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A Multi-Objective Affinity-Based Savings Algorithm for Improving Processes in Centralized Warehousing Operations

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A Multi-Objective Affinity-Based Savings Algorithm for Improving Processes in Centralized Warehousing Operations

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Abstract

Traditional approaches to improving material management processes in warehousing operations tend to focus on one of three major areas: facility design, order picking and sorting, and order batching. In an effort to improve total system savings, a new affinity function is developed and applied to batching logic to create a multi-objective problem. The proposed multi-objective function incorporates user input to increase adaptability to changing demand and flexibility to changing requirements. Computational experience shows the new function leads to solutions that deviate no more than 25% from the most efficient distance based picking route by the same batching logic, while creating savings in the sorting process at the centralized warehouse. The new function reduces savings loss from noncompliance of order pickers through its multi-objective design and is quick to respond to a rapidly changing climate by effective user input. The promising results of the proposed function open the door for additional objectives to be applied to the same logic to expand the objective to include goals like on-time performance.

Dedication

Ad Maiorem Dei Gloriam.

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1. Introduction

Pine Bluff Arsenal (PBA) operates as a manufacturing and storage location for the United States Army. PBA supports America's joint warfighter through the manufacturing and storage of specialized ammunitions, smoke, and chemical, biological, and nuclear defense equipment. The installation must maintain an effective level of readiness and response time to properly support the warfighter at home and abroad. For this reason, PBA's Director of Material Management approached the University of Arkansas' Industrial Engineering Department to research new material management techniques in hope of increasing efficiency. PBA expects a surge in the flow of material after receiving a joint chemical and biological (CB) logistics hub designation, and must maintain standards set by Pine Bluff Arsenal's command divisions.

Pine Bluff Arsenal's primary operations to support the US Army include manufacturing along with storage and logistics operations. PBA manufactures over 135 products in a "campaign style" run. In this process, a highly manual manufacturing line is set up, and batches of a product are run to fulfill an order. Subsequently, the line is then shut down or retrofitted for another product to be run in full. Due to the designation of manufacturing runs, it is not possible to implement just-in-time manufacturing or invest in automation for products that may not be produced again for a year or more. This left little opportunity for streamlining repetitive manufacturing processes.

The storage and logistics operations yielded a much greater scope of opportunity for process improvements. Pine Bluff Arsenal has about 1.2 million square feet of storage space spread over nearly 400 buildings on a 13,500-acre installment. The CB logistics hub designation has led to a future expansion of nearly 1 million square feet. The constant traveling between current facilities and future buildings leaves several areas for possible improvement for the researchers to explore. The three major areas to be explored will be 1) where material will be stored on the installment, 2) how material will be picked by material handlers, and 3) how to route order pickers. A summary of material management operations is divided into swim lanes, and the candidate areas of focus are bolded in Figure 1: Material Management Operations.

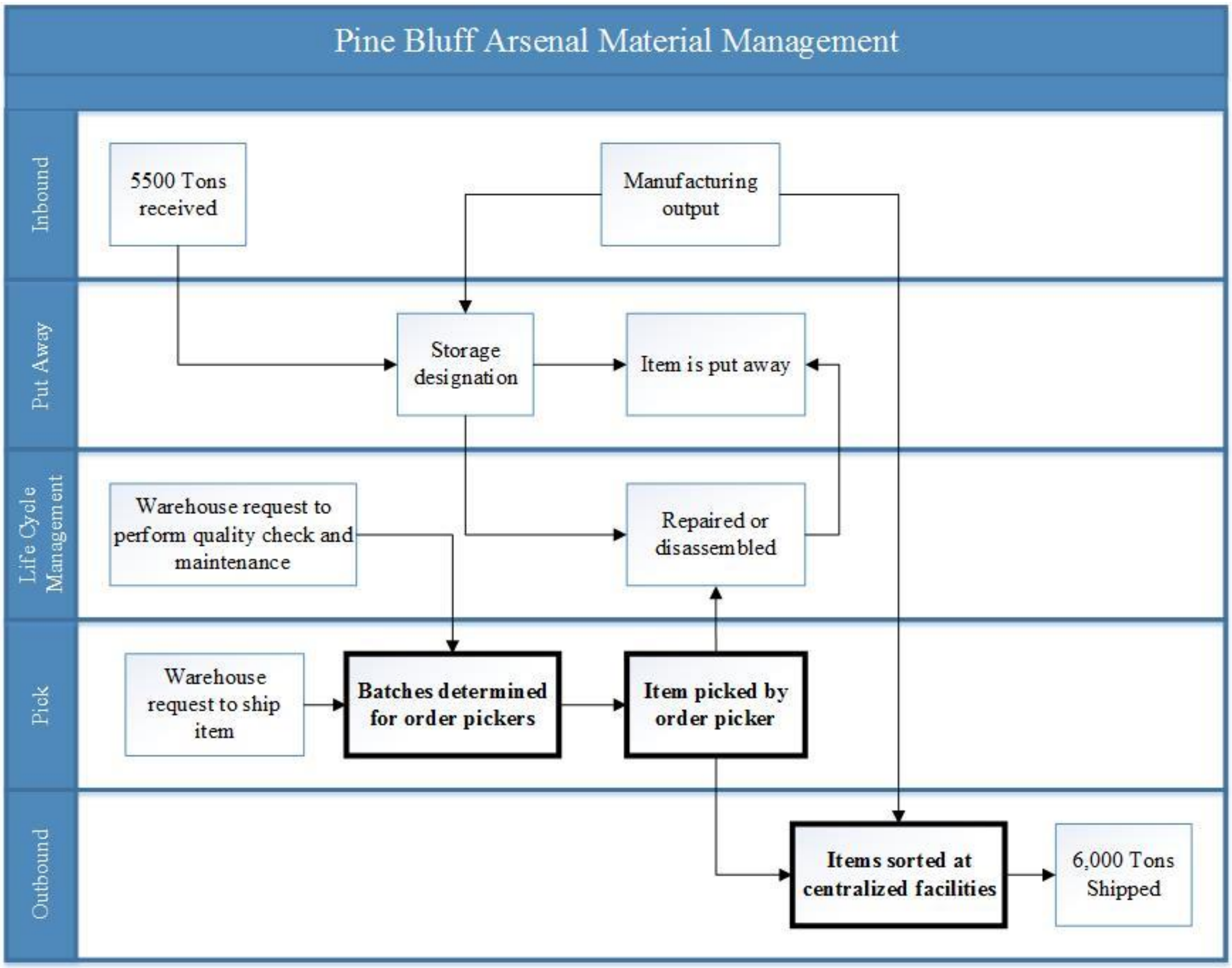

Figure 1: Material Management Operations

By balancing feasibility, practicality, and optimality, a new methodology was developed to improve process planning for the material management division of Pine Bluff Arsenal. This new methodology will create greater efficiency via a holistic systems view rather than focusing on improving efficiencies associated with a single part. The new approach will allow the system to pull products through processes in response to capabilities rather than push them to subsequent levels, possibly creating bottlenecks or inefficiencies. Furthermore, process planners will be able to accommodate changing working conditions after expanding the proposed algorithm to become more robust and applicable to the total system. The hope of a more robust planning processes is to create a more flexible and adaptable system. Tompkins, White, Bozer, and Tanchoco (2010) describe flexible systems as able to handle a variety of requirements without being altered, and define adaptability as the ability for facilities to accommodate varying demands. Flexibility is important for PBA because of the diverse types of products stored on the installation, while adaptability will improve response sensitivity to surging demand in times of need. Efficient process planning will improve operational effectiveness and facilitate the future expansion of warehousing space on the installation.

In the following section, several methods of process improvement will be explored including storage plans, sort and pick methods, and order batching and routing techniques. The problem will be formally defined along with justification for the chosen method in Section 3. Problem Definition. The methods will be explained in Section 4; where information about data is provided, a new savings function for the Clarke-Wright savings algorithm is defined, and the model used is outlined. Experimental results are provided in Section 5, while a discussion of significance is included in Section 6. Finally, a conclusion is presented in Section 7 as well as ideas for future research.

2. Literature Review

Reducing costs for Pine Bluff Arsenal is essential for future growth. The installment picks material from a collection of over 400 warehouses and storage buildings. This order fulfillment process is vastly different than standard warehousing operations where fulfillment is typically completed in a single building. However, the procedures remain largely the same. The material management team receives warehouse requests or orders to pick or pull an item from a warehouse, and then route to a centralized pickup/deposit (PUD) location. At the PUD location, materials are sorted, broken down for storage, or prepared for outbound shipments. Pine Bluff Arsenal's material management process can be modeled as a typical order fulfillment center for the purpose of reducing costs because of these similar methods. Bartholdi and Hackman (2017) explain that 55% of warehousing costs are the result of order-picking operations. Of those operations, traveling and searching make up 70% of the operating time (Bartholdi and Hackman, 2017). In order to reduce the time spent in these operations and subsequently reduce costs, three decisions must be made: where to store items, how to pick items, and how to route pickers to the items (Petersen and Aase, 2004). Petersen and Aase (2004) discover that picking time can be decreased by nearly 20% by changing any two of these strategies. These three decisions will be explored more in depth to determine the most suitable application for improvement of PBA's material management strategy.

