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# Clustering Techniques for Barge to Boat Assignment

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This paper focuses on the development of clustering methods to determine effective assignments of barges to tow boats for intra-river transport. Barges are clustered such that dwell time, handling, and transit are minimized while constraints associated with pick-up and delivery requirements, physical tow sizes, and travel time are considered. The results from this paper indicate that 'complete linkage' and 'partitioning around medoids' clustering methods outperform the other grouping models considered in terms of maximizing boat utilization.

**Significance:** This paper adapts existing clustering methods for use in the inter-river barge transport problem and introduces a new heuristic that provides good solutions in less time than existing methods. The results include higher boat utilization and lower requirements for outsourcing.

**Keywords:** Transportation, Scheduling, Barge, Freight Transport

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## 1. INTRODUCTION

Management personnel in all transportation industries face a complex decision making environment where a large number of planning and operational problems must be solved. This decision making environment in the intra-river barge industry is no exception. In that industry, individual barges are typically grouped into "tows" and transported by tow boats upstream or downstream. Deciding which barges to group together is a complex task based on such information as the barge origin ports, destination ports and pick-up time windows. These barge grouping decisions have a huge impact on the handling, and dwell costs associated with barge transportation.

This paper discusses the development of barge clustering decision support heuristics for the intra-river transportation industry. The research is motivated by the barge assignment problem encountered at American Commercial Barge Line LLC (ACBL), the largest and most diversified barge transportation company in North America. Each year ACBL transports over 45 million tons of cargo and is currently operating 3200 barges and 124 towboats in the inland waterways (www.acbl.net). This considerable delivery network provides an interesting practical basis for the work presented herein. This paper has a specific focus on the barge assignment problem on the Ohio River.

### 1.1 Intra-River Barge Operations

An individual barge on the Ohio River typically has the following operational cycle; the loaded barge is picked up at its origin port by a boat, delivered to its final destination port, unloaded, and cleaned. The empty barge is then reloaded with a commodity, perhaps after being transported empty to a new customer port location, and then the loaded barge is available for pick-up. Boats rarely push a single barge, but rather a tow or group of several barges. Therefore decisions have to be made as to which barges will be grouped in the same tow. These barge grouping decisions affect both the handling and dwell costs. Handling costs are the costs associated with physically moving the barges during pick-up and delivery activities. Whenever a barge is added (picked-up) or removed (delivered) from the tow, various tow-building and tow-breaking costs are incurred. A tow consisting of barges with many different pick-up (origin) and delivery

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(destination) ports will incur high handling costs at the various origins and destinations of the barges in the tow. Forming tows of barges all with the same origin and destination ports will minimize the handling costs. However tow groupings that minimize the handling cost will most likely not minimize the dwell cost.

The dwell cost is the opportunity cost incurred when a barge must wait for a boat to pick it up. The barges only generate revenue when they are moving. Picking up a barge as soon as it is available will minimize the dwell costs. Therefore forming tows of barges all with similar pick up availability times will minimize dwell costs. Unfortunately the strategy of grouping barges based on common origin and destination ports will minimize the handling costs while the conflicting strategy of grouping barges based on pick-up times will minimize dwell costs. Neither strategy is likely to concurrently minimize total cost for most problem settings.

This paper investigates several barge grouping methods, based on clustering techniques, which seek to balance the tradeoff between handling and dwell costs. In addition, these barge grouping methods must consider the problem-specific constraint of maximum tow size. There is a limit to the number of barges that can be pushed at the same time by a boat. This limit is based on the power of the boat, the lock characteristics on the river, and the current water conditions. For the Ohio River study the maximum number of barges that can be pushed at the same time is 15. The term “group” used throughout this paper describes the set of loads or barges assigned to the same boat. A group has the characteristic of possibly containing more than 15 barges because additional barges could be added to the group as others are delivered to their destination. However, no more than 15 barges will be carried at one time. Each boat can only carry one group at a time, but a boat can carry more than 1 group over the full planning horizon. Barges not assigned to a group during a specified planning horizon must be subcontracted to a third party at a high cost.

Figure 1 provides information regarding labeling conventions used in the clustering heuristics. The Ohio River model makes use of 27 primary nodes representing pick-up locations on the river. In reality, these nodes are not points but are actually short river segments where barge pick-ups and deliveries are commonly required. The first node (node 1) corresponds with the western-most point in the Ohio River at the confluence of the river with the Mississippi River in Cairo, Illinois. The 27$^{th}$ node is at the eastern-most navigable point in the river near Pittsburgh, Pennsylvania. The 27 nodes are separated by 26 river segments not equal in length with segment numbers corresponding to their downstream nodes as indicated in Figure 1.

