Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
May 3, 2018
A Regional Conference of the Society for Industrial and Systems Engineering

Ustranscom Closewatch Process Improvements: Improvement of Shipment Delivery Date Prediction

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Abstract: The purpose of this study is to propose an improved algorithm with which to minimize shipment prediction error at United States Transportation Command (USTRANSCOM). The focus of this study was to improve USTRANSCOM's ability to predict late shipments in order to alert their customers. Specifically the study focused on the development of improvements to the current model used to predict shipments labeled as important in the supply-chain at TRANSCOM. An algorithm was developed to improve average difference between prediction and actual arrival by nearly three days. However, we found that the best solution to USTRANSCOM's issue of remediating late arrivals may not be with predictive algorithms but rather a change to USTRANSCOM processes.

Keywords: Closewatch Dashboard, Electronic Data Interchange (EDI), Required Delivery Date (RDD)

1. Introduction

This study examines the structure of United States Transportation Command's (USTRANSCOM) supply-chain shipment processes to propose an improved algorithm with which to minimize shipment prediction error. In doing so, this paper will follow the four-step Systems Decisions Process from Parnell (2011): problem definition, solution design, decision making, and solution implementation. This methodology is important because of the complex nature of USTRANSCOM and to allow the study to remain within a manageable scope.

The foundation of this study relies on the understanding of the fundamental supply chain at USTRANSCOM. For the past several years USTRANSCOM's Logistics Sustainment Division (TCJ4-L) has struggled with identifying and predicting high priority containers that will be late to their final destination. USTRANSCOM does not have real-time tracking capabilities and needs to develop a solution to this problem in order to alert clients when their shipments are going to be late. USTRANSCOM identifies crucially important items that are added to what is known as a Close Watch Dashboard. Any container can be added to this Close Watch Dashboard and will be monitored throughout its shipment process to determine its estimated delivery date relative to the initial contractual delivery date. This contractual delivery date is known as the Required Delivery Date (RDD). Currently, a Close Watch dashboard has been created at USTRANSCOM for clients to access and view the status of their shipments. For example, at any given time, the Defense Logistics Agency (DLA), a major customer USTRANSCOM, has about 3,000 containers moving around the world. Of these containers, about 8% of them are added to the Close Watch list (Erhardt 2017) to be monitored and ensure accurate arrival time.

Because USTRANSCOM is unable track individual shipments in real time, USTRANSCOM TCJ4-L has developed an initial algorithm to predict shipment arrival times. This algorithm uses information about the current position of the container within the supply-chain, as well as historical data of certain segments of the supply chain, to estimate the day the container will be delivered. This estimated delivery date from the algorithm is then compared to the contractual RDD between USTRANSCOM and the customer to determine if the shipment will be flagged as late in the Close Watch Dashboard, requiring further action from USTRANSCOM.

This report examines the current TRANSCOM predictive algorithm, evaluates its success, and proposes an improved algorithm to predict arrivals of shipments for USTRANSCOM's Closewatch Dashboard. This report will examine the different methods that can be used to improve the USTRANSCOM processes in predicting and improving the shipping methods of containers. Specifically, we want to propose an improved algorithm with which to minimize shipment prediction error.

2. Problem Definition

2.1 Project Description

This paper will explore methods to improve the current USTRANSCOM predictive algorithm that is used to assess the delivery date of important shipments. USTRANSCOM does not have real-time tracking capabilities for shipments like many private shipping corporations do in the ocean segments. USTRANSCOM uses data from the last recorded Electronic Data Interchange (EDI) event for a given shipment to predict arrival date.

2.1.1 Project Scope & Definition

The project objective is to develop an improvement to the existing predictive algorithm that calculates if and how late a Close Watch item will arrive at its destination. This model will provide a more accurate prediction than the current algorithm used by USTRANSCOM. The model we developed evaluates intermodal (land and sea based) shipments. Air-based shipments were not considered within the scope of our work.

