed time.

This assumption often turns out to be overly restrictive in many realistic settings. A generalization of the exponential model is the (two-parameter) Weibull model, which introduces an extra scale parameter. This parameter allows the hazard rate to be increasing, constant, or decreasing over time. If the parameter equals one, the Weibull model reduces to the standard exponential model.

Below we report our analysis using duration analysis. We estimated the delay time at the locks using both the exponential and Weibull models. The log-likelihood ratio test rejects the exponential model decisively. We therefore discuss only the results from the Weibull model, which is presented in Columns 4 of Table 5. The overall results are rather similar to those of OLS analysis of the log-delay time. The effects of lockage and vessel types are statistically significant, so are the impacts of real time traffic intensity. The effect of helper boat is more significant in the Weibull model than the previous two, with a p-value slightly above 5 percent. Last, the scale parameter is estimated to be 1.73 and significantly different from zero, clearly favoring the Weibull model over the simpler exponential model.

We now proceed to model vessel lockage times. We adopted a somewhat different specification than the model for delay time because of a different set of factors is behind the lockage process. In particular, we dropped the two traffic intensity measures from our model. The reason is simple; once the wait is over, the time a vessel needs to pass through the lock is little affected by the surrounding traffic. This conjecture is supported by our preliminary analysis, which indicated that the effects of the two traffic intensity measures are largely negligible. On the other hand, we included two additional variables: number of barges (Barge NBR) and total tonnages (Tonnage), which are expected to affect the lockage time for a vessel. Our model for lockage time thus takes the form:

$$LockageTime_t = \beta_0 + \beta_1\, Double_t + \beta_2\, Other_t + \beta_3\, TowBoat_t + \beta_4\, Helper_t + \beta_5\, BargeNBR_t + \beta_6\, Tonnage_t + \sum_{j=2}^{12} \lambda_j Month_{t,j} + \sum_{j=1}^{6} \delta_j Day_{t,j} + \varepsilon_t$$

The results for the above model are reported in Column 5 of Table 5. There exist significant effects from lockage and vessel characteristics. The number of barges, after controlling for lockage types, still exhibits significant effects on the lockage time. A similar effect is found for the total tonnages. Interestingly, the effect of helper boats on the lockage time turns out to be positive for lock 20, although the magnitude is quite small. (Note that magnitudes of the coefficients of the indicator variables are directly comparable among themselves; but not directly comparable with those continuous variables, such as number of barges or tonnages.) As with the models on delay time, there exist some systematic variations due to time of year and day of week effects. Last, the adjusted R-square is as high as 0.78, more than twice of those of OLS models for the delay time. This comparison suggested that the lockage time, to a large degree, can be explained by systematic difference in lockage, vessel, and cargo characteristics. In contrast, the delay time significantly affected traffic conditions and is subject to a substantially larger amount of stochastic variations that cannot be explained by observed covariates.

We next report the regression analysis on lock 24. The same sets of models are employed to analyze its delay time and lockage time distributions. The results are given in Table 6. It is seen that the overall pattern is qualitatively similar. In particular, the two traffic intensity variables are shown to play an important role in vessel delay time. For the Weibull model, the scale parameter is estimated to be 1.95 and statistically significantly different from 1. Also, like the results for lock 20, the presence of a helper boat reduces the delay time but has little effect on the actual lockage time.

Table 6. Single Robust Regression on Lock 24.