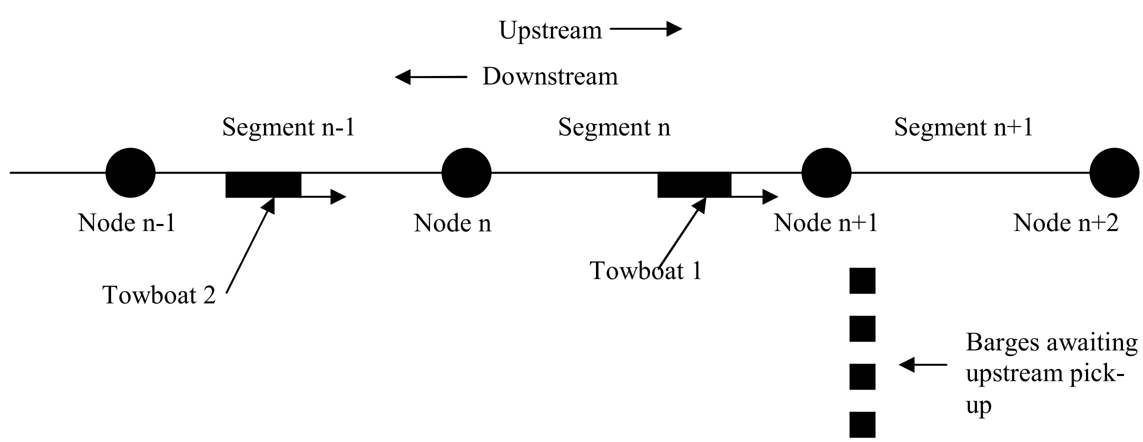


**Figure 1.** Local versus global optimization and labeling conventions.

Historically, human dispatchers have made all the decisions regarding barge groupings and boat dispatching. These dispatchers rely on personal experience when grouping barges into tows and when determining the tow dispatching times. Prior to this research, no automated decision tools have been employed for dispatching at ACBL.

This paper presents the findings associated with using clustering methods to support effective barge grouping. A new barge grouping heuristic has been developed specifically for this problem instance and is compared to five well-known clustering techniques using a set of ‘real world’ data while problem specific constraints are taken under consideration. The new barge grouping heuristic achieves a good solution to the intra-river transportation problem in the presence of multiple ports, constraints on tow capacity, bi-directional travel, constraints in time, and various types of barges. The new barge grouping heuristic also serves as an initial solution to an integer programming model or a non-hierarchical clustering model (See Drosos et al., 2001 and DePuy et al. 2002).

## 2. RELATED LITERATURE REVIEW

In its broadest interpretation, the problem presented in this paper is a specialized version of the capacitated clustering problem (CCP) as discussed in Koskosidis and Powell (1992). Perhaps most similar to the work presented herein is that of Bausch et al. (1998). In that paper, the authors make use of a spreadsheet-based simulation model to schedule coastal tankers and barges. Although operationally different, their general approach of using an integer linear set partitioning model to select schedules for each vessel is similar to that employed in this paper.

There are numerous examples of real-time vehicle dispatching tasks in all modes of transportation. While most of these examples involve the dispatcher in charge of traffic control manually making decisions, several recent advances are noteworthy. As Dror and Powell (1993) claim, "The most dramatic change in transportation over the last decade has been in telecommunications, which gives us the ability to collect and display data, in real time, and communicate instructions back to the field." Larson *et al.* (1991) developed the Barge Operations System Simulator for assisting the dispatcher in the task of sizing the fleet barges and boats. They simulated dispatchers' procedures for dispatching boats towing barges from point to point within a harbor. Vukadinovic and Teodorovic (1994) discussed the process of loading, transport and unloading of gravel by inland water transport. A model for the dispatcher's decision-making process was developed concerning the number of barges left at or taken from ports using fuzzy logic. Similarly, Vukadinovic *et al.* (1997) demonstrated the feasibility of a dispatch decision support system that could decrease the workload for the dispatcher and improve the quality of decisions based on a neural network approach in the similar environment of rail travel. Sforza (1991) considered the problem of determining the departure times of trains when planned schedules are modified due to various reasons.

Cluster Analysis, though known by many other names such as numerical taxonomy in biology and unsupervised pattern recognition in artificial intelligence literature, essentially addresses the following problem (Everitt, 1980): "Given a collection of n objects, each of which is described by a step of p characteristics or variables, derive a useful division into a number of classes. Both the number of classes and the properties of the classes are to be determined." The solution generally sought is a partition of the n objects, that is a set of clusters where an object belongs to one cluster only, and the complete set of clusters containing all the objects. To guarantee a globally optimum solution, all possible enumerations need to be examined for all possible numbers of clusters, 1 through n, where n is the number of objects.