2.1.2 Justification

USTRANSCOM's high volume of late shipments is costly and leaves customers dissatisfied. Specifically, USTRANSCOM is concerned with Class I (food) shipments arriving late to deployed soldiers. Late shipments have a significant impact on troops deployed in low-volume locations. Without accurate shipment predictions, USTRANSCOM is unable to correct Class I (typically food) shipments, leaving deployed troops without food and supplies. This causes numerous issues including a reduction in troop morale as a threat to food spoilage. USTRANSCOM TCJ4-L, Colonel Erhardt, highlights that a more accurate prediction of arrival would give USTRANSCOM greater flexibility to alter the course of a shipment (Earhardt 2017). If this problem is not addressed USTRANSCOM will not be able to reliably ensure the delivery of Class I supplies to soldiers for time sensitive training and major events.

2.2 Supply-Chain Overview

The understanding of supply-chain operations in international shipping is crucial to understanding the predictive algorithm. In general there are two forms of international shipping. The first form of shipping is by air. Although air delivery is the quickest method, it is also the most costly and is typically avoided for Class I shipments (Earhardt 2017). The second form known as intermodal shipping and is the focus of this research. Intermodal shipping combines line-haul (trucking) and ocean-based shipping (Rodrigue 1998). The ocean segment of intermodal shipping is almost always the longest segment of the shipment and contains the most uncertainty (Erhardt 2017).

2.2.1 USTRANSCOM Intermodal Shipping Process

An example of the USTRANSCOM Shipping Process is outlined in Figure 2.2.1 below.

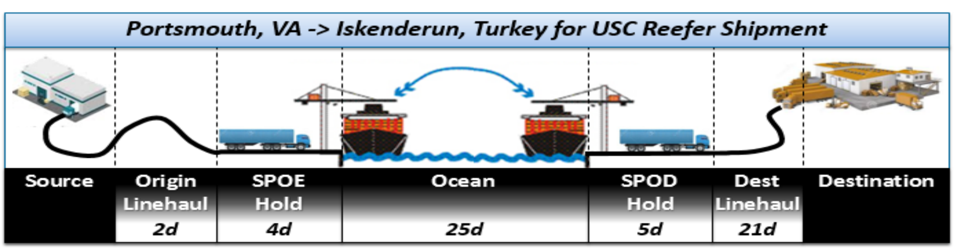

Figure 2.2.1: USTRANSCOM Supply Chain Overview (Montague, Sustainment Dashboard Discussion)

USTRANSCOM shipments begin with a delivery contract between the supplier and the customer where a shipment is booked. This contract includes a Required Delivery Date (RDD), which is the mandatory date the carrier is expected to have the shipment delivered to the destination. In the example in Figure 2.2.1, the container begins at the source warehouse in Portsmouth, VA. The container then travels by linehaul (movement of cargo by truck) to the Sea Port of Embarkation (SPOE). The SPOE Hold is where containers are held and wait to be loaded onto a ship. Once loaded onto a ship the container will travel by ocean. The ship will dock in the Sea Port of Debarkation (SPOD). At the SPOD Hold the container will be held until it is loaded onto another line haul truck for the destination linehaul segment. Finally the shipment is delivered to its final destination.

ISBN: 97819384961-2-7

2.2.2 Electronic Data Interchange (EDI) Events

Upon arrival at each segment of the shipment process, an EDI event of arrival date is recorded for each container. Each EDI event is recorded and stored in several databases for USTRANSCOM to monitor the status of a shipment. Databases include the Integrated Development Environment/Global Transportation Network (IGC), Global Air Transportation Execution System (GATES), the Integrated Mission Support for Surface Deployment and Distribution Command (iSDDC), and Pipeline Asset Tool (PAT). USTRANSCOM attempts to compile the data from these databases into a single data source (Montague, *20170511_ISDDC_WESTPOINT_ANALYSIS.xslx)*.

The main problem in predicting when a shipment will arrive is the reliability of EDI events being recorded along the shipment route. Due to all the different human factors and interactions, there is a significant amount of error when it comes to recording EDI events. To remedy the issue of missing EDI events, USTRANSCOM makes different rules and assumptions within the recorded data in order to fill gaps of missing or duplicated EDI events. The collection of reliable EDI data is essential for knowing the current status of a shipment and crucial for creating an accurate algorithm to predict shipment delivery dates (Lapp 2017).

