Rafael Jimenez Autonomous University of Juarez City, Mexico

Rogelio Florencia Autonomous University of Juarez City, Mexico

Vicente García Autonomous University of Juarez City, Mexico

Abraham Lopez Autonomous University of Juarez City, Mexico

ABSTRACT

Mobile ateliers, also called pop-up stores, sell their products away from their warehouse. Therefore, it causes them to go back to it once a product in their mobile store runs out since the customer is waiting for them at the store. The need to spend as little time searching for the product at the warehouse is of the utmost importance. To solve this problem, the authors have decided to attack it as an order picking problem. With the use of the elephant search algorithm, they aim to optimize the time it takes to retrieve the product needed to form the warehouse by giving the sales representative the optimum picking order route, so he can go in and out of the warehouse in as few steps as possible.

INTRODUCTION

According to Euromonitor (Dele, 2018), a market research company, apparel, and footwear fashion sales totaled \$1.7 trillion globally in 2017. As many stores have gone online and e-commerce flourishes, consumers are still reluctant to shop online for clothing. In a report by Fung Global Retail & Technology (Weinswig, 2017) no apparel e-commerce site made the top 10 preferred outlets, giving Amazon, one of

DOI: 10.4018/978-1-5225-8131-4.ch008

the world largest e-tailers, a 3.7% apparel market share (Weinswig, 2017). One of the main advantages regular clothing retailers have versus e-tailers is giving the customer a chance to try on items before they can buy them.

To take advantage of these business and shopping trends, mobile ateliers were created in an effort to bring their products closer to their potential customers. Mobile ateliers work by having an offsite warehouse where they store the vast majority of their products and take only a few samples of each product in their mobile store. They lure customers with affordable prices by gathering in shopping markets, providing the opportunity to try on their products before committing to buying them. One of the major obstacles they need to overcome is when they need to resupply their mobile store at the start of a shift, as they have to count which and how many product items they have to pick up from the warehouse. Also, when the store runs out of product items and they have to go back to the store to pick more samples. This task is time-consuming, as the traversal of the warehouse in search of the products needed to fill the order might take too long.

To solve this type of problem, we have decided to treat it as an order picking problem and to answer it applying an Elephant Search Algorithm (ESA). The ESA algorithm was first suggested by Wang, Deb, and Coelho (2015) and models the behavioral herding patterns of elephants as they look for food in the wild. These search characteristics are implemented in an algorithm that searches for the best solution to a problem.

PROBLEM DESCRIPTION

Mobile ateliers are migrant stores that travel to a different location each day. Therefore, the amount of inventory they can carry is minimal. To store the majority of their inventory, they make use of an offsite warehouse. When the mobile store's sales associate needs to resupply their store at the beginning of each day and during the day when the supply runs out, a mid-shift resupply is required, and a ticket is generated. This ticket acts like a list of inventory items, and the sales associate needs to pick up from the warehouse; since the list is out of order, and the sales associate must traverse the warehouse multiple times to complete the ticket order, we must optimize the order in which the sales associate must pick up all the items on the ticket to avoid losing time and reduce the steps taken to fulfill such order.

Mobile Store

A mobile atelier, also called popup stores and mobile stores, are temporary retail stores that sell merchandise of many kinds, most notably fashion clothes and accessories. Mobile ateliers move around the city from day to day, typically located in popup markets that have high foot-traffic areas and busy streets. To be able to move around to different locations each day, mobile ateliers do not carry all their inventory with them, so they make use of an offsite warehouse.

Offsite Warehouse

An offsite warehouse is part of a mobile atelier, and it is composed of building space and storage racks that are each made up of four storage units. Each storage rack is used to store an individual clothing

item, and its storage units are used to store the storage rack's clothing item on one of its available sizes: small (S), medium (M), large (L), and extra-large (XL).

PROPOSED METHODOLOGY

To solve the order picking problem, we have decided to implement a search algorithm based on the behavior of elephants as they roam the wild in search for food (Deb, Fong & Tian, 2015).