2.1 Material Storage

The first decision to evaluate in an effort to improve material handling practices is the storage strategy of items across the base. Two major storage strategies for piece-picked materials are family storage and assigning a location based on pick density. Storage by family occurs when similar items are stored in the same geographical location. This strategy provides good space utilization when classed with similar items, simplifies put-away if classed by vendor, or reduces the need for specialized equipment if grouped with similarly handled products (Bartholdi and Hackman, 2017). When products are stored by similar shape and size, storage equipment, such as racking systems, is able to be more effectively used by reducing the amount of unused space. A majority of Pine Bluff Arsenal does not have storage equipment like racking or conveyers, so grouping materials by similar shape and size would have little impact. Put-away operations can be simplified when storage strategies take vendor or source identification into account. When a majority of inbound material can be stored in a similar geographic location without breaking cases and pallets into smaller units, the number of touches and interactions required to store the material is drastically reduced. Grouping similarly handled product reduces the need to create non-value added movement of equipment. When similarly handled materials are grouped in the same location, equipment necessary to pick those items can be effectively staged. In operations like those at PBA, this can prevent forklifts from being moved several miles per day. Additional indirect savings can be accumulated by reducing the risk of damaged equipment associated with these costly moves.

The idea of class storage is to increase the throughput by including the most demanded materials at the best locations (Bartholdi and Hackman, 2017). Pick errors are increased when changing from a random storage model to a class based storage model because similar items are more likely to be stored next to each other. The scientific approach to determining where materials are stored involves determining the pick rate, and developing a generalized assignment model to find a product's optimal position. The generalized assignment problem (GAP) is used to optimize assignments constrained by a series of resources. In a warehousing operation, the GAP looks to minimize the cost, or distance traveled to an average pick location by assigning a product to a specific location and being constrained by a finite number of pick locations. Ang, Lim, and Sim (2012) find that travel is not always minimized in optimized storage assignments because replenishments schedules are affected by production and supplier relationships. However, the linear policy they develop outperforms common algorithms like class-based turnover and class-based duration-of-stay (Ang, Lim, & Sim, 2012).

The GAP has been shown to be NP-hard by Sahni and Gonzalez (1976), meaning that a feasible solution cannot be found with a polynomial time algorithm. For this reason, several algorithms have been developed to categorize products and create a class-based storage system. Either qualitative information (product relationships) or quantitative information (using from-to analysis) are used to implement these algorithms (Tompkins et al., 2010). Most algorithms can be used with either type of information "given that flow values can be converted to relationship ratings and vice versa" (Tompkins et al., 2010, p303). These algorithms look to minimize the cost of moving objects between areas of a facility. Many of these algorithms are used in the planning of new warehouses in order to create an implementation and storage plan for the inbound materials. Other algorithms use a pairwise exchange method to make rewarehousing or expansion decisions feasible and realistic (Tomkins et al., 2010). A different class-based storage algorithm takes the Pareto principle into consideration. Heragu (2008) explains items should be classified into class A, B, C, or D categories. Class A are the top products making up 80% of the demand, while diminishing demand amounts are associated to the three remaining categories. In this classification method, class A includes no more than 20% of the total products while subsequent groups are slightly larger. Class A should then be located closest to the PUD point; class B will be just beyond class A, and so on (Heragu, 2008). One of the simplest storage policies is random storage. This strategy allows any new items to be stored in any location available. While theoretically every possible storage location has an equal chance of being assigned a new product, items are assigned to the closest available space in practice (Heragu, 2008). The outcome of a class-based storage plan versus a random storage plan in a parallel aisle warehouse is seen in Figure 2: Storage Policy Comparison.

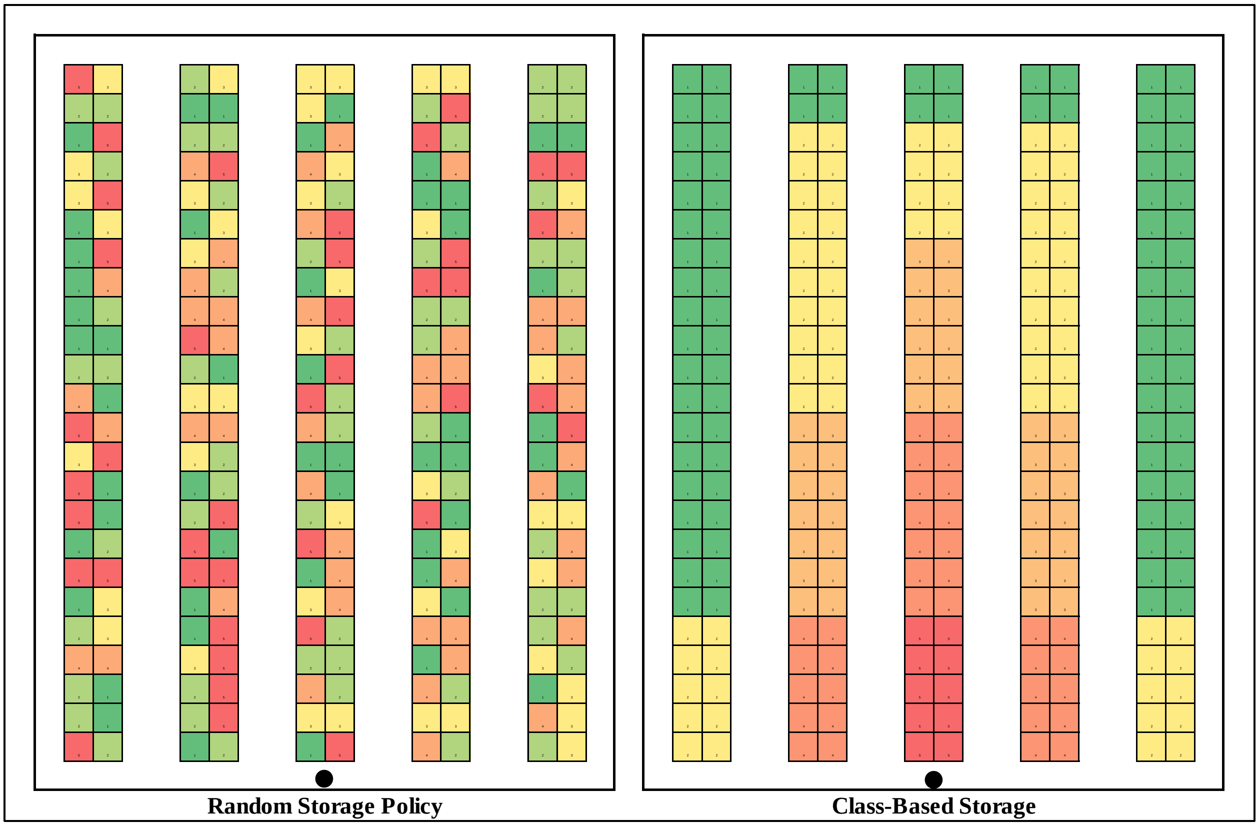

Figure 2: Storage Policy Comparison

Determining a policy for material storage is essential to creating efficiency and effectiveness in facility logistics. Policies are numerous and range in complexity, from random storage assignments to solutions determined by solving generalized and quadratic assignment problems. No single strategy may be perfect for any given facility, and any solution approach may need to be adapted for specific needs. Rewarehousing and changing storage policies may incur heavy costs if not in a quick turn facility. These strategies should be considered when new facilities are built or implemented when other major changes are taking place. In slow turn facilities like Pine Bluff Arsenal, changing storage policies would require a major amount of resources, costs, and time to complete for a marginal improvement.

2.2 Sorting Orders

Sorting orders before outbound shipments is another major decision for improving material handling performance. The primary strategies to sort orders are pick-then-sort and sorting while picked. Pick-then-sorting occurs when an order picker goes and picks several orders at a time before returning the picked materials to a drop off location. At the drop off location, the orders are then sorted into outbound shipments. This causes additional touches to a process during order fulfillment. Assigning a single picker to an order and a single order to a single route will eliminate the need for this extra touch before shipment according to Tompkins et al. (2010). In this case, order picking over long distances becomes less effective because batch size will be decreased and resource utilization may also decrease. In particularly small order sizes, order pickers can pick orders, sort them, and prepare it for shipping during the pick process (Tompkins et al., 2010). Resources must be carried with the order picker to pick locations when order pickers perform sort-while-picking strategies. Routes tend to be shorter under this strategy because additional shipping materials will occupy space on material picking equipment.

Another disadvantage of sorting during the pick process occurs when the same object is demanded twice, but for two different orders. An overlap effect occurs when an order picker only picks items for a single shipment. The picker will need to return to the same location twice for the same product demanded in two separate orders. Marchet, Melacini, and Perotti (2011) describe picking waves as a group of orders during a time period where orders are processed and picked before moving to the next order wave. Picking efficiency and costs are affected by the decision of wavelength. Long wave durations lead to more work in progress, more required equipment, and increased costs (Russell and Meller, 2003). The challenge of selecting the correct wavelength is to balance increased costs with the added efficiency of combining orders, which both increase proportionally to the wavelength according to Marchet et al (2011). Russell and Meller describe the relationship between batch size, total picking time of all orders, and total packing time in Figure 3: Batch Size vs Total Pick and Pack Times (Russell and Meller, 2003). As more orders are included in a batch, the picker becomes more efficient, and can pick a set of orders quicker. However, the time to sort and pack orders pre-shipment increases. Total processing time for Russell and Meller's findings was calculated and presented in Figure 4: Batch Size vs Total Processing Time (Russell and Meller, 2003). A point of diminishing returns for total processing time becomes apparent in this example.