2.3 USTRANSCOM Specific Processes-Close Watch Dashboard

As an initial solution to predicting the delivery of Closewatch shipments, USTRANSCOM developed an interface in which clients could see if a shipment was estimated to be late. Currently, USTRANSCOM begins this process by identifying and categorizing containers that have been labeled as “crucially important” from its customers. This is accomplished through weekly conference calls (Lapp 2017). Items deemed crucially important from this conference call are manually added to what is known as the Closewatch Dashboard. A container or Transportation Control Number (TCN) that is added to this list is monitored throughout its shipment process to determine its estimated delivery relative to the RDD. However, the algorithm behind this predictive model can be improved. This report examines the current TRANSCOM predictive process and evaluates its success. An enhanced predictive algorithm will forecast when containers are going to be late with greater accuracy. This report will examine the different methods that can be used to improve the USTRANSCOM processes in predicting and improving the shipping methods of containers.

2.3.1 Current Predictive Algorithm

Once a shipment is placed into the Closewatch Dashboard, USTRANSCOM uses its predictive algorithm to predict whether a shipment will arrive late relative to its RDD and will flag any potential late shipments. The basis of the algorithm uses historical data to estimate how long a shipment will spend in each future segment. The process analyzes up to 15 years of historical data to estimate the length of each process segment. The historical data is broken down into streams (Contract Type, SPOE, SPOD, and Type of Cargo) and each stream/segment is independently analyzed (Montague, Sustainment Dashboard Discussion). The algorithm first calculates each shipment’s current status. It determines which shipments have not been delivered and have had some activity in the past six months. This allows the algorithm to determine the shipment’s last reported location to calculate which segment of the shipment is currently located. The algorithm’s next step is to add the number of days spent in the past segments. The algorithm then assumes that the shipment will leave the current segment on the following day. This assumption was made to keep the algorithm simple as an initial model. Finally, the algorithm uses the historical means of the remaining segments to estimate how many days until projected delivery (e.g. 51 More Days). The number of days spent in the past segments are added to the estimate for the number of days in the current segment plus the sum of the historical means of the future segments. The total number of days estimated in the shipment process are then added to the original shipment date. This final estimated delivery date is compared to the RDD. If the final estimated delivery date is greater than the RDD, then the shipment will be flagged as late in the Closewatch Dashboard (Montague, Sustainment Dashboard Discussion).

2.3.2 Assessment of Current Algorithm

USTRANSCOM provided our team with three data sets to explore the problem. The first data set included EDI events of every shipment from the past 10 years. The data set included USTRANSCOM’s predicted arrival date, as well as the date the shipment actually arrived at its destination (Montague, Sustainment Dashboard Discussion). The data set included 941,392 observations, which were then filtered to remove data points that did not contain perfect information or did not make sense (data populated in each column). The second data set provided a snapshot of every USTRANSCOM shipment in route on two dates: May 17, 2017 and July 5, 2016 (Montague, *20171027_ISDDC_HISTORICAL_COMPARE_Explore.xslx).* These observations were used as random data points with which to assess our algorithm. Our team compared the improved algorithm run on these dates to the historical results of the shipment’s actual delivery date.

In order to improve USTRANSCOM’s predictive algorithm our team needed to assess the accuracy of the current algorithm to the improved algorithm. The current algorithm was assessed using a shipping data snapshot that covered shipments

ISBN: 97819384961-2-7

from May 17, 2017 and July 5, 2016 (Montague, *20171027_ISDDC_HISTORICAL_COMPARE_Explore.xslx)*.Overall, our team found that the current algorithm predicts shipments will not arrive on time 67% of the time(either late or early). Shipment predictions using the current USTRANSCOM algorithm were off by a mean of 30.2 days. We can conclude that while the USTRANSCOM algorithm provides an initial solution to the problem of late containers, the algorithm is largely inaccurate and does not provide USTRANSCOM with an adequate solution to their problem.

3. Solution Design

3.1 Introduction to the Improved Predictive Algorithm-Main Assumptions

After assessing the current algorithm we determined that the largest issue with the Current Algorithm is the assumption a shipment will leave its current segment the subsequent day. Especially in the ocean segment, where shipments experience the highest amounts of variance. A method needed to be developed to provide a more accurate assessment of when a shipment would leave its current segment.