Order Picking

As described by de Koster, Le-Duc and Roodbergen (2007): "Order has been identified as the most labor-intensive and costly activity for almost every warehouse".

An order picking optimization is based on the Traveling Salesman problem in which a salesman must traverse all available cities (locations), passing thru each of them only once. In the application of order picking to a warehouse (Boxer & Kile, 2015; Boysen, de Koster & Weidinger, 2018) an employee (Groose, Glock, Jaber & Neumann, 2015; Henn, Koch, Doerner, Strauss & Wäscher, 2010) receives a ticket describing a list of available items and quantity of each item; the employee must collect by using as fewer steps as possible (Dallari, Marchet & Melacini, 2009). To fulfill this order, the employee must go to each of the picking locations in the warehouse grabbing an item in the order if it can be found in that picking location (de Koster, Le-Duc, & Roodbergen, 2007).

Elephant Search Algorithm

The algorithm to be used to solve this problem is the Elephant Search Algorithm (ESA) (Wang, Deb & Coelho, 2015; Alihodzic, Tuba, Capor-Hrosik, Dolicanin & Tuba, 2017; Bukhsh et al., 2018; Tuba & Stanimirovic, 2017). The ESA is based on the behavioral characteristics of elephant herds, which divides the agents into two groups (Strumberger, Bacanin, Tomic, Beko & Tuba, 2017; Tuba, Capor-Hrosik, Alihodzic, Jovanovic & Tuba, 2018; Tuba, Alihodzic & Tuba, 2017). One group is modeled after male elephants, and its main function is to search for food in far off spaces. The other agents are modeled after the behavioral patterns of female elephants as they form groups to do local search near their matriarch. When male elephants find a food source, the matriarch will move towards that food source taking with her the whole group. An example of the interactions between elephants while searching for food can be seen in Figure 1, where we can see male elephants searching outside the group for food and female elephants and babies doing a local search inside the group.

The authors of this search algorithm, Wang et al. (2015), lists the assumptions taken from the elephant's biological behavior as:

• Each elephant has a visual range, like that in the wild, and each elephant is on the lookout for other elephants that might threaten this visible range. In this algorithm, the visual field is calculated by the Euclidean Distance. Male's visual distance is farther than females as they are alone in the wild and are in the highest risk of danger. The elephant is allowed to move randomly in search of food within his visual range.



Figure 1. Description of the behavior of an Elephant Herd while searching for food Source: Wang et al. (2015), adapted by authors

- When two elephants encounter each other in their visual range, they have a contest to see who is the strongest one; in the algorithm, this is done through a comparison of their fitness values. The elephant that has the lowest fitness value is considered to be the weakest and must leave the strongest one's area. The weakest elephant must flee the area in a random direction that is not the same as the strongest elephant's path. This behavior can be observed in Figure 2.
- The clan is composed of only one female group, and this female group is always together.
- Each elephant has a maximum given lifespan. When one elephant dies, a new baby must be born. The new baby's gender is inherited from the elephant that just died, this is done to keep the clan's gender balanced and group size stationery.

The algorithm identifies elephants into k clans. Each elephant member j in clan ci moves according to the clan's matriarch, the elephant with the best value in each generation. In the population, there



Figure 2. Elephant with the lowest fitness flees from another elephant with better fitness Source: Wang et al. (2015), adapted by authors.

are four types of elephants: Males, Females, Matriarch and Baby. The characteristics of each type of elephant, according to Wang, Coelho, Gao and Deb (2016), and Bentouati, Saliha, El-Sehiemy and Wang (2017), will be detailed below.