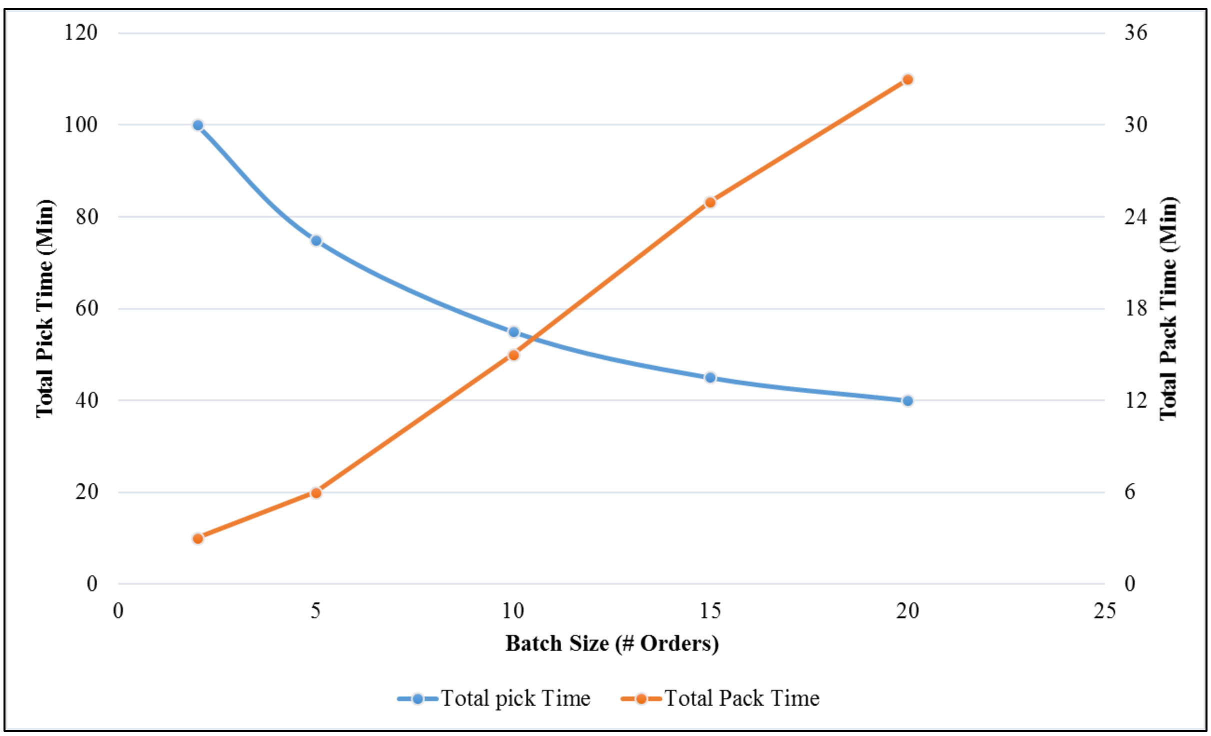

Figure 3: Batch Size vs Total Pick and Pack Times (Russell and Meller, 2003)

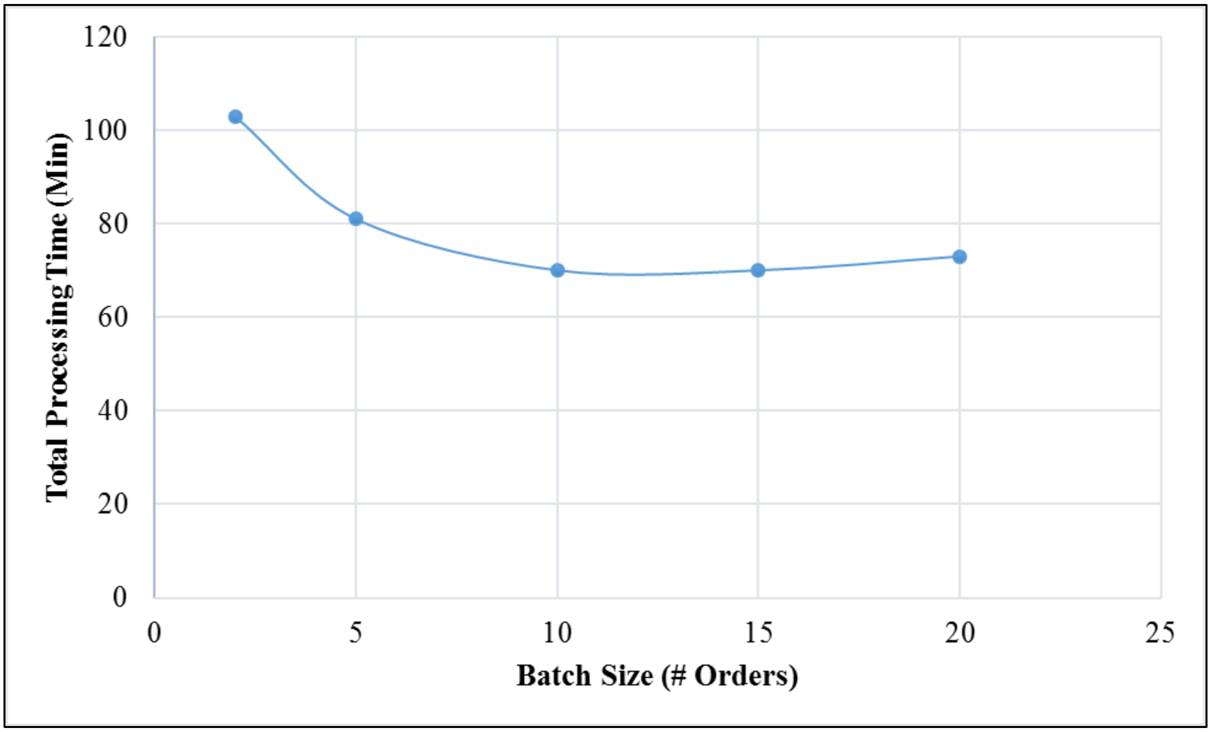

Figure 4: Batch Size vs Total Processing Time (Russell and Meller, 2003)

The main alternative to sort-while-picking operations is pick-then-sort. In these operations, an order picker goes on a pick route, and returns all items to a sort area where sorting occurs before being shipped outbound. This strategy is typically easier to improve by individual components. Meller (1997) develops an algorithm to organize the arrival of items at the sorting area in a sequence to maximize the sorter's throughput. Marchet et al. (2011) also describes a pick-then-sort system where pickers retrieve each single item from a batch or wave, and transport the items to the sorting system or area. Sorting system costs and the number of orders to be sorted share a convex relationship according to Parikh and Meller (2007). These systems tend to have a greater workload-imbalance than traditional batch picking systems, which becomes more apparent as order size increases, item distribution is more non-uniform, and the number of waves increases (Parikh and Meller, 2007).

Parikh and Meller (2007) compare a sort-while-picked batch strategy with a zone pick-then-sort strategy to determine the most effective strategy for different systems. Sort-while-picking batches is the most effective decision for low through put operations, while zone pick-then-sort strategy works best for high throughput operations (Parikh and Meller, 2007). Many factors, like order size, batch size, item variation, and equipment capacity, should be taken into account when making the decision of how to sort items pre-shipment.

2.3 Order Routing and Batching

The final major improvement alternative is correctly and efficiently routing material handlers to the warehouses around the installment. The policies of routing pickers determine the sequence products are picked according to Petersen and Aase (2004). Creating routes by grouping orders into batches is often the best or only way to receive picking efficiency if orders consist of relatively few items (Gademann and Velde, 2005). This process is often modeled as a traveling salesman problem or vehicle routing problem. Bartholdi and Hackman (2017) explain that these problems are difficult because no general, fast solution is known, randomly generated instances can be time-consuming to solve even in small instances, and good solutions are often complex and difficult to describe. Heragu (2008) describes a routing problem where a vehicle serves each location once per day, capacity is not exceeded, and the total travel time or distance is minimized. A big step in solving the vehicle routing problem is to solve the order batching problem as well. In this step, orders are simultaneously assigned to a batch, and pick routes are determined for each batch to minimize the cost (Gademann and Velde, 2005). This method will reduce total travel time and reduce the distance while increasing throughput and due date performance according to Gademann and Velde (2005). Muter and Oncan (2015) define the goal of an order batching problem as one of constructing batches in a way that minimizes the total distance traveled by order pickers. According to Charkhgard and Savelsbergh (2015), the order batching problem should minimize processing time to pick an order. Processing time is comprised of travel time, search time, pick time and set up time (Charkhgard and Savelsbergh, 2015). Tomkins, White, Bozer, and Tanchoco (2010) break down order processing into these categories along with the distribution of associated times seen in Figure 5. Both problems are often very difficult optimization problems because an optimal set must be determined with respect to a combination of resource constraints, customers, and operational constraints (Jerabek, Majercak, Kliestik, and Valaskova, 2016). Gademann and Velde (2005) prove the problem is NP-hard when batches include more than 2 orders. For this reason, numerous algorithms and heuristics have been developed to minimize the objective function with hopes of reducing costs.