Our team maintained the framework of the current algorithm and focused our efforts on improving the next day assumption of the current segment, keeping the assumption that shipments would spend the same number of days in future segments as their calculated historical mean.

When applying our calculations for the new algorithm, given the data we were provided, we made the assumption that imperfect data would not be able to be used in our calculations. We also assumed that every possible stream had the same segment averages. (i.e. a shipment from New York to Qatar uses the same average shipment time as New York to Charleston). We were forced to make this assumption due to our data limitations. This assumption is acceptable because once implemented with full data at USTRANSCOM, utilizing segment averages for each individual stream, the algorithm will only improve the results we provided in this report.

3.1.1 Pipeline Access Tool (PAT)

The database Pipeline Asset Tool (PATs) provides shipment schedules from individual carriers of when ships will arrive at the SPOD after the ocean segment. This tool is extremely valuable in that this data provides accurate information to know when a shipment will leave the ocean segment. The use of PATs data has the ability to greatly minimize variations within our predictions in the ocean segment (Mitchell, 2017). USTRANSCOM provided the team with hundreds of PATs dates to compare to the ten year historical data. We conducted an analysis using five hundred shipments with PATs dates. Using these 500 shipments we compared our algorithm run with and without the PATs date. Our algorithm evaluated without a PATs date averaged 29 days predicted off. When we analyzed our algorithm with the PATs date, we found that the mean dropped to 19 days predicted off. This is a 34% improvement in the prediction. While PATs provides useful information, implementation of PATs into the algorithm would require large amounts of organizational negotiations to get backend access to PATs information (Montague, *On_Ocean_TCNs_15FEB18_RESPONSE.xslx*).

3.1.2 Accounting for Extremely Delayed Shipments: Optimal Percentile for Algorithm

It was discovered during in the solution design process that several shipments were delayed in a specific segment well past the typical number of days a shipment spends in that given segment. In order to account for these extremely delayed shipments, we decided to augment the algorithm by considering these shipments in our estimate. The historical data was plotted into Cumulative Distribution Functions (CDF's) for each segment. Using this information, it was determined the optimal percentile for the number of days spent in each segment to minimize the average number of predicted days off from actual. The optimal percentiles for delayed shipment in each stream are as follows: Origin Line haul 95th, SPOE Hold 90th, Ocean 95th, SPOD 95th, Destination Line haul 90th percentiles. The sensitivity analysis to determine these optimal percentiles will be discussed in Section 4.2.

3.1.3 Improved Predictive Algorithm

Our proposed improved predictive algorithm uses much of the current algorithm as the foundation for our improvements. After assessing the current algorithm we came to the conclusion that the largest error in prediction occurs in the current segment of the predictive model. The improved predictive algorithm is defined below:

1. Identify the current segment location of a shipment and how many days that shipment has spent in its current segment.
2. Determine if a PATs date exists. If a PATs date does not exist, move to step 3. If a PATs date does exist:
   a. And the current date is less than or equal to the PATs date, then assume the PATs date is the date that the current segment will be completed. Compute the number of days estimated to be spent in the current segment.

ISBN: 97819384961-2-7

Sum the number of days spent in the past segments, the estimated number of days spent in the current segment and the historical means of future segments. Determine estimated delivery date. Compare the delivery date to RDD. End Algorithm.

b. And the current date is greater than the PATs date, then assume that the shipment will leave its current segment the following day. Determine the number of days estimated to be spent in the current segment. Sum the number of days spent in the past segments, the estimated number of days spent in the current segment and the historical means of future segments. Determine estimated delivery date. Compare the delivery date to RDD. End Algorithm.

3. Add the number of days spent in any past segments together.
4. Estimate the number of days that will be spent in the current segment:
   a. If the number of days spent in the current segment is less than the Historical Mean for the specific segment of that stream then assume the estimated number of days spent in the current segment is the historical mean for that segment. Move to step 5.
   b. If the number of days spent in the current segment is greater than the Historical Mean for the specific segment of that stream then assume the estimated number of days spent in the current segment is the optimal x percentile for that segment. Refer to figure 3.3.
5. Sum the number of days spent in the past segments, the estimated number of days spent in the current segment and the historical means of future segments. Determine estimated delivery date. Compare the delivery date to RDD. End Algorithm.