Matriarch

A matriarch is the oldest living female elephant and leader of the clan. It is considered the elephant with the best fitness of the clan and as such dictates the direction the clan is going to. $\mathcal{X}_{best,ci}$ defines the matriarch of the clan *ci* and its movement is determined by:

$$\mathcal{X}_{new:ci} = \beta \cdot \mathcal{X}_{center,ci} \tag{1}$$

where $\beta \in [0,1]$ is a parameter that controls the influence of the $\mathcal{X}_{center,ci}$ which is defined as:

$$\mathcal{X}_{center,ci,d} = \frac{1}{n_{ci}} \sum_{l=1}^{n_{ci}} \mathcal{X}_{ci,l,d}$$
(2)

where $1 \le d \le D$ indicates the d^{th} dimension, and D is its total dimension. nci is the number of elephants in clan ci. $\mathcal{X}_{ci,l,d}$ is the d^{th} of the elephant individual $\mathcal{X}_{ci,l}$. This means that the center is an average of all current solutions in the clan.

Female Elephants

Female elephants always stay with the clan under the rule of a matriarch. They are responsible for doing local search digging for more details under the influence of the matriarch of their clan ci. Female elephants move according to the following equation given in:

$$\mathcal{X}_{new,ci,j} = \mathcal{X}_{ci,j} + \alpha \cdot \left(\mathcal{X}_{best,ci} - \mathcal{X}_{ci,j} \right) \cdot r \tag{3}$$

where $\mathcal{X}_{new,ci,j}$ is a new position for elephant j in clan ci and $\mathcal{X}_{ci,j}$ represents the last position of the elephant, \mathcal{X}_{best} is the best solution in the clan ci, $\alpha \in [0,1]$ is an algorithm's parameter that indicates the influence of the matriarch's best solution over the clan, finally $r \in [0,1]$ is a random number that improves diversity.

Male Elephants

Male elephants leave the clan and wander off in random directions searching for food. They are responsible for expanding the search range by exploring solutions. In each generation and within each clan mci elephants with the worst fitness values are moved according to the equation:

$$\mathcal{X}_{worst,ci} = \mathcal{X}_{min} \cdot \left(\mathcal{X}_{max} - \mathcal{X}_{min} \right) \cdot random \tag{4}$$

where \mathcal{X}_{max} and \mathcal{X}_{min} represent the lower and upper bound of the solution space respectively, and parameter $random \in [0,1]$ is a random number that changes between all parts of the solution.

Baby Elephants

Baby elephants are born as older elephants die, they are born the same sex as the recently dead elephant they replace and inherit its fitness. They stay with the female elephants until they reach adulthood and leave the group if they are born male.

The structure of the elephant herding algorithm is summarized in Algorithm 1.

Justification of the Proposed Solution

The proposed solution makes use of a newly created metaheuristic algorithm that is not that well known and few works using it has been done. By using it we try to expand the recognition and potential of the elephant search algorithm as an algorithm suitable for solving order picking and traveling salesman problems.

METHODS AND MATERIALS

In this section we describe how to solve an order picking problem with the ESA algorithm. First, we define our domain as a main store and a warehouse layout.

```
Algorithm 1. Pseudocode for the elephant herding algorithm
```

```
Initialization
  Set generation counter t = 1
  Set maximum generations MaximumGenerations
  Set maximum population
  Initialize the population to a randomized solution
      repeat
         Sort all the elephants according to their fitness
         for all clans ci in the population do
                   for all elephants j in the clan ci do
                            Update \mathcal{X}_{ci}, j and generate \mathcal{X}_{new}, ci, j by Eq. (3)
                            if \mathcal{X}ci, j = \mathcal{X}best, ci then
                                      Update \mathcal{X}ci, j and generate \mathcal{X}new, ci, j by Eq. (1)
                            end if
                   end for
         end for
         for all clans ci in the population do
                   Replace the worst elephant in clan ci by Eq. (4)
         end for
         Evaluate population by the newly updated positions
    until t < MaximumGenerations</pre>
return best found solution
```

Main Store

The main store is built inside a Freightliner MT45 truck, which is reconditioned to be used as a mobile store. This main store has at least 1 product sample from each product in one of its available sizes S, M, L, and XL. The main store is where the order tickets are generated to be fulfilled inside the warehouse.