All clustering methods operate on a notion of similarity (or dissimilarity) with objects that are similar with respect to one or more characteristics forming clusters. Similarity can be measured in several different ways depending on the type of data (Anderberg, 1973). There are several transformations that can be used to convert similarities into dissimilarities, and depending on these transformations they possess certain desirable properties based on the concept of distance (Tryon and Bailey 1970).

Two main classes of clustering heuristics exist: *hierarchical* and *non-hierarchical*. In hierarchical heuristics, the data are not partitioned into a particular number of classes or clusters in a single step. Instead the classification consists of a series of partitions, which may run from a single cluster containing all individuals, to n clusters each containing a single individual. Most hierarchical heuristics yield a *dendrogram* or tree structure of clusters. The non-hierarchical techniques on the other hand yield only one partition though the actual heuristic itself may be iterative. In this paper a new grouping heuristic is compared to four hierarchical clustering models (single, complete, average and Wards) and one non-hierarchical clustering model (partitioning around medoid).

Although the specific barge transportation problem domain presented within this paper has not been addressed in the literature, a number of authors have addressed barge fleet management problems. Swedish (1998), for example, used discrete-event simulation to solve fleet sizing problems. DePuy et al. (2004) introduce fleet management strategies to assist with operations at barge tow building locations. Bush et al. (2003) also examine barge fleet management tasks using iterative techniques with optimization and simulation.

## 3. SOLUTION METHODOLOGY

This paper develops a new barge grouping heuristic and applies five well-known, general clustering techniques to the barge grouping problem for comparison.

### 3.1 Barge Grouping Heuristic

A grouping heuristic has been specifically developed for ACBL's barge grouping problem. The development of this heuristic focuses on forming barge groups to minimize barge handling and dwell time while considering the operational conditions/restrictions of the problem. This barge grouping heuristic is divided into two main phases. The first phase seeks to add barges to current groupings that are already assigned to boats. Since barges are continuously in transport there is a need to continuously update barge groupings. Therefore, any 'current' barge groupings are reviewed to determine if any currently available barges or barges scheduled to be available in the future can be added to the groups. If no current groupings exist, the barge grouping heuristic proceeds immediately to phase 2. In the second phase of the heuristic, new barge groupings are formed for those barges not included in a current grouping. A boat will be assigned to each of these barge groupings. As mentioned earlier, any barges not transported by ACBL can be subcontracted to a third party at a significantly higher cost.

### 3.1.1 Phase I—Expanding Current Groupings

The first phase of the barge grouping heuristic is to separate current groupings into upstream and downstream groups that are currently in transit on the river. To eliminate backtracking, upstream barges (i.e. origin port # < destination port #) and downstream barges (i.e. origin port # > destination port #) are never placed together in the same group. Each current grouping is characterized by its current river position and the port number of its most extreme destination (i.e. largest destination port # for upstream groups, smallest destination port # for downstream groups). Barges are added to the current groupings in such a way as to try to minimize the group's dwell and handling costs. Therefore the goal is to group barges with common origin and delivery ports as well as similar available pick-up times. A hierarchy of barges is developed based on minimizing these costs. For each current barge grouping, additional barges are considered based on availability during the next 3 day period. The three day period was a standard set by ACBL based on the companies experience in barge transportation. Longer periods have much greater stochasticity of demand and short periods do not have sufficient planning information about available barge traffic. The major grouping standards revolve around the following two principles:

1. It is desirable for new barges to have the barge has the same destination as a barge currently in the group <u>and</u> a barge's origin port should be located between the group's current position and extreme destination. Also the barge should be available for pick up when the boat arrives at the pickup location.
2. A barge's origin port should be located between the group's current position and extreme destination <u>and</u> the barge's destination port should be located between the group's current position and extreme destination. The barge should be available for pick up when the boat arrives.

At this point the utilization of the group is checked. The utilization of a group is the number of barges carried divided by 15. For each river segment traversed weighted by the length of the river segment. If the group's utilization is greater than 70%, the group is accepted and removed from consideration for new barge additions. While the 70% utilization threshold was suggested by ACBL, the methods presented in this paper could easily be modified to use a different threshold parameter. If the group's utilization is less than 70%, the barges added to the group in steps 1 and 2 are removed from the group and returned to the list of unassigned barges for future consideration in phase II.

### 3.1.2 Phase II-Formation of New Barge Groups

The second phase of the barge grouping heuristic seeks to form new groups for those barges not assigned during phase I to an existing group. Again, barges are grouped according to a hierarchy developed to minimize both handling and dwell costs.