3.1.4 Sensitivity Analysis for the Optimal Percentile

As discussed in Section 3.1.2 in order to account for extremely delayed shipments in our prediction we needed to consider estimates greater than the historical mean. Every other segment not being tested was held constant at the 75th percentile. At each percentile, we recorded the mean number of days off from the actual delivery date. The percentile from each segment that minimized the mean number of days from the actual delivery date was selected. The percentiles selected from the sensitivity analysis are highlighted in yellow in Table 3.1.4.

Table 3.1.4 Sensitivity Analysis while all other Segments held at the 75th Percentile

Mean Number of Days from Actual Delivery Date													
Percentile	40	45	50	55	60	65	70	75	80	85	90	95	100
Origin	28.501	28.513	28.5132	28.498	28.498	28.497	28.508	28.491	28.479	28.452	28.395	28.286	36.612
SPOE	28.49	28.49	28.49	28.49	28.492	28.492	28.492	28.491	28.491	28.491	28.48	28.498	28.493
Ocean	28.928	29.054	29.105	29.165	29.142	28.959	28.749	28.491	28.057	27.766	27.651	27.556	46.025
SPOD	25.492	28.492	28.492	28.492	28.495	28.495	28.5	28.504	28.5	28.5	28.5	28.447	43.995
Destination	28.484	28.484	28.484	28.484	28.484	28.484	28.484	28.492	28.5	28.5	28.461	28.734	43.9

3.1.5 Results

Given the data provided, we found that the improved algorithm reduces the number of predicted days off from actual by nearly three days. On average, the current algorithm has a mean difference from of 30.2 days. The improved algorithm has a mean difference of 27.4. These results demonstrate an improvement in the new algorithm. If the improved algorithm is able to be implemented, we are confident it will reduce the predicted number of days off. However, these results are somewhat limited in accuracy because of significant data issues.

One major data issue we faced was incomplete data due to a failure by USTRANSCOM contractors' ability to record complete and accurate EDI events. This issue caused us to eliminate large amounts of incomplete shipment data, dramatically lowering our sample size and making it difficult to draw conclusions. Another major data issue we faced was that we were not provided the actual data that is made available to USTRANSCOM when running its algorithm. Instead, we were forced to use universal, calculated averages based on historical data and randomization techniques in order to obtain optimal percentiles for each specific segment and stream.

3.1.6 Statistical Significance

In order to assess the statistical significance of the results of the improved algorithm against the original USTRANSCOM algorithm we conducted a paired t-test to determine if the mean difference between the new and improved algorithm is significant. The hypothesized mean difference of our paired t-test is 0. Based on this statistical test and with a confidence level of 95%, we obtained a p-value of 3.392×10^{-7}. Based on this result, we can reject the null hypothesis because our p-value is less than our alpha value of .05. Therefore, we should conclude that the mean difference of the improved algorithm (about 3 days less than the initial algorithm) is significant.

4. Solution Implementation

4.1 Implementation at USTRANSCOM

Upon receiving our improved algorithm, USTRANSCOM can code the algorithm into their systems to monitor all of their shipments. When customers go to view when their shipment will arrive, the algorithm will populate a predicted arrival date. Percentile code easily implemented in new SQL code. The PATs date portion of the coding will not be as easily implemented at USTRANSCOM. PATs is a separate database. Current access is front end web based. USTRANSCOM needs back end access regularly to be truly useful. Backend access is an organizational negotiation issue.

4.1.2 Conclusion

While our new algorithm will certainly improve the reliability of predictions from the current algorithm, we found that there really is no accurate way to predict shipment arrival time without large changes in USTRANSCOM processes. There will always be high amounts of variability in the shipping industry that make it difficult to make extremely accurate predictions. Therefore, predictive algorithms may not be the best solution to USTRANSCOM's problem. Future solutions that may be more beneficial may include improvements to EDI collection, greater use of shipment schedules, as well as consolidated databases. The best solution overall, if possible, would be to adopt methods used by other shipping corporations that track shipments in real time.

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ISBN: 97819384961-2-7