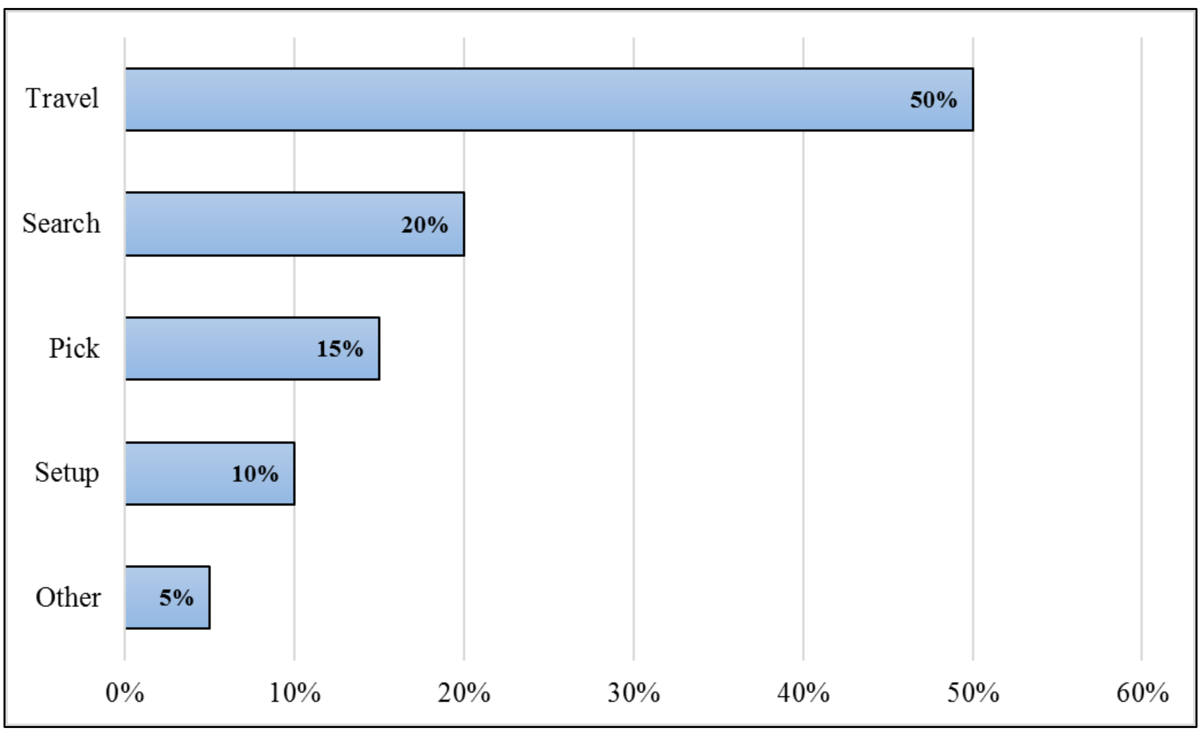

Figure 5: Order Processing Times (Tomkins, White, Bozer, and Tanchoco, 2010)

One of the most prominent and popular heuristic algorithms for this problem is the Clarke-Wright savings algorithm. This algorithm is popular because of its solution speed, flexibility, ability to handle several operational constraints, and ability to generate near optimal solutions (Ballou, 1999; Jerabek et al., 2016). The objective function of this method is to minimize the total distance traveled by all vehicles, and to indirectly minimize the number of vehicles needed to complete the problem (Clarke and Wright, 1963). This method looks to calculate savings by including two stops on the same path rather than returning to the depot, and evaluates the savings for each stop (Clarke and Wright, 1963). The largest savings are then combined into the same route, and this process continues until constraints are violated or no improving solution exists (Ballou, 1999). In small problems with few constraints, Ballou (1999) shows the Clarke-Wright algorithm averages solutions just 2 percent outside the optimal solution.

Ballou (1999) describes another method for problems without strict timing constraints or the need for consideration of time windows called the sweep method. This two-step method partitions all possible stops into geographic zones, and creates routes within each zone using a tear drop shape or other traveling salesman algorithm (Ballou, 1999). This method is quick to find solutions but lacks the flexibility to handle multiple constraints.

Min and Jin (2016) distinguish two major categories of vehicle routing problems: vehicle routing with transportation between a depot and customers allowing for backhaul, and vehicle routing with pickups and deliveries between customer locations. Min and Jin (2016) go on to develop a model for minimizing costs subject to several constraints, such as mileage limits and time constraints for pickup and delivery to various customer location. A two-stage algorithm, prioritizing distance and checking the delivery window afterwards, is developed and compared to the results of the Clarke-Wright savings algorithm results for the same problem (Min and Jin, 2016). Some outcomes show improvement compared to the Clarke-Wright results in mileage and cost savings, but other results are unreasonable or infeasible (Min and Jin, 2016).

Hwang and Kim (2007) develop another algorithm to minimize travel distance. This method combines normal order-batching logic with cluster analysis (Hwang and Kim, 2007). Cluster analysis is a combination of statistical methods to assign members to a group or cluster based on similar properties (Hwang and Kim, 2007). A model is then developed to calculate this similarity with respect to common routing policies through a parallel aisle warehouse, and a heuristic is developed to solve the zero-one integer program. The heuristic developed by Hwang and Kim (2007) tends to perform better than traditional heuristics only when order sizes are large. Smaller order sizes fail to improve much because the heuristic tends to ignore the discrimination of constraints associated with the routing policies (Hwang and Kim, 2007).

Muter and Oncan (2015) try to find an exact solution to the order batching problem rather than a set of solutions provided by the most common algorithms. A set for each cluster of orders is derived from a set-partitioning heuristic before relaxing the constraints to a linear program. The next step is to develop a pricing sub-problem to minimize costs associated with sets of orders found from the first algorithm. After these steps are performed, a set of solutions is then further reduced with branch and bound logic applied to the pricing solutions. Muter and Oncan (2015) were able to generate an algorithm for cluster analysis, and relax the optimization process to produce a batch creating method performing exceptionally accurate and efficient. This process is incredibly complex and time consuming for application in industry for marginally better results compared to simple, understandable heuristics.

Two main focuses when batching orders include proximity of location and time window. Travel time is minimized and throughput is increased when orders are batched by proximity, while due date performance is improved when batching is based on time windows (Gademann, Van den Berg, and Van der Hoff, 2001). Most heuristics tend to focus on proximity batching to reduce costs; few focus on due date performance. Gademann, Van den Berg, and Van der Hoff (2001) look to focus on improving on-time performance when developing a new heuristic for the order batching problem. In the development of this new algorithm, the authors assume order pickers will pick in waves. This means a set of batches will be picked by a group of order pickers, and each picker picks a single batch while sorting that batch during the pick process (Gademann, Van den Berg, and Van der Hoff, 2001). Each batch is assigned a lead time, which is the sum of travel time to the location plus the extraction time. The problem will then look to assign orders into a batch to minimize the largest lead time. A branch and bound algorithm is employed to solve this problem with respect to the normal order batching problem constraints. This method becomes easier to solve when class based storage or randomized storage is used. The more extraction times contribute to the lead time of batches, the harder to solve it becomes. The algorithm remains relatively easy to solve in practical situations (Gademann, Van den Berg, and Van der Hoff, 2001).

Several algorithms and heuristics have been developed to optimize both travel distance and on-time performance. These algorithms are often for the order picking process only, and make assumptions including upstream and downstream operations' ability to feed processes and react to increased throughput. The assumptions of traditional order batching processes tend to lack a total systems design approach. Communication and technology improvements have made it possible to connect previously different and distinct processes into cohesively operating systems.

3. Problem Definition

After researching several methods of the three facility process improvement categories, it became clear there is no single solution to implement without customization. Pine Bluff Arsenal experiences unique challenges when compared with other order fulfillment processes, because material is spread between 400 buildings located over 13,500 acres rather than under a single roof. This means routing order pickers in the most efficient route to destinations should create the most direct savings, because traveling to a destination takes an overwhelming amount of time compared to other duties needing to be performed. These savings can immediately disappear with noncompliance of the order picker. Rather than increasing the efficiency of a single operation, it would be more resilient to non-compliance to create cost savings beyond the order pickers routing sequence. Sorting orders can increase cost savings at the centralized warehouse by reducing the number of touches before a product is shipped outbound when sorting is considered on the pick route. Parikh and Meller (2006) compare strategies and find for low throughput systems, like Pine Bluff Arsenal, sort-while-picked batch picking outperforms other strategies. Furthermore, business demands and resources change rapidly with little notice, and processes must be adaptable to facilitate these occurrences. For example, a storm recently damaged a considerable portion of Pine Bluff Arsenal's fleet of vehicles rendering them unusable for order picking. A sudden event, like recent Syrian chemical attacks, causes Pine Bluff Arsenal's demand to surge with little lead time. This causes a strain in the centralized warehouse where product must be quickly and accurately sorted to meet deadlines despite not having time to properly increase labor.

The proposed algorithm should reduce the cost of material management processes and improve the adaptability of the system. The Clarke-Wright Savings Algorithm consistently provides near optimal solutions for minimizing the distance traveled by maximizing the savings associated with including multiple stops on the same route. Redefining the savings function to an affinity measure while retaining the same algorithmic logic, should allow costs to be reduced and allow a process planner to input information into the algorithm, making the process more adaptable to sudden changes not considered by the original savings function. In order to accommodate both order batching and order sorting methods, the new proposed affinity function will include two components and a user defined variable. The first component includes a distance based clustering component that identifies the relative location between all orders, while the second component will account for the amount of savings added by sorting an order when it is picked. The user may then pick a weight parameter between 0 and 1 to indicate how much weight they want to apply to the first component of the affinity function. The remainder of the value will be applied to the shipping similarity component. When this parameter is set to 1, the new function will yield a batch consisting of the shortest route between orders. When this parameter is set to 0, the new function will return a batch completely sorted and ready for final shipment. A more complete explanation of this function is explained in Section 4.3 Savings Function Redefined. This user defined weight will allow a process planner to determine what resource restrictions or sudden surges should be taken into account before running the algorithm. This empowers the user to properly assign responsibility to better equipped teams when preparing the daily workload. Partial savings' ability to be captured is a major assumption of this model. This means that when 25% weight is applied to the sorting component, 25% of the maximum savings is captured. This assumption is further explored in Section 6. Discussion. Allowing a user to input information into this hybrid function will allow it to accommodate more information, and create a more robust algorithm.