Warehouse Layout

The offsite warehouse, as seen in Figure 3, is used to store products and it is composed of 80 rack locations. Each rack location has two racks stacked one rack on top of another to form 40 pickup locations. Each rack is divided into four storage keeping units (SKUs), eight aisles, three cross-aisles, for a total of 640 different products stored each into its own SKU.

As seen in Figure 3, the origin marks the starting location of an employee entering the warehouse to fulfill an order. Since we have 40 picking locations, labeled in boldface each with 16 SKUs, not having an optimized route for filling an order would take an employee the traversal of the entire warehouse in a worst-case scenario.

Origin										
	o1			o2			о3		o 4	
1/2	o1	21/ 22	41/42	o11	61/62	81 / 82	o21	101/102 121/122	o31	141 / 142
3/4	o2	23 / 24	43/44	o12	63 / 64	83 / 8 4	o22	103/104 123/124	o32	143 / 144
5/6	о3	25 / 26	45 / 46	o13	65 / 66	85 / 8 6	o23	105/106 125/126	o33	145 / 146
7/8	o 4	27 / 28	47 / 48	o14	67 / 68	87 / 8 8	o24	107/108 127/128	o34	147 / 148
9/10	о5	29 / 30	49 / 50	o15	69 / 70	89 / 90	o25	109/110 129/130	o35	149 / 150
	о5			06			о7		08	
11/12	06	31/32	51/52	o16	71/72	91/92	o26	111/112 131/132	o36	151 /152
13/14	о7	33 / 34	53/55	o17	73 / 74	93 / 9 4	o27	113/ 114 134 / 135	o37	153 /154
15/16	08	35 / 36	55/56	o18	75 / 76	95 / 96	o28	115/116 135/136	o38	155 /156
17/18	o 9	37 / 38	57/58	o19	77 / 78	9 7 / 98	o29	117/118 137/138	o39	157 /158
19/20	o10	39 / 40	59 / 6 0	o20	79 / 80	99 / 10 0	o30	117/120 139/140	o40	159 /160
	09			o1 0			o11		o12	

Figure 3. Example of the offsite warehouse

Order Picking as a Traveling Salesman Problem

As a way of solving an order picking problem, we have decided to transform it into a Traveling Salesman Problem (TSP) (Theys, Bräysy, Dullaert & Raa, 2010; Key & Dasgupta, 2015) to remove unused pickup locations, generate an adjacency matrix of an overall reducing the problem's complexity.

EXPERIMENTATION

A series of experiments were carried out to assess the performance of the algorithm given a series of different configurations.

The algorithm was implemented using Java version 8 Update 181. Experiments were performed on a platform with the following specifications: AMD RyzenTM 5 1600 CPU running at a base speed of 3.6 GHz, 16GB of RAM, and Windows 10 Student Edition. All three test orders were randomly generated with no duplicates allowed. To create these orders, we used 19%, 46%, and 75% of the total number of products in the warehouse respectively, giving us three orders of 122, 295 and 467 elements each.

To test the performance of the ESA on different sized orders, we created 8 different algorithm configurations from three factors, shown in Table 1, based on popular test configurations by other researchers (Wang et al., 2015; Deb et al., 2015; Wang et al., 2016).

Fastan	Levels			
Factors	Low (-)	High (+)		
Number of Elephants	50	100		
Clan	5	10		
Generations	400	800		

Table 1. Factors and levels analyzed during testing

RESULTS

These tests were done to evaluate the performance of the ESA under different configurations using three different sized orders, by doing so we can appreciate how configurations can improve a metaheuristic algorithm, as well as finding an approximate configuration best suited for a given order size.

The tests were done running 30 times each of the eight configurations, available in each of the three orders. The average fitness was calculated using each of the resulting fitness values. The best solution is the lowest fitness value achieved during the test of one order. The worst solution is the highest fitness value found during the test of one order.