Parameter estimates (Standard errors in parentheses)				
	Regression on Delay Time	Regression with Traffic Effect	Survival Regression on Delay Time	Regression on Lockage Time
Constant	-7.282 (0.529)***	-7.307 (0.469)***	-6.580 (0.453)***	-3.578 (0.058)***
Lockage_C	1.065 (0.366)***	0.856 (0.325)***	0.712 (0.278)**	0.964 (0.049)***
Lockage_NC &NS	0.623 (0.284)**	0.464 (0.252)*	0.382 (0.241)	0.710 (0.031)***
Vessel_T	0.973 (0.401)**	0.765 (0.355)**	0.961 (0.340)***	0.106 (0.044)**
Assistant_J	-0.774 (0.358)**	-0.592 (0.317)*	-0.457 (0.273)*	-0.032 (0.039)
Num_brg	___	___	___	0.012 (0.003)***
Tonnage	___	___	___	0.011 (0.001)***
February	0.916 (0.552)*	0.534 (0.490)	2.242 (0.473)***	-0.137 (0.061)**
March	0.658 (0.398)*	0.342 (0.353)	0.480 (0.338)	-0.280 (0.045)***
April	1.651 (0.374)***	1.105 (0.333)***	1.479 (0.321)***	-0.348 (0.042)***
May	2.198 (0.375)***	1.560 (0.334)***	1.858 (0.320)***	-0.371 (0.042)***
June	1.053 (0.414)**	0.635 (0.367)*	0.853 (0.352)**	-0.391 (0.046)***
July	2.808 (0.369)***	1.619 (0.332)***	2.051 (0.316)***	-0.390 (0.042)***
August	2.461 (0.374)***	1.525 (0.335)***	2.567 (0.319)***	-0.353 (0.042)***
September	1.881 (0.381)***	1.358 (0.338)***	1.709 (0.322)***	-0.299 (0.043)***
October	1.468 (0.381)***	0.803 (0.339)**	1.149 (0.325)***	-0.303 (0.043)***
November	1.317 (0.382)***	0.891 (0.339)***	1.205 (0.326)***	-0.259 (0.043)***

December	0.700 (0.417)*	0.471 (0.369)	0.653 (0.353)*	-0.197 (0.046)***
Monday	-0.573 (0.197)***	-0.613 (0.175)***	-0.711 (0.167)***	0.026 (0.022)
Tuesday	-0.447 (0.193)**	-0.473 (0.172)***	-0.652 (0.165)***	-0.004 (0.021)
Wednesday	-0.757 (0.198)***	-0.553 (0.175)***	-0.679 (0.170)***	-0.005 (0.022)
Thursday	-0.616 (0.193)***	-0.431 (0.171)**	-0.608 (0.164)***	0.025 (0.021)
Friday	-0.360 (0.199)*	-0.218 (0.176)	-0.520 (0.169)***	0.020 (0.022)
Saturday	-0.763 (0.196)***	-0.778 (0.174)***	-0.791 (0.167)***	-0.012 (0.022)
Traffic_1	___	0.641 (0.107)***	0.428 (0.104)***	___
Traffic_2	___	0.964 (0.046)***	0.789 (0.055)***	___
Log(Scale)	___	___	0.667 (0.018)***	___

Note: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

4. Prediction

We next considered the problem of prediction at the locks using the proposed model. In particular, we attempted to predict the expected delay and lockage time for a vessel with a given set of characteristics and time at locks. In principle, we can take a given set of vessel characteristics, lockage attributes, and time factors, and plug them into the models estimated in the previous model to predict the expected delay and lockage time. One complication arises here because we do not know the level of traffic intensity for a scheduled arrival in question. For this purpose, we needed to first predict the traffic intensity at the lock at an arbitrary point of time such that our constructed models could be used for predictions in a realistic setting.

Recall that we calculated, for two types of vessels, a traffic intensity measure by counting the number of arrivals at the locks with a 3-hour window for a given arrival, less than two hours earlier and one hour later than the arrival. We modeled the traffic intensity or essentially the arrival process for the two types of vessels (double lockages and other types) in a similar manner. For each vessel type and a given arrival time, we expressed its expected traffic intensity as a function of month, day of week, and time of day:

Traffic intensity = *f* (month, day of week, time of day)

One possibility is to model the unknown function as a linear function of month and day of week dummies and a smooth function of time of day, for instance, using a polynomial. One potential problem with this approach is that the specification is somewhat arbitrary. For example, we experimented with a linear predictor with the month and day of week dummies; a polynomial of time of day of degree 4, the adjusted R-square is as low as 0.08, and the correlation between the predicted and actual traffic intensity is around 0.3.