4. Methods

Several techniques were used to increase the robustness and validity of the model. Initial data pulls were from daily operations and communication with key stakeholders. These data pulls were analyzed for trends and then used to create distributions to feed the model. The major assumptions used for data collection include assumptions about distances and associated distributions, order sizes, and locations. After processing data, a new affinity function is defined and applied to batching logic to maximize affinity and indirectly maximize system savings. Combining these assumptions with the new function, the batching algorithm is reevaluated to simulate 4 months' worth of simplified orders.

4.1 Facility Information

Building distances were measured and categorized based on their locations on the installment. This information was derived from a data pull based on building information and storage techniques. Data was cleansed to eliminate repetitive or missing data before determining the behavioral trend. Before the contents of warehouses were analyzed, it was important to understand the distances between buildings for the savings algorithm. The distances between warehouses and the likelihood of a stop at each location are critical components to the evaluation of the problem.

First and foremost, the distance between warehouses must be evaluated. There are over 400 buildings located in 26 regions across the base. To improve the simplicity of the model and emphasize the results, buildings were aggregated by geographic location. Regions on the installment are labeled by relative latitude and longitude location. For example, a building located in the 3rd latitudinal region and 2nd longitudinal region will be in the 32nd composite region. Each composite region can consist of multiple buildings i.e. 32-100, 32-200, 32-220, etc.

Distances between buildings were computed between these composite regions. The weighted center of all storage buildings in the 32nd region is measured to the weighted center of all storage buildings in the 51st region, and so on. A simplified figure and detailed example is presented in Appendix A. This will reduce the number of distances computed from a 400 x 400 matrix to a 26 x 26 matrix because only the distance between section is calculated rather than building to building. After analyzing warehouse distances between sample regions, the sample distances were distributed lognormally with a location parameter of 9.095 and a scale parameter of 0.8563. These distances are recalculated after the model batches a single month of orders. Reevaluating the distances is done in an effort to reduce the variance of calculating the distance to the weighted center of a region. The distance index, when employed in practice, will only have to be done a single time, and will include the distance to each location on the installment. New buildings and storage locations can easily be added to the matrix.

4.2 Order List

Lists of orders were generated based on the analysis of 6 months' worth of data. The most important data fields necessary for the calculations are Order Number, Quantity, Size, Location, and Owner. Order Number is the unique name of the product to be picked. It comes from a warehouse request to move an item from one location to another. Quantity is the number of parts to be moved, and size is the amount of space this product needs. Size, in this example, takes into consideration the quantity. However, in practice, size can be adjusted to reflect the unit of measure's size and must be multiplied by the quantity. Location is the building to which an order picker must go to pick the order before returning to the centralized warehouse. Order numbers, quantity, and size are all notional information input to the model for results. All five informative categories are easily acquired from the Army's enterprise resource planning tool and this information changes each day.

The most important categories for use in the algorithm are location and owner. Location is the building name where an order picker must go to pick the product before returning it to the centralized warehouse. After analyzing 6 months of warehouse requests and movements, the distribution of warehouse moves was nearly uniform to every building except the centralized warehouse. The centralized warehouse and its internal moves are removed from the evaluation because these orders are fulfilled by order pickers who do not leave the centralized warehouse, while other orders must be fulfilled by order pickers who are certified material handlers. The internal orders should not be considered for use in the algorithm because they require a different and irrelevant set of resources for the purpose of this analysis. Owner is also an important factor to consider. Products having the same owner are more likely to be shipped to the same destination. The savings associated with picking orders with a high likelihood of being shipped together will be discussed in the following section. The distribution of owners was analyzed in the existing storage data. There were 22 unique owners found, but three primary owners made up 87% of all products stored at Pine Bluff Arsenal. The owners were then categorized into four major sections: AAA, BBB, CCC, DDD. The first three are the largest owners, while the final section included the other 19 owners. The distributions associated with each section were 51%, 18%, 18%, and 13% respectively. After determining the distribution of order locations throughout the base and the owner likelihood, a list of orders must be generated.

Warehouse requests were extracted from Pine Bluff Arsenal's enterprise resourcing system for 6 months of movements. The sample generated had an average of 60 moves per day. A normal distribution with a mean of 60 and a standard deviation of 5 was then used to generate the number of orders needed to be filled per day for analysis. The information included in the month's worth of random orders will be used for each building configuration in order to limit the variation between each run. This list of orders will be combined with the previous building matrix to form a new savings function for evaluation.

4.3 Savings Function Redefined

The Clarke-Wright Savings Algorithm defines savings as the distance saved by adding an additional stop to a route before returning to the start point. This is a major limitation of the function for systems like Pine Bluff Arsenal's material management processes. Savings can be captured beyond the distance traveled due to the multiple operations needed to completely fulfill an order. One major savings possibility overlooked by the Clarke-Wright Savings Algorithm is obtained by picking orders with a high likelihood of being shipped together. If orders being shipped together are picked together, this can reduce the number of touches necessary to prepare the order for its outbound shipment. Two important steps are necessary to begin creating a more robust batching function to employ into the algorithm. The first step is to define a proximity measure for determining which orders are located near each other. Then a second component will be defined for detecting an item's likelihood of being shipped with other items.

The first part of the multi-objective batching function consists of a distance based component. It takes into consideration the distance traveled to the next location, and looks to find the shortest distance to include into the batch. In order to do this, a matrix must be set up to describe the distance between all orders listed for the day's work. This creates an array of n x n size with n being the total number of orders to be batched. To mitigate the domination of the distance side of the equation, it and the owner similarity should be on the same scale. A comparison of every order is evaluated and then assigned a value of its relative position from the furthest point from itself. When evaluating the distances between two orders, each order is subtracted from each possible location and divided by the range of order distances. The relative trip distance for order *i* compared to the farthest possible trip is seen in Equation 1. The distance between order *i*'s position and order *j*'s position, d_{ij}, is divided by the difference of the farthest orders needing to be batched for the wave. This means when product *i* and *j* are located at the smallest possible distance to be traveled and the ratio is subtracted from 1, $\overline{d_{ij}}$ approaches a value of 1. When the distance between *i* and *j* begins to reach the max distance possible across the base, the value of $\overline{d_{ij}}$ becomes 0. Smaller distances are given a higher affinity through this evaluation.

$$\textbf{Equation 1:} \quad \overline{d_{ij}} = 1 - \frac{d_{ij}}{d_{max}}$$

This proximity ratio produces a number between 0 and 1, where 1 signals a set of products are located in the same building and 0 signals the two products are located at the most distant possible locations. By reducing the distance value to a unit scale, a binary variable can be used in the shipping similarity component without being dominated by the distance scale. Alternatively, a constant β can be estimated and multiplied by the similarity value to bring the adjusted value to the same scale as the distance between two orders. After the distance side of the equation is established, robustness can be added by taking item shipping similarity into consideration.

Items sharing the same owner are more likely to be shipped together. When an order picker picks multiple orders with the same owner, the centralized warehouse will have fewer touches. Several orders can be offloaded from the picking equipment to the pre-shipment staging area all together, or moved on a single pallet together. Reducing the number of touches increases savings directly by reducing the amount of labor required to manage the products, and indirectly by reducing the likelihood of causing damage or losses. The affinity associated with owners in this multi-objective algorithm will be defined by whether the order being evaluated for inclusion to the batch shares an owner with an item already located in the batch of orders. This is a binary variable where a value of 1 indicates a shared owner is included in the existing batch while a value of 0 indicates the order being evaluated for inclusion does not have its owner currently located within the batch. The owner similarity variable will be combined with the proximity component resulting in a new batching function seen in Equation 2.

Equation 2: $$A_{ij} = \left(w * \bar{d}_{ij}\right) + \left((1-w) * o_{ij}\right)$$

$$s.t. \quad w \leq 1$$

In this equation, A_{ij} is the affinity of batching order *j* into the batch containing order *i*. The two parameters $\overline{d_{ij}}$, the distance between the location of order *j* and the last order included in the batch containing order *i*, and o_{ij}, the owner similarity value of order *j* and the batch containing order *i*, are summed together to yield the total affinity of including order *j* in the batch containing order *i*. The distance component differs from Clarke-Wright's savings definition for distance savings, and is determined by including the next closest stop on the route. This value is calculated for each possible combination of stops on an order route and is explained in Equation 1. Both sides of the equation are on a 0 to 1 scale making sure neither side dominated the other through its relative scale. A user defined weight, w, is used to allow an analyst to swing the weight of importance between sides of the equation. This will allow incremental evaluation of the new function under different conditions. The balanced equation can be evaluated in conjunction with the user defined weights to see how the total batch distance and other outcomes are affected.

4.4 Running the Modified Algorithm

To run the proposed multi-objective affinity algorithm, we must first calculate the distances between the locations of all orders for the batch run and the origin of the order picker. Each order distance is first scaled between zero and one as described in Equation 1. A random seed order is picked, and every order remaining is taken into consideration for adding to a batch. The second side of the equation containing the owner similarity must be reevaluated after each iteration to ensure a new product inserted into the batch is considered in each future candidate order. The highest affinity is then chosen to be included into the batch with respect to the capacity constraints of the problem. The user-defined weight is incremented by 0.25 from 0 to 1 to obtain 5 solutions for each day of orders. The entire month of orders was run before changing the building configuration yielding 85 data points. After the building configuration was changed, the entire month of orders was run again for another 85 data points. This was repeated for 4 months and a total of 340 data points; 68 points recorded at each level of the user defined weight.