1. Group barges with same origin and same destination port numbers that are available for pick up within 3 days one another.
2. For each group formed in step 1, add barges whose origin port number is the same as the destination port number of any barge in the group.
3. Add barges whose origins are within 3 ports of either an origin or destination port already in the group <u>and</u> whose destination port is between the extreme origin and extreme destination of the group in an effort to improve boat utilization.
4. Add barges whose origin and destination are between the extreme origin and extreme destination of the group.

After the completion of phase 2, any barge not included in a group is subcontracted to a third party carrier.

### 3.2 General Clustering Procedures

Five general clustering techniques are also considered for this barge grouping problem; average linkage, single linkage, complete linkage, Wards minimum variance method (Anderberg, 1973) and partitioning around medoids. Each of these clustering analysis procedures starts by measuring each of a set of $n$ objects on each of $k$ variables. Next a measure of similarity (or dissimilarity) must be obtained and some heuristic or set of rules must be employed to cluster the objects into subgroups based on the inter-object similarities (or dissimilarities). The ultimate goal is to arrive at clusters of objects which display small within-cluster variation, but large between-cluster variation.

For this barge grouping problem, a custom function is necessary to form a set of dissimilarity measures to be used within each clustering procedure expressed as a dissimilarity matrix. Specifically, distances between origins and destinations are determined, then a farthest neighbor-clustering heuristic is applied in order to cluster barges based on distances between points. The farthest neighbor clustering heuristic separates data points that are far from each other geographically and temporally. Barges with dissimilar pick-up dates that are far apart (i.e. greater than 3 days) are assigned a large distance penalty in the dissimilarity matrix. In order to satisfy the constraint of carrying no more than 15 barges at any point in time, the dissimilarity matrix is updated to have a very large distance value for each cluster that reaches the threshold size of 15. The main characteristics of this matrix include some already discussed factors:

1. The dimensions of the matrix are $n$ x $n$ (symmetric), where $n$ is the number of barges that we are considering for clustering.
2. Upstream loads are considered separately from downstream loads and the diagonal entries of the dissimilarity matrix are zeros.
3. The day constraints (<=3 days) and the capacity constraints (<=15 at a particular time) are applied such that pair of barges with pick up dates that are greater than 3 days apart and exceed the capacity constraints are assigned a very large dissimilarity constant of 100.
4. For those barges that meet the date and capacity constraints, a measure of their geographical dissimilarity is computed as follows: Barges with the same origin and destinations locations are assigned a small dissimilarity constant of “1”. Increased dissimilarity values are used as the origin and destination locations distances amplify. An upper bound of at most 4 river segments was considered resulting in a constant of 16. Any pair that did not fit the above constraints was assigned a “100” to symbolize total dissimilarity.

Once the barge dissimilarity matrix has been obtained, that information is used to form clusters of objects such that the objects within a given cluster are similar to one another, but differ from objects in other clusters. This dissimilarity matrix is input into S-Plus (1999) to create dendrograms.

One major issue facing all clustering techniques is the number of clusters to form. There is a wide variety of criteria and guidelines for attacking that problem. A generally agreed upon approach is to solve for different numbers of clusters (i.e. 2, 3, 4, etc.) and then decide among the alternative solutions based on a priori, practical, common sense or more technical criteria. Previous practical knowledge from ACBL leads us to seek a number of clusters in the upper 20’s. With that notion in mind a series of trials of different hierarchical clustering techniques is performed to determine the best possible solutions. All of the clustering heuristics that are described in the next section differ significantly from the already established heuristics due to the fact that they address the constraints of capacity, time, and direction (upstream, downstream). Run times for these clustering techniques range anywhere from 2 to 5 seconds on a PC platform with the use of S-Plus. However, reading and assessing the dendrogram results is the most time consuming activity.

## 4. EXPERIMENTAL RESULTS

ACBL provided a data set describing 495 barges. The data has been extracted from historical data for a one week period (arbitrarily selected). Two hundred and twenty seven loads are downstream and the remaining 268 are upstream. Both the barge grouping heuristic approach described in section 3.1 and the hierarchical and non-hierarchical clustering approaches based on the dissimilarity matrix described in section 3.2 were applied to the data and the results are presented later in this section. Initially, this section describes the hierarchical and non-hierarchical clustering approaches in greater detail.

### 4.1 Single-Linkage Clustering

This method produces long chains, which form loose clusters. The dissimilarity between two clusters is the minimum dissimilarity between members of the two clusters (nearest neighbor method) (Anderberg, 1973). All of the assumptions that were discussed earlier that involve the dissimilarity matrix and the constraints of the problem have been implemented. When the values of the Euclidean distance coefficient for all pairs of objects have been computed, a map of sorts, called a tree (dendrogram) is produced. The dendrogram shows at a glance the degrees of similarity between all pairs of objects (barge identifiers). On the bottom of each dendrogram the barge identifiers can be seen. The height dimension of the dendrogram shows the number of times a particular merge is performed. Figure 2 is an example dendrogram portraying the upstream load merging clusters.