In Table 2 we have the results for the order consisting of 122 randomly generated items, the best average fitness of 428.86 was achieved using 100 elephants, 10 clans, and 800 generations. The best solution was given by the configuration of 100 elephants, 10 clans and 800 generations, while 50 elephants, 5 clans and 400 generations gave the worst solution and fitness.

The results of the order with 295 products are shown in Table 3, the best average fitness was achieved using 100 elephants, 10 clans, and 800 generations, the best solution was found using 100 elephants, 5 clans, and 800 generations, and the worst solution was given by five of the eight configurations.

In the third and last test order, shown in Table 4, again the best average fitness was achieved by using the configuration of 100 elephants, 10 clans, and 800 generations, which also had the best solution. The worst solution was given by using 50 elephants, 10 clans, and 400 generations.

Elephants	Clans	Generations	Items in order	Avg. Fitness	Best Solution	Worst Solution
	5	400	122	484.63	419	504
50		800	122	462.75	420	494
50	10	400	122	474.4	444	501
		800	122	451.46	414	491
	F	400	122	462.68	424	497
100	5	800	122	450.15	381	490
100	10	400	122	434.66	366	478
		800	122	428.86	377	460

Table 2. Test results for the order with 122 items

Elephants	Clans	Generations	Items in order	Avg. Fitness	Best Solution	Worst Solution
	5	400	295	519.4	407	546
50		800	295	503.28	420	546
50	10	400	295	512.12	414.5	546
		800	295	499.2	413	546
	5	400	295	497.55	361	546
100		800	295	471.3	346	537
100	10	400	295	467.73	358	521
		800	295	447.88	369	501

Table 3. Test results for the order with 295 items

Table 4. Test results for the order with 467 items

Elephants	Clans	Generations	Items in order	Avg. Fitness	Best Solution	Worst Solution
	5	400	467	511.3	309	552
50	5	800	467	498.1	341	552
50	10	400	467	511.66	406	554
		800	467	516.23	369	552
	5	400	467	481.65	315.59	552
100		800	467	450.53	304	546
100	10	400	467	463.1	360	552
		800	467	442.2	261	506

CONCLUSION AND FUTURE RESEARCH

This chapter shows how we can adapt a problem set into a new different one with a less complex and easier problem to solve. With the help of a newly created algorithm we can solve order picking problems using a transformation to make them a TSP problem and work with its resulting adjacency matrix.

Future work must be done in studying the changing effect of different configurations of parameters in these emerging metaheuristic algorithms to take full advantage of them since they haven't been widely applied.

REFERENCES

Alihodzic, A., Tuba, E., Capor-Hrosik, R., Dolicanin, E., & Tuba, M. (2017, November). *Unmanned aerial vehicle path planning problema by adjusted elephant herding optimization*. Paper presented at 2017 25th Telecommunication Forum (TELFOR). doi:10.1109/TELFOR.2017.8249468

Bentouati, B., Saliha, C., El-Schiemy, R., & Wang, G. (2017). Elephant Herding Optimization for Solving Non-convex Optimal Power Flow Problem. *Journal of Electrical and Electronics Engineering* (*Oradea*), *10*(1), 31–40.

Boysen, N., de Koster, R., & Weidinger, F. (2018). Warehousing in the e-commerce era: A survey. *European Journal of Operational Research*, 1–16. doi:10.1016/j.ejor.2018.08.023

Bozer, Y., & Kile, J. (2008). Order batching in walk-and-pick order picking systems. *International Journal of Production Research*, 46(7), 1887–1909. doi:10.1080/00207540600920850

Bukhsh, R., Javaid, N., Iqbal, Z., Ahmed, U., Ahmad, Z., & Nadeem, M. (2018). Appliances Scheduling Using Hybrid Scheme of Genetic Algorithm and Elephant Herd Optimization for Residential Demand Response. In L. Barolli, M. Takizawa, T. Enokido, M. Ogiela, L. Ogiela, & N. Javaid (Eds.), *32nd IEEE International Conference on Advanced Information Networking and Applications Workshops (IEEE WAINA 2018)* (pp. 210-217). IEEE. doi:10.1109/WAINA.2018.00089