The key effect to be evaluated is to understand how this new affinity function and user defined weight affects the outcome of the batching algorithm. The total distance traveled in a batch is recorded along with the order count of each run. This will allow the user to understand how much work will be loaded onto the order pickers and material handlers on an average trip. The average distance to each order is derived by dividing the total distance traveled in a batch by the order count. This is important to analyze to understand if the distance to pick each item get significantly further to pick. In other words, will adding a single product to the batch become considerably costlier? Analysis of variance will be performed to see how incremental changes in the user-defined weight will affect these two metrics. A model was designed in excel to record these statistics. An outline of the model inputs and outputs can be seen in Figure 6: Model Inputs and Outputs.

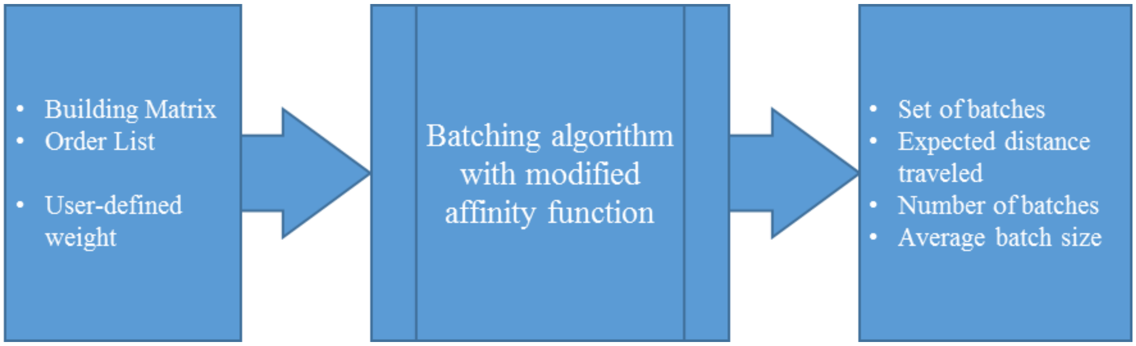

Figure 6: Model Inputs and Outputs

The proposed function's output will be compared to understand the impact of redefining the objective function. A Tukey comparison will be performed to compare the means of each increment's effect on total distance traveled and average distance to each order.

5. Results

The five levels of the model's outputs were then analyzed in a one-way analysis of variance. Before the ANOVA, a box plot was created for both average distance traveled per batch and average distance traveled for each order at each level. The average distance traveled per batch can be seen in Figure 7: Boxplot of Average Batch Distance, and the distance traveled to each order is seen in Figure 8: Boxplot of Order Distance. The reults of the distance weighted outcomes are seen when the weight is defined at 1, and it performs the best in each metric. Outliers in these metrics will remain in the pool because they explain the outcome of an iteration. The algorithm is followed strictly so there is no belief the point in the average batch distance or two points in order distance are incorrect in their measure.

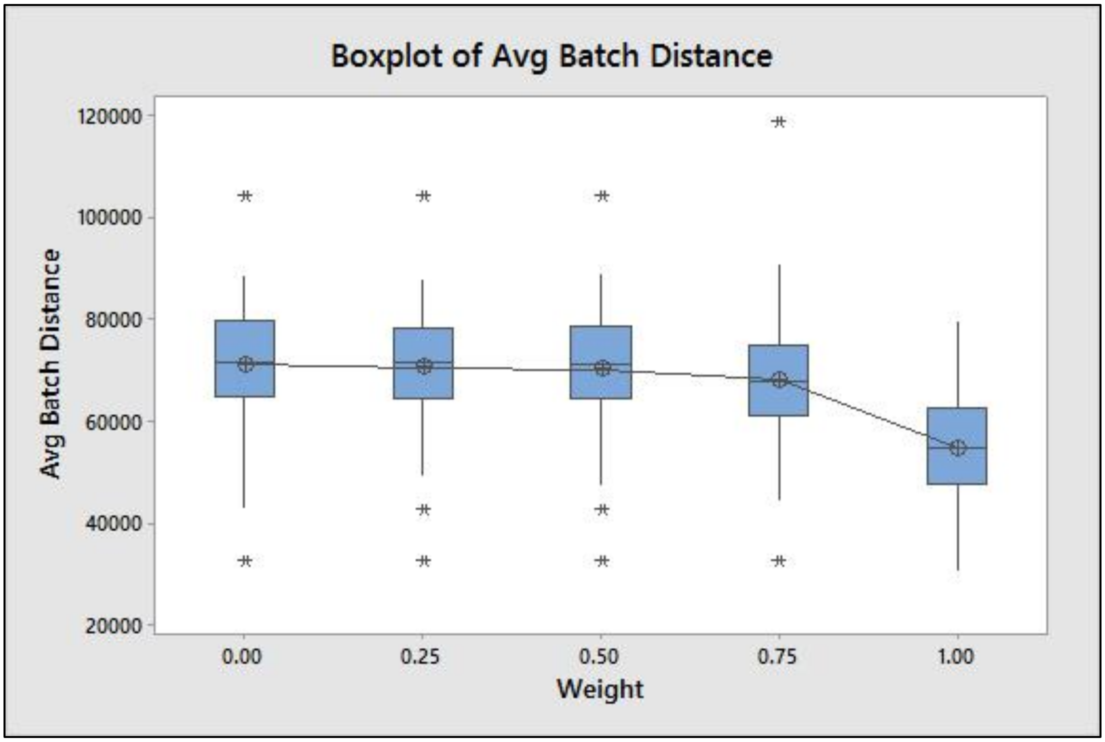

Figure 7: Boxplot of Average Batch Distance

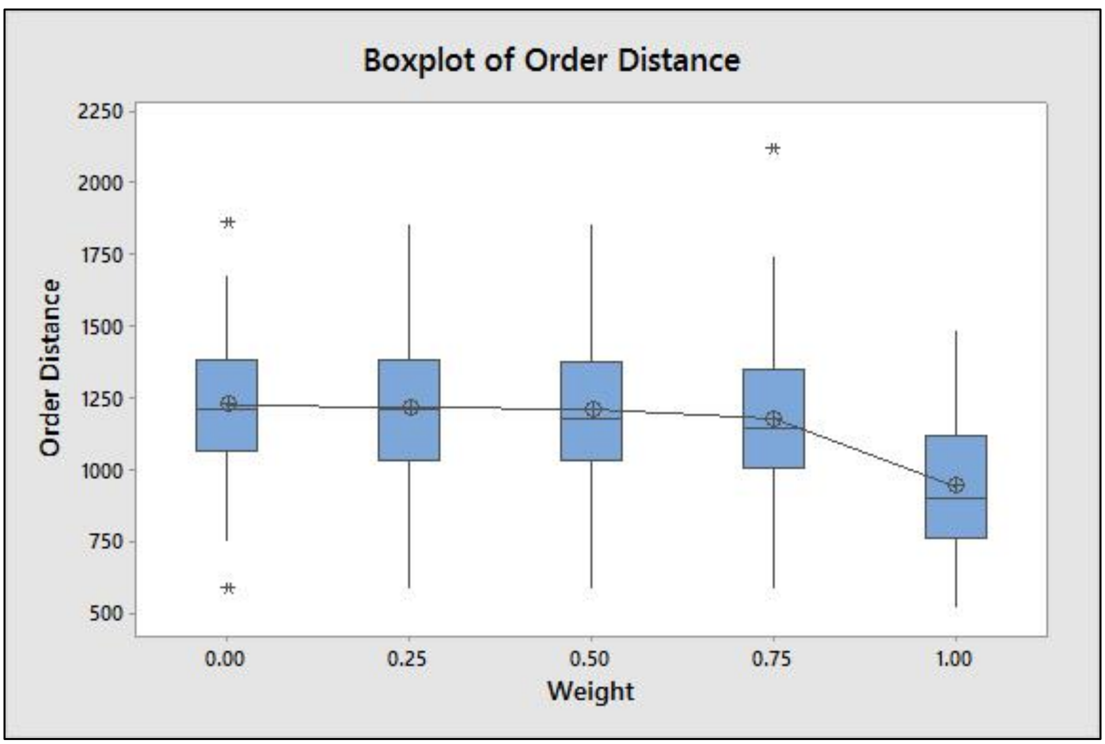

Figure 8: Boxplot of Order Distance

The user defined weight's extreme points of 1 and 0 show the most difference with a mean difference of nearly 3 miles. However, the mean difference in the same two extremes for distance to each order is only about 0.05 miles. Further results on the average batch size are included in Table 1: Means of Average Batch Distance, and Table 2: Means of Average Order Distance.

Table 1: Means of Average Batch Distance

Weight	**N**	**Mean**	**StDev**	**95% CI**
0.00	68	70945	11823	(68078, 73811)
0.25	68	70467	12095	(67600, 73334)
0.50	68	70011	12242	(67144, 72877)
0.75	68	68015	12948	(65149, 70882)
1.00	68	54509	10887	(51642, 57376)

Pooled StDev = 12017.7

Table 2: Means of Average Order Distance

Weight	**N**	**Mean**	**StDev**	**95% CI**
0.00	68	1222.3	244.4	(1163.8, 1280.9)
0.25	68	1213.3	243.5	(1154.8, 1271.9)
0.50	68	1206.2	250.2	(1147.7, 1264.8)
0.75	68	1173.1	265.0	(1114.5, 1231.6)
1.00	68	940.9	222.3	(882.3, 999.4)

Pooled StDev = 245.471

Two one-way ANOVAs were then performed with the distances as the responses and the weight as the factors. Groupings having equal means with a 5% significance level is the null hypothesis for the ANOVA analysis. Equal variances were assumed for the analysis because each sample came from the same population. ANOVA results for each measure are provided in Table 3: ANOVA Results.