The dendrogram must then be examined and interpreted to obtain usable clusters. Consider for example, the center portion of the dendrogram in Figure 2, which is depicted in Figure 3. The lowest level clusters would be at the bottom of the dendrogram. In Figure 3, there are 4 low level clusters;

Cluster 1: Barges 477, 478, 479 and 480.
Cluster 2: Barges 465 and 466.
Cluster 3: Barges 488, 489 and 490.
Cluster 4: Barges 491, 492 and 493

According to the dendrogram, Clusters 3 and 4 could then be combined if boat capacity permits the combination. This is, of course, a desired outcome. Similarly, Cluster 1 could be combined with several other higher level clusters and this cluster could, in turn, be combined with Cluster 2 and the combined Cluster 3 and 4. These high level clusters are very likely to exceed boat capacity constraints, so practically speaking one must consider only a few cluster combinations.

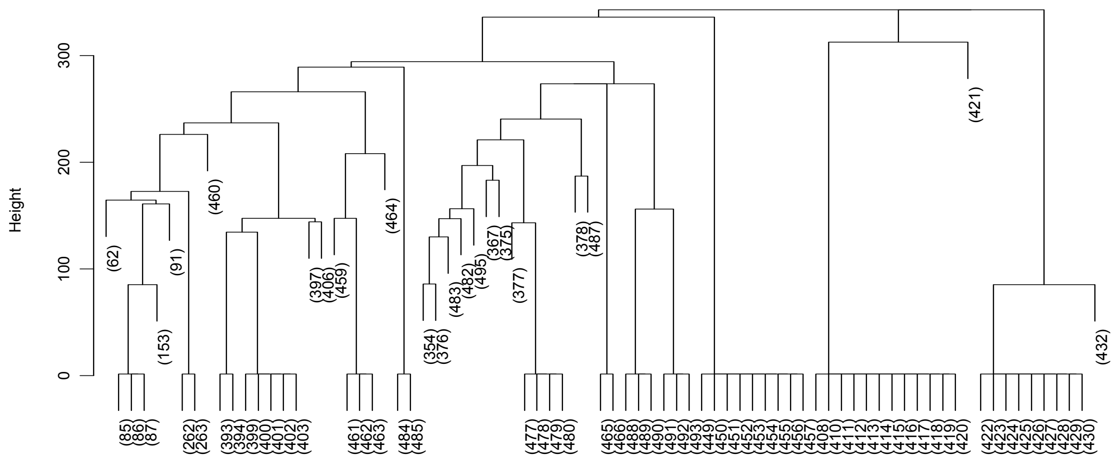


**Figure 2.** Single-Linkage Clustering dendrogram for Upstream Loads

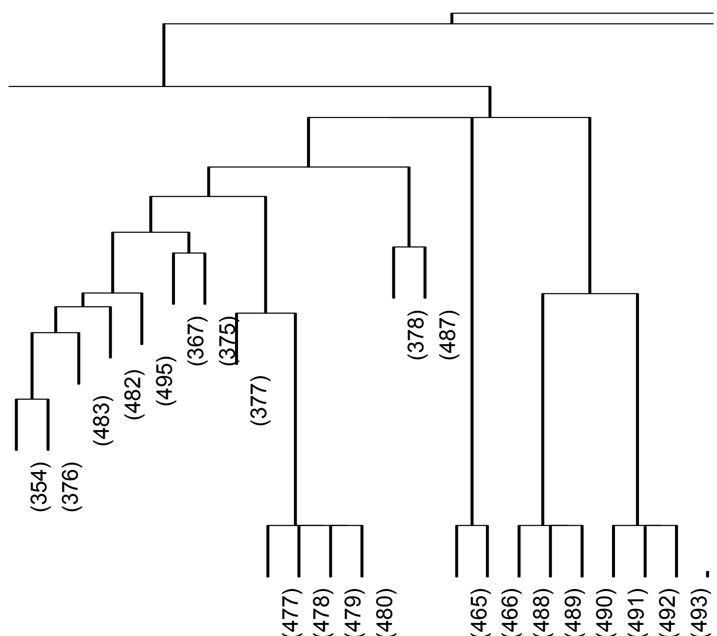


**Figure 3.** Dendrogram interpretation for upstream loads

**4.2 Average Linkage Clustering**

In this method, the dissimilarity between clusters is calculated using average values. Unfortunately, there are many ways of calculating an average. The most common and recommended method (Anderberg, 1973) is the Unweighted Pair-Groups Method Average (UPGMA). The average distance is calculated from the distance between each point in a cluster and all other points in another cluster. The two clusters with the lowest average are joined together to form the new cluster (Anderberg, 1973). The dendrograms for the upstream loads can be seen in Figure 4.