Dallari, F., Marchet, G., & Melacini, M. (2009). Design of order picking system. *International Journal of Advanced Manufacturing Technology*, *42*(1-2), 1–12. doi:10.100700170-008-1571-9

de Koster, R., Le-Duc, T., & Roodbergen, K. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, *182*(2), 481–501. doi:10.1016/j. ejor.2006.07.009

Deb, S., Fong, S., & Tian, Z. (2015). *Elephant Search Algorithm for Optimization Problems*. In *The Tenth International Conference on Digital Information Management (ICDIM 2015)*. IEEE. doi: 10.1109/ ICDIM.2015.7381893

Dele, V. (2018). Global Apparel and Footwear Valued at US\$ 1.7 Trillion in 2017, Yet Used Clothing Worth Millions Disposed of Every Year. Retrieved from https://www.businesswire.com/news/ home/20180504005285/en/Global-Apparel-Footwear-Valued-1.7-Trillion-2017

Groose, E. H., Glock, C. H., Jaber, M. Y., & Neumann, W. P. (2015). Incorporating human factors in order picking planning models: Framework and research opportunities. *International Journal of Production Research*, *53*(3), 695–717. doi:10.1080/00207543.2014.919424

Henn, S., Koch, S., Doerner, F., Strauss, C., & Wäscher, G. (2010). Metaheuristics for the Order Batching Problem in Manual Order Picking Systems. *Business Research*, *3*(1), 82–105. doi:10.1007/BF03342717

Key, R., & Dasgupta, A. (2015). *Warehouse Pick Path Optimization Algorithm Analysis*. Paper presented at Int'l Conf. Foundations of Computer Science.

Strumberger, I., Bacanin, N., Tomic, S., Beko, M., & Tuba, M. (2017). *Static drone placement by elephant herding optimization algorithm*. Paper presented at 2017 25th Telecommunication Forum (TELFOR). doi: 10.1109/TELFOR.2017.8249469

Theys, C., Bräysy, O., Dullaert, W., & Raa, B. (2010). Using a TSP heuristic for routing order pickers in warehouses. *European Journal of Operational Research*, 200(3), 755–763. doi:10.1016/j.ejor.2009.01.036

Tuba, E., Alihodzic, A., & Tuba, M. (2017). *Multilevel image thresholding using elephant herding optimization algorithm.* Paper presented at 2017 14th International Conference on Engineering of Modern Electric Systems (EMES). doi: 10.1109/EMES.2017.7980424

Tuba, E., Capor-Hrosik, R., Alihodzic, A., Jovanovic, R., & Tuba, M. (2018). Chaotic elephant herding optimization algorithm. In 2018 IEEE 16th World Symposium on Applied Machine Intelligence and Informatics (SAMI) (pp. 213-216). IEEE. doi: 10.1109/SAMI.2018.8324842

Tuba, E., & Stanimirovic, Z. (2017). *Elephant herding optimization algorithm for support vector machine parameter tuning*. Paper presented at 2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI). doi: 10.1109/ECAI.2017.8166464

Wang, G., Coelho, L., Gao, X., & Deb, S. (2016). A new metaheuristic optimization algorithm motivated by elephant herding behaviour. *International Journal of Bio-inspired Computation*, 8(6), 394. doi:10.1504/IJBIC.2016.081335

Wang, G., Deb, S., & Coelho, L. (2015). *Elephant Herding Optimization*. In S. Deb, L. Willyanto & S. Fong (Eds.), 2015 3rd International Symposium on Computational and Business Intelligence (pp. 1-5). IEEE. doi: 10.1109/ISCBI.2015.8

Weinswig, D. (2017). *Deep Dive: Retail Revolution – US Apparel Shifts in 20 Charts*. Retrieved from http://www.deborahweinswig.com/wp-content/uploads/2017/03/Retail-Revolution-US-Apparel-Shifts-in-20-Charts-March-8-2017.pdf