Instead of using a simple and somewhat arbitrary parametric functional form, we opted to use nonparametric methods to model the traffic intensity. In particular, we used the kernel estimation method, which models the conditional mean of a variable *Y* based on a vector of observed covariates *X*. The estimator takes the general form:

$$m(x) = \sum_{i=1}^{n} \frac{K_h(x - X_i)}{\sum_{j=1}^{n} K_h(x - X_j)} Y_i \,.$$

The kernel method models the conditional mean as a weighted sum of observed Y_is, where the weights are determined according to the distance between the given *x* and the observed X_is. There are two key ingredients of a kernel regression model, the kernel function *K*, and its bandwidth *h*. The former is usually a symmetric nonnegative function peaking at zero, which captures the distance between *x* and each X_i, and the latter determines the rate at which the value of a kernel function declines with departure from the center. Popular choice of the kernel function for continuous variables includes the Gaussian kernel, the uniform kernel, and the *t* kernel for fat-tailed distributions. Traditional kernel regression methods have difficulty dealing with discrete variables due to their lack of smoothness. Recent advances in the kernel regression method by Li and Racine (2008) provided a novel method of smoothing discrete variables using kernel methods. In our estimation, we employed Li and Racine's kernel estimation method that allows for both continuous and discrete variables. Details for the method can be found in Li and Racine (2007).

The most critical parameter in kernel regression is the bandwidth, which determines the degree of smoothness of the fitted curve. Ideally, the choice of bandwidth balances the tradeoff between goodness of fit and variation. An overly small bandwidth produces wiggly curves with large variations, whereas a large bandwidth tends to oversmooth the data and thus lose important features of the underlying curve. There exist generally two methods of bandwidth selection: plug-in method and cross-validation. The former selects a bandwidth that minimizes an expected loss usually under the assumption of normality; the latter uses a data-driven method to minimize the expected mean squared errors or Kullback-Leibler distance. In our study, we followed the second route and used the method of least squares cross validation that minimizes the expected mean squared errors of the prediction.

For a given time *t*, denote the predicted traffic intensity measures for double lockages and other types of vessels by $\hat{S}_{t,d}$ and $\hat{S}_{t,o}$ respectively. The predicted delay time and lockage time at a lock is then calculated according to the following formulae:

$$\widehat{DalayTime}_t = \hat{\alpha}_0 + \hat{\alpha}_1\, Double_t + \hat{\alpha}_2\, Other_t + \hat{\alpha}_3\, TowBoat_t + \hat{\alpha}_4\, Helper_t + \hat{\alpha}_5\, \hat{S}_{t,d} + \hat{\alpha}_6\, \hat{S}_{t,o} +$$

$$\sum_{j=2}^{12} \hat{\gamma}_j Month_{t,j} + \sum_{j=1}^{6} \hat{\eta}_j Day_{t,j}$$

$$\hat{LockageTime}_t = \hat{\beta}_0 + \hat{\beta}_1\, Double_t + \hat{\beta}_2\, Other_t + \hat{\beta}_3\, TowBoat_t + \hat{\beta}_4\, Helper_t + \hat{\beta}_5\, BARG\_NBR_t$$

$$+ \hat{\beta}_6\, Tonnage_t + \sum_{j=2}^{12} \hat{\lambda}_j Month_{t,j} + \sum_{j=1}^{6} \hat{\delta}_j Day_{t,j}$$

where the estimated coefficients are obtained from models presented above.

To illustrate the prediction method, we provide an example of predicting delay time with the actual traffic intensity replaced by predicted traffic intensity based on the kernel estimator. To save space, we only present results for lock 20. We first estimate the real time traffic intensity for each observation in the sample using kernel regression methods, with the bandwidth selected by the least square cross validation method. Based on only three explanatory variables, month, day of week, and time of day, the predictions turn out to be remarkably good. The correlations between the actual traffic intensity and predicted traffic intensity are 0.73 and 0.70, respectively, for double lockages and other types of vessels. To check the impact of using predicting rather than actual traffic intensity, we reran the linear model discussed in Section 3 with actual traffic intensity replaced by predicted intensity. The results are presented in Table 7.

Table 7. Prediction of Delay Time Using Kernel Regression on Lock 20.