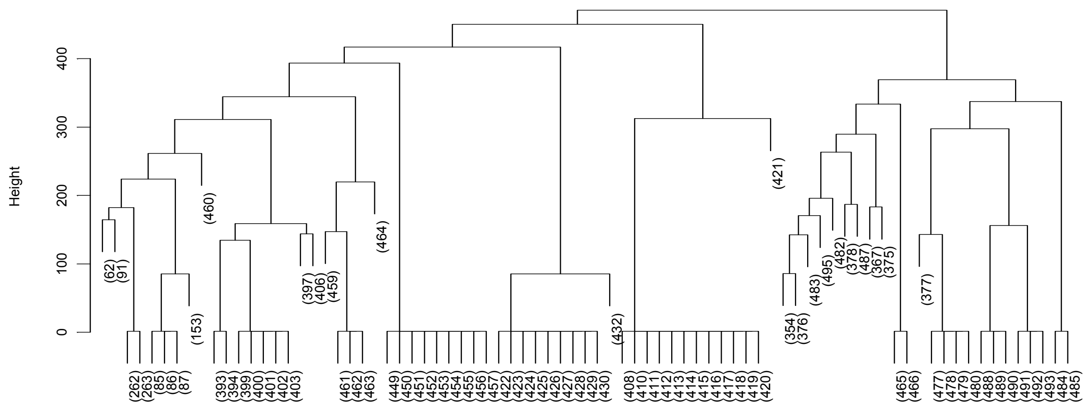


**Figure 4.** Average Linkage Clustering Dendrogram for Upstream Loads

**4.3 Complete Linkage Clustering**
In complete linkage, the distance between two clusters is the maximum distance between an observation in one cluster and an observation in the other cluster. Complete linkage is strongly biased toward producing clusters with roughly equal diameters, and it can be severely distorted by moderate outliers (Milligan, 1980). The dendrogram for the upstream loads can be seen in Figure 5.

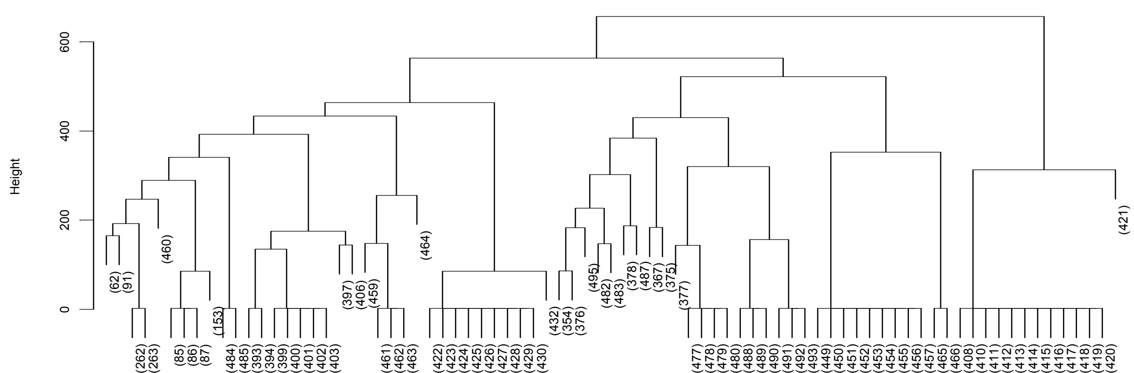


**Figure 5.** Complete Linkage Clustering Dendrogram for Upstream Loads

**4.4 Ward's Clustering**
In WARD's minimum-variance method, the distance between two clusters is the ANOVA sum of squares between the two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation (Anderberg, 1973). The dendrogram for the upstream loads is shown in Figure 6.