Table 3: ANOVA Results

Analysis of Variance for Average Batch Distance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Weight	4	1.32E+10	3.28E+09	22.77	0.000
Error	335	4.84E+10	1.44 E+08		
Total	339	6.15E+10			
Analysis of Variance for Order Distance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Weight	4	3.85E+06	9.63E+05	15.99	0.000
Error	335	2.01E+07	6.02E+04		
Total	339	2.40E+07			

After determining at least one mean is statistically different from the others in both metrics, a Tukey comparison of means was performed to group means together. Three groups are created when comparing the means of average batch distance, and two groupings appear when analyzing the average distance to the next order. When the distance based component was weighted fully, the mean produced is statistically different in both measures. There is significant overlap in the groupings of average batch distance, but the remaining means in the average distance to the next order remain in a grouping together. These results are visualized in Table 4: Tukey Pairwise Comparison Results.

Table 4: Tukey Pairwise Comparison Results

Grouping Information for Average Batch Distance			
Weight	N	Mean	Grouping
0.00	68	70945	A
0.25	68	70467	A
0.50	68	70011	A
0.75	68	68015	A
1.00	68	54509	B

Means that do not share a letter are significantly different.

Grouping Information for Order Distance			
Weight	N	Mean	Grouping
0.00	68	1222.3	A
0.25	68	1213.3	A
0.50	68	1206.2	A
0.75	68	1173.1	A
1.00	68	940.9	B

Means that do not share a letter are significantly different.

A comparison of distances traveled and the rate change is presented in Figure 9: Comparison of Distances Traveled. The percent change in distance as the weight changes is nearly the same for both the total batch distance and distance to the next order. When changing the preference weight, the number of additional miles to the next order ranges from 2 miles to 3 miles for an entire batch run. Neither batch distance nor distance to the next order grows in length by more than 25% from the shortest distance to the longest distance.

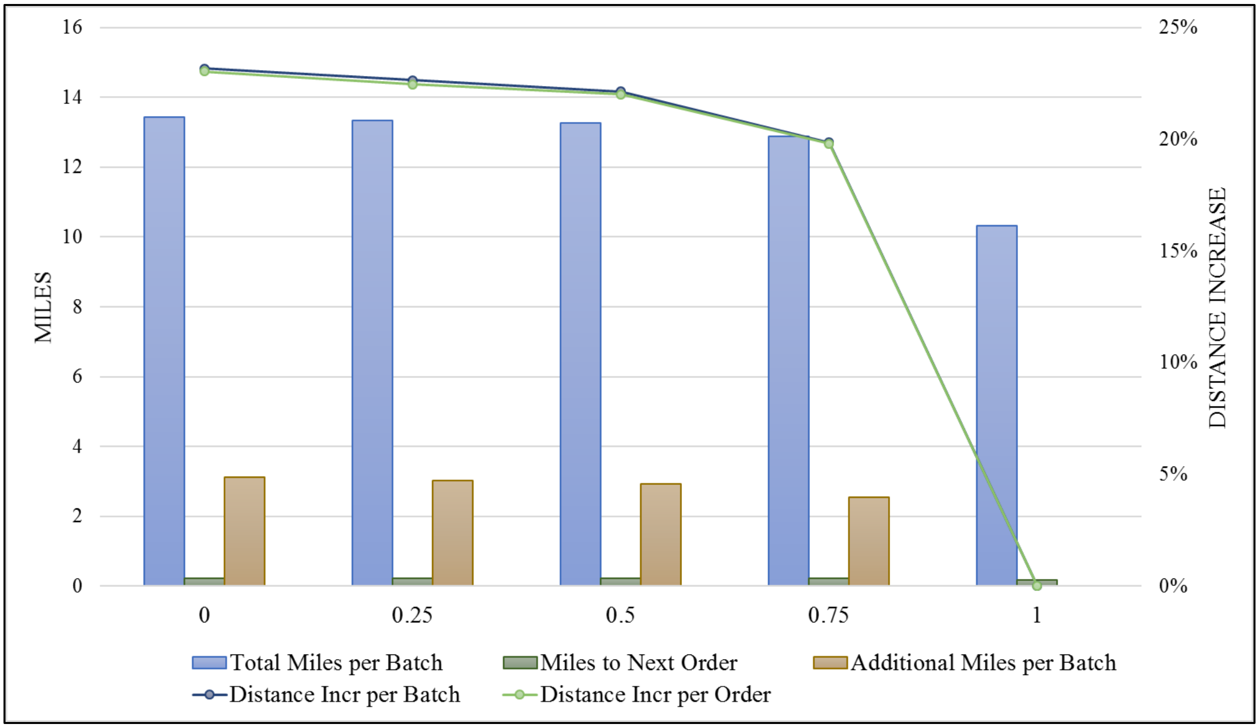

Figure 9: Comparison of Distances Traveled

6. Discussion

Most attempts at optimizing order picking and batching are designed for use in parallel aisle warehouses, or at the very least, within a single building. Commonly applied algorithms are designed with unchanging conditions, which is rarely the case in industrial applications. Large material management operations, like Pine Bluff Arsenal, have rapidly changing requirements and resource availability. Many resources are constantly exposed to the climate, causing faster degradation and higher chances of failure. The requirements of US Army installments are affected by sudden changes in the geo-political climate, and processes must be adaptable to change. Neither changing resource availability nor geo-political climates are considered in common order batching and routing algorithms. These fluctuations can drastically alter system requirements causing the need for new practices at the very least. Changing requirements, especially those with little lead time, can be accounted for by incorporating human interaction into the planning process. The primary goal of creating the new affinity function was to allow for user input, and create a more robust algorithm for changing demands and resources.

The new function can yield a nearly minimized traveling distance when the user defines the balancing weight at 1 by batching orders based on proximity. The same algorithm produces a presorted order batching result when the weight is defined as 0. The order picker will return with a set of orders to be shipped outbound without the need for sorting at the centralized warehouse. The results of the new algorithm are promising for future expansion. The mean distance traveled decreases for both average distance to next order and total distance traveled to complete a batch as more weight is applied to the first component of the affinity function. This is expected because more affinity is slowly applied to the distance side of the equation. As weight is decreased to zero from one, the algorithm slowly begins to evaluate if the order located just beyond the closest stop can create more savings in the sorting process. In other words, the savings created by sorting the materials on the pick route outweighs the extra distance driven. The freedom to swing this weight makes the new algorithm especially sensitive to rapidly changing system needs. If a storm leaves a considerable number of order picking trucks out of service, the planning analyst can swing the weight to one so the order pickers can make the most efficient routes and let the centralized warehouse sort material before outbound shipments are made. After chemical attacks or other unforeseen CBRN events, the demand for products located at Pine Bluff Arsenal drastically increases. Theaters of war must be resupplied after an event like recent chemical attacks in Syria, while newly deployed units must be properly prepared entering into a new theater. When these major events occur, large orders are placed to Pine Bluff Arsenal with relatively short lead times. In these situations, the process planner can swing the weight toward zero to generate batches to be picked based on shipment destination.

Order pickers will then return to the centralized warehouse with completely or semi presorted materials, depending on the level of the weight chosen.

A Tukey comparison performed after the ANOVA results presented reason to believe not all means were equal. The grouping information for both average distance traveled for a batch as well as distance to next order are seen in Table 4: Tukey Pairwise Comparison Results. The extreme points of the user defined weight caused the means to be included in separate groupings for both average distance traveled for a batch and distance to the next order. This was expected because the batching objective is different when the weight changes. The objective of the algorithm is to minimize distance traveled when the weight is defined as 1; the objective becomes to maximize shipping similarity of products when the weight is set to 0. However, both of these objectives are satisfied because the goal of the new algorithm is to maximize affinity of the entire system. This objective makes the new algorithm much more adaptable to change. All points between the extreme points of the user defined weight are included in the same grouping. This is important because it indicates the distance does not significantly vary as the weight is changed in the intermediate range. When the weight applied to distance favorability drops below 50%, the process planner can make an overly conservative estimate without drastically affecting the distance order pickers will travel. The groupings do imply statistically significant changes in the mean distance traveled for a batch when the emphasis placed on distance is above 50%. Figure 9: Comparison of Distances Traveled is included to encourage further discussion on the significance of grouping. Just because these means are deemed statistically different from a Tukey pairwise comparison, does not mean they are practically different from one another. As is seen in Figure 9, the number miles for an additional order to be included is relatively small compared to the total distance traveled. Even in the most liberal routes, the order picker is traveling no more than 25% further. This additional travel is justified because the savings sacrificed on the distance is captured by the savings in the centralized warehouse's lesser need to sort materials.

A major assumption to this application is that the partial sorting of orders constitutes a corresponding savings. For example, when 25% emphasis is placed on the shipping similarity, 25% of the max savings is captured at the central warehouse. This is a reasonable and conservative estimate because these savings are not likely to be all or nothing. Increasing the weight in favor of the shipping similarity will increase the distance an order picker is expected to take beyond the next closest alternative. Because it is a binary value on the shipping side of the function, orders included are more likely to be included only if they are in the same outbound shipment. A quickly increasing curve is a more likely relationship between the ability of this new function to capture savings than the assumed linear relationship. This may be why the grouping of mean distance traveled quickly approaches a grouping with the zone picked alternative, where the weight is set to 0. This assumption provides an ample area of additional exploration.