Parameter estimates (Standard errors in parentheses)	
Constant	-7.655 (0.468)***
Lockage_C	0.505 (0.162)***
Lockage_NC &NS	1.079 (0.270)***
Vessel_T	0.448 (0.230)*
Assistant_J	-0.170 (0.147)
February	-0.010 (0.846)
March	-0.174 (0.483)
April	0.277 (0.488)
May	0.404 (0.494)
June	0.121 (0.521)
July	0.646 (0.484)
August	0.632 (0.485)
September	0.138 (0.484)
October	0.292 (0.488)
November	0.320 (0.486)
December	0.571 (0.531)
Monday	0.200 (0.187)
Tuesday	-0.183 (0.192)
Wednesday	0.081 (0.186)
Thursday	0.247 (0.188)
Friday	0.258 (0.190)
Saturday	0.285 (0.188)
Traffic_1	0.524 (0.191)***
Traffic_2	2.064 (0.134)***

Note: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Some comments are in order. First we noted that most coefficients remain close to the results reported in the previous section, indicating the using the predicting traffic intensity produces similar results to the original. The overall impact of this replacement can be assessed by comparing the adjusted R square, which reduces from 0.33 for the original model to 0.23 of the current one. This reduction of overall significance is due to the stochastic and systematic variations in real time traffic intensity that are not captured by our explanatory variables and our approximate models. Nonetheless, the coefficients for the two predicted traffic intensity variables remain statistically significant, and more importantly, this adjusted R square is still considerably bigger than 0.13 for the baseline model, which does not include measures of traffic intensity. We also note that the overall significance of month and day of week dummies decline in the current model. This is actually expected because the predicted traffic intensity measures are constructed as a function of month and week dummies. Using them in the regression jointly with those dummies variables introduces a slight degree of multicolinearity. On the other hand, since the traffic intensities are modeled as nonlinear (nonparametric) functions of those dummy variables, it does not appear to be problematic.

The above example demonstrates the effectiveness of our methods for modeling and predicting the amount of time a vessel shall expect at the locks. It also provides further evidence on the importance of incorporating some measures of traffic intensity in the modeling of delay time. Using the parameters obtained from historical data in conjunction with prediction of traffic intensity, one is able to produce reliable prediction of time usage at the locks.

5. Conclusion and Policy Implications

In this study, we analyzed systematically the arrival, waiting, and lockage time of vessels at the locks of Upper Mississippi River. Particular attention is paid to model the abovementioned processes separately to isolate and identify important determining factors in the each stage of the overall lockage process. Our key findings reveal important differences in the determination of these processes. In addition to the commonly considered factors such as vessel characteristics and tow configuration, the real time traffic intensity at the locks play a key role in determining the amount of time a vessel has to wait at the lock. On the other hand, the actual lockage time can be more systematically explained by vessel and lock specific attributes and the timing factor.

We used the proposed models to estimate the delay and lockage times of vessels at locks on the Upper Mississippi River. Our results suggest that these models successfully capture the salient features of the delay and lockage processes. We further proposed a nonparametric model for the traffic intensity of various types of vessels at the gate. The model allows us to combine the estimated coefficients from the delay and lockage time models and the predicted traffic intensity to forecast the expected amount of time for a vessel under arbitrary pre-specified conditions. Our numerical examples provide convincing evidence to support the inclusion of traffic intensity measures in the estimation and prediction of vessels' time use at the locks.

Last, the proposed models and predictions methods can be combined with simulated models, such as Smith et al. (2009), to provide a self-contained framework for waterway traffic simulations, which can be used to evaluate the potential impacts of various structural and non-structural alternatives, and changes in waterway and lock conditions. For example, our results indicated that the helper boats can only provide limited relief to waterway congestion. To be more specific, our investigation seems to suggest that helper boats are effective in reducing the amount of waiting time to a certain degree, but does not seem to affect the actual time required to pass through the lock once a vessel enters the lockage process. Of course, more detailed analysis is required to shed further insight into these specific alternatives; we expect our models to provide a useful set of tools to aid in the investigation of these important issues.

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