**4.5 Partitioning Around Medoids Clustering Method**
This particular clustering heuristic clusters objects that are measured on interval-scaled variables, and it can also be applied when the input data is a dissimilarity matrix. A general description of partitioning around medoids can be found in Kaufman and Rousseeuw (1990). In order to obtain k clusters, the method selects k 'representative' objects in the data set. The corresponding clusters are then found by assigning each remaining object to the nearest representative object. Of course, not every selection of k representative objects gives rise to good clusters. The goal is to select representative objects so that they are centrally located in the clusters that they define. To be exact, the average distance (or average dissimilarity) of the representative object to all the other objects of the same cluster is minimized. For this reason, such an

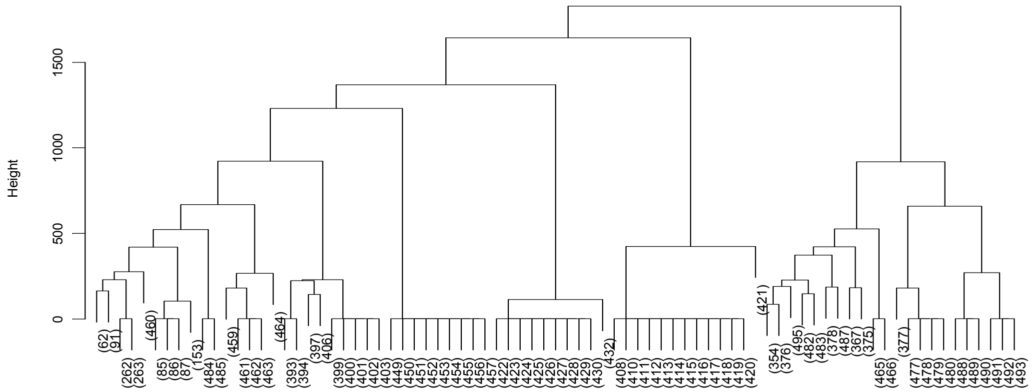


**Figure 6.** Ward's Clustering Dendrogram for Upstream Loads

optimal representative object is called the *medoid* of its cluster and the method of partitioning around medoids is called the *k-medoid* technique.

By construction, the k-medoid method tries to find "spherical" clusters, that is, clusters that are roughly ball-shaped. These spherical clusters are called clusplots. The clusplot for the upstream load data can be seen in Figure 7. These clusplots are easier to interpret than the dendrograms of the previous clustering methods since the spherical clusters of the clusplots yield final barge groups i.e. do not require additional post processing.

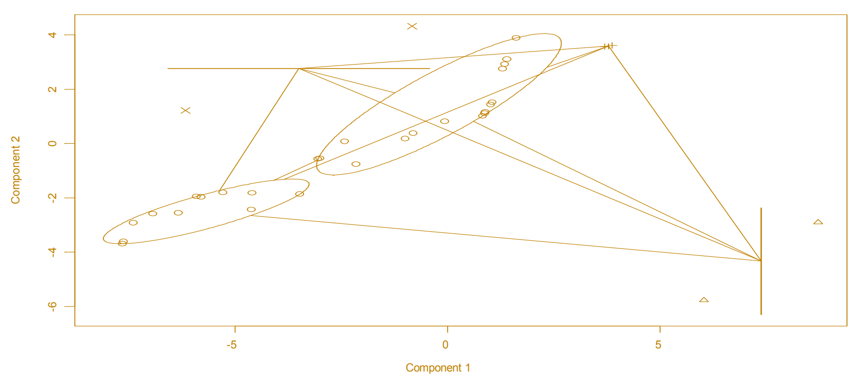


**Figure 7.** Clusplot for Clustering Around Medoids for Upstream Loads

**4.6 Summary of Results**

The results of the six solution methods presented in this paper are summarized in Table 1. Four performance measures are used to compare the solution results. Good solutions are those with high values of boat utilization. Concurrently, it is desirable to have a minimum number of boats used, a minimum number of barges outsourced to third parties, and a minimum number of groups of barges. As can be seen in Table 1, all of the clustering methods generated solutions requiring 13 boats. While no one method dominated the others in terms of all performance measures, complete linkage achieved the best overall results by minimizing the number of third party barges and number of groups while achieving a utilization that is the second highest of those found. Partitioning around medoids results in the highest levels of boat utilization but achieves this result with a higher level of outsourced barges and with a larger number of groups.

The barge grouping heuristic introduced in section 3.1 was developed specifically for this particular barge application. No other barge grouping methods could be found in the literature. The remaining clustering techniques were pre-existing but were modified and coded to accommodate the use of the customized dissimilarity matrix developed in this paper. Although the barge grouping heuristic does not perform as well as the various clustering techniques relative to all of the four metrics, it does produce results that are acceptable in an aggregate sense. These 'good' solutions are obtained in a small amount of time in comparison to the clustering groups. As pointed out earlier, each of these techniques result in fast

**Table 1.** Summary of results

| Solution Method | # Boats Used | % Utilization | # Third Party Barges | # Groups |
|---|---|---|---|---|
| Barge Grouping Heuristic | 13 | 70.54% | 36 | 26 |
| Single Linkage | 13 | 70.35% | 24 | 26 |
| Average Linkage | 13 | 72.14% | 34 | 25 |
| Complete Linkage | 13 | 73.73% | 24 | 25 |
| Ward's Method | 13 | 71.89% | 32 | 25 |
| Partitioning around Medoids | 13 | 75.60% | 33 | 26 |

solutions, but the clustering methods require a significant additional interpretation step that the barge grouping heuristic does not require.