Because this methodology provides well behaved results, future exploration can readily be undertaken for an even more robust function. Order batching techniques generally are employed to decrease the distance traveled by order pickers. This new function goes beyond that objective in hopes to create greater systems savings for the installment, and improve the robustness by allowing a process analyst to contribute subjective and sometimes volatile information to produce more pertinent batches of orders. Other order batching techniques, like Gademann, Van den Berg, and Van der Hoff's model (2001), focus on producing batches to improve on-time response rates. There is no reason to believe the proposed affinity function cannot be extended beyond its current form to include both performance savings and on-time performance improvements. A possible form of this new equation may include 3 parts: the proximity component, shipping similarity factor, and timeline priority, t_i, associated with order i. A piece-wise linear function would have to be constructed between the values of 1 and 0 to provide value to the timeline priority. In the piece-wise linear function, 1 would be associated with the most urgent orders while 0 will be orders with a delivery date well in the future. The user-defined weights in this function would need to sum to 1, and the weight placed on the delivery date should have a minimum value or even a constant value. This affinity function could look similar to the one seen in Equation 3 below, where W denotes a set of weights.

Equation 3: $A_{ij} = \left(w_1 * \bar{d}_{ij}\right) + \left(w_2 * o_{ij}\right) + (w_3 * t_i)$

$$s.t. \quad \sum_W w_i = 1$$

Developing the function to properly describe the urgency captured by lead time is a future focus of research. The amount of weight or ranges of weights to associate with the savings generated by the time focus is also important to explore. It is unlikely orders would be picked with zero emphasis on required delivery date, unless the range of delivery dates is very small. However, Pine Bluff Arsenal and other long-term storage facilities often get requests for items with long lead times. It is not uncommon for material management at PBA to have one or two weeks lead time for some products, while others have 24 or 48 hours lead times. Prioritizing the more urgent orders to decrease late shipments is the most apparent source of savings, but reducing the amount of clutter in the centralized warehouse will improve the centralized warehouse workers' efficiency. The proposed affinity function shows that altering the batching algorithm does not cause drastic changes to the results. Future research should be done to further expand the proposed affinity function to improve process efficiency as a system, and improve on-time performance.

7. Conclusion

As technology and communication continue to improve, it is important for storage facilities to be adaptable and flexible to the rapidly changing climate. Planners often try to create strategies to reduce costs and improve efficiency as much as possible when designing the layout and construction of a new storage facility. The three main decisions of warehouse planning fall into facility layout design, order sorting, and order batching. Often times, these areas are optimized individually before stitching them together into a complete process. Current literature also looks to improve a single area only; hoping to create total system savings. Most heuristics and algorithms are developed to optimize these problems without considering the volatility of resource availability or unexpected demand. In most cases, this is an acceptable assumption to make because material handling resources are rarely exposed to harsh environmental factors and demand rarely spikes unexpectedly due to seasonal or other common predictors. For Pine Bluff Arsenal and other military storage facilities, this is not the case. Pine Bluff Arsenal was built in the 1940s for a mission completely different than its mission today. For this reason, facility layout is not aligned with PBA's current mission, and rewarehousing would require a vast amount of resources and time while disrupting current operations. The layout of the installment requires order pickers to drive several miles per day from building to building. Resource constraints makes it infeasible to store certain material handling equipment at each storage facility. This means equipment must be constantly moved to different buildings and is often left outside for convenience's sake of transportation. The lifespan of essential resources is drastically reduced by exposure to harsh environmental factors and the additional risk required to move the equipment. Resource availability can experience a major change due to the development of a storm.

The US Army demand can be hard to predict with constantly changing geo-political environments. Rogue regimes, seen in places like Syria and North Korea, can create a sudden need for the specialty materials stored at Pine Bluff Arsenal. The need will arise with little warning and short lead times. The need for military storage facilities to be flexible and adaptable is essential to maintaining a prepared response team. This thesis presents a new and adaptable affinity function. The proposed affinity function allows a process planner to consider changing resource constraints and geo-political climate before batching orders for daily operations. This will allow total system savings to be maximized with respect to its changing constraints.

The change in distance traveled by order pickers varies by less than 25% when changing from distance focused batching to sorting focused batching. This increase in distance traveled is justified in longer batch runs seen in operations like Pine Bluff Arsenal. The extra distance traveled for sake of sorting should create additional savings in the centralized warehouse. Gademann and Velde (2005) state that pick routes are still at the discretion of the pickers. Despite distance based heuristics like the Clarke-Wright algorithm, an order picker may decide to take a less than optimal route to the next location. When order pickers fail to follow the algorithm's path, all savings are lost. The proposed algorithm will allow for savings to be captured as long as the weight is not placed at 1 for the distance emphasis on the equation.

The proposed function is resistant to noncompliance by its design and responsive to changing requirements by user input. Changing the affinity function gives promising results to highly manual pick processes where distance between pick locations is large. Another advantage of the proposed function is the ability to be employed into existing systems, like PBA, without the need for additional resources or costly rewarehousing strategies. It has an opportunity to be expanded to further increase its robustness by including a time weighted component to the affinity function. Overall, the new affinity function, applied to batching logic has the potential to increases the total systems' savings of material management operations, making a system more adaptable to changing demands, and flexible to varying requirements.

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Appendix A

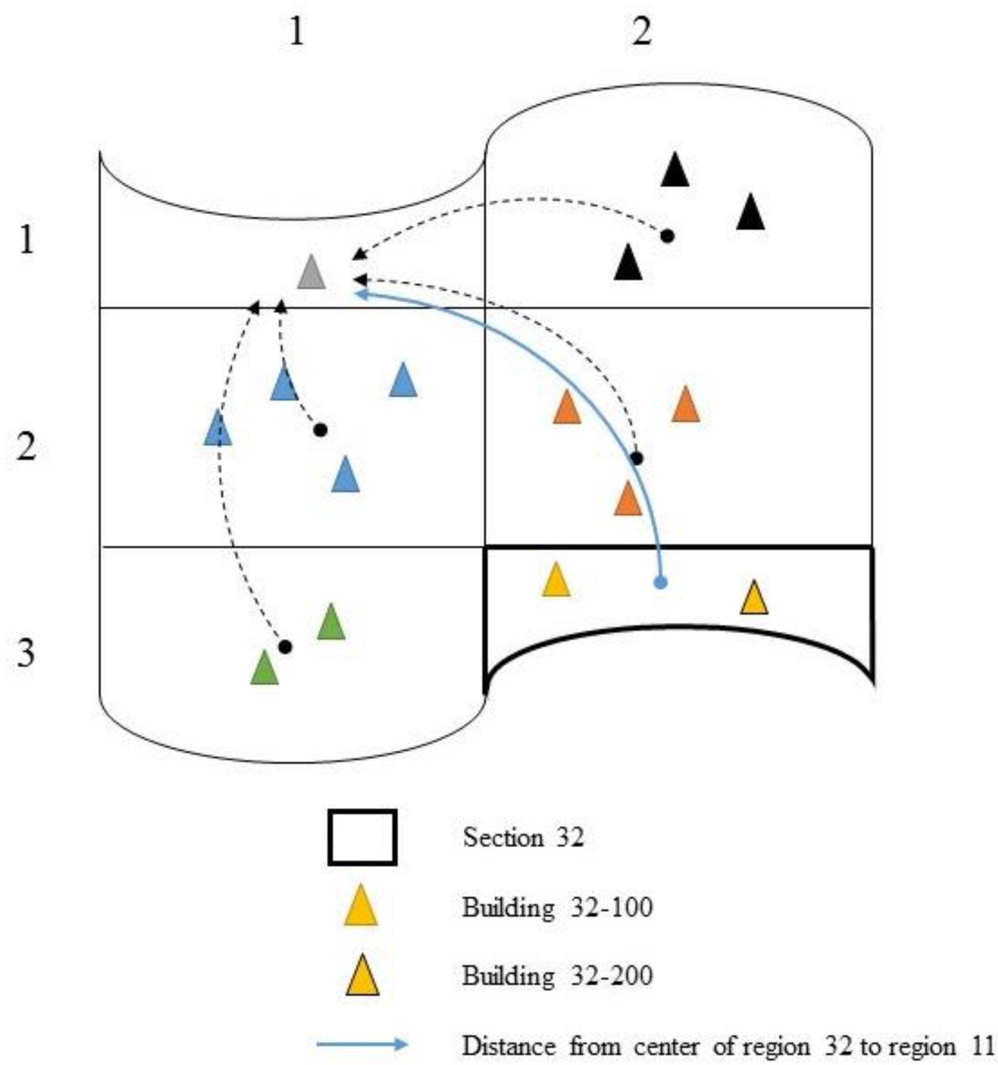

Figure 10: Installment Layout Example

The above is a simplified example of how areas are designated on Pine Bluff Arsenal. The area is divided into 3 vertical regions and 2 horizontal regions. Each section is named by combining the vertical address with the horizontal address. The outlined section is the intersection of the 3rd vertical region and 2nd horizontal region, giving it a section name of 32. Each building name within this section begins with its regional address. In section 32, the two buildings are called 32-100 and 32-200. Naming buildings in this manner conveys information about its exact location on the base and its relative location to other buildings. Warehouses located in the same region often share similarities. At Pine Bluff Arsenal, 50 series buildings all have higher ceilings and loading docks. Other buildings have floor bays and require special equipment to load products into trucks.

The distances used for calculations are measured from the center of the buildings in one geographic region to the center of the buildings located in another geographic section. This reduces the calculation complexity of the measurements for experimentation. The distance between every building where material is stored should be measured and recorded for application in the proposed algorithm change.