## 5. CONCLUSIONS AND FUTURE RESEARCH

A summation of average group utilizations from best to worst for each one of the described methods is provided in Figure 8. The figure indicates that each of the methods have approximately four groups with 100% boat utilization. The complete linkage method has a larger number of groups with high utilization. Therefore, the conclusion is that complete linkage clustering for this set of data achieves the best solutions with partitioning around medoids and Ward's method also performing well with respect to utilization. Judging from the results one can conclude that although partitioning around medoids achieved better slot utilization levels (75.60%) than complete linkage (73.89%), partitioning around medoids did not necessarily result in minimal costs.

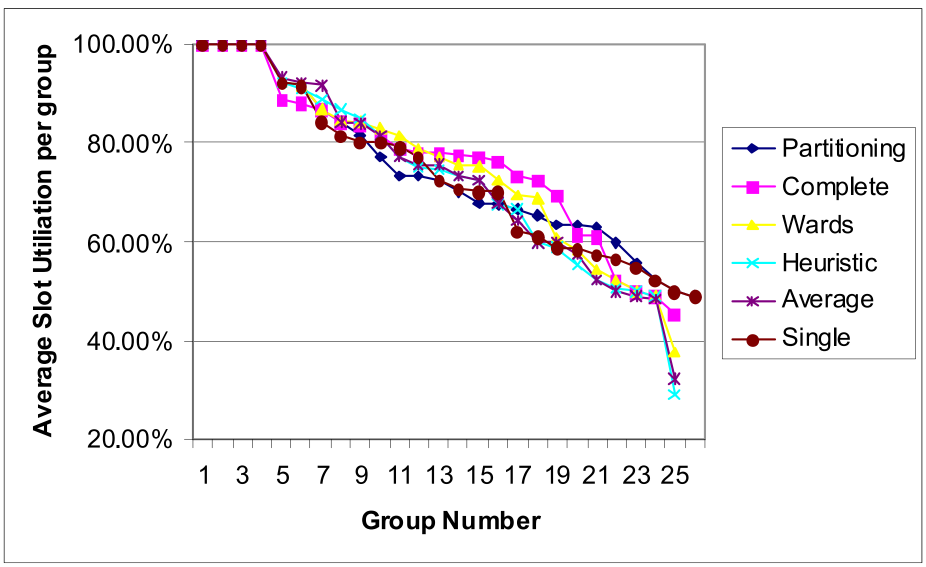


**Figure 8.** Average Slot utilization % per group for all methods

Other factors such as the total number of groups formed, the number of leftover barges for outside assistance, the ports that these tows left from or arrived at, the associated handling costs, the number of empty slots per tow, etc, are also of interest. Another interesting observation is that the clusters that partitioned around medoids were a lot more compact in the sense that the method forced clusters of groups with very close origins and destinations and moved away from forming groups that travel the length of the river (whereas complete linkage is the total opposite). The heuristic method has the potential of yielding the best set of results if a few alterations in the heuristic code are applied. With the heuristic clustering algorithm we can interpret the results in shorter periods of time. However, based on the utilization computations for this particular set of data it is recommended that complete linkage clustering or partitioning around medoids should be the methods used. The fact that these models performed better than the rest of the clusterings (for this set of data) does not necessarily imply that these methods should be used in general. Further investigation with different sets of data is needed in order to state with confidence, which one of the described clustering models should be applied.

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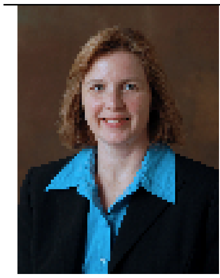
**BIOGRAPHICAL SKETCH**

Dimitrios Drosos, Ph.D. has been an employee of UPS SCS since 2002. His first assignment was working for the Industrial Engineering department as an Industrial Engineering supervisor. Throughout his career he completed rotations in solutions, operations and was the B&F coordinator for the Central District before being promoted to a section manager in 2005. Some of his assignments included working on operations improvement projects, work measurements, volume and staffing forecasting and facility layouts for existing clients. In the past 3 years he has developed and implemented a new engineering team called Post Solutions Engineering that its main goal is the successful implementation and engineering design of new awarded businesses. Dimitrios holds a BS, MAT and MA in Mathematics and a Ph.D. in Industrial Engineering from the University of Louisville.



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