Doğuş Üniversitesi Dergisi, 19 (1) 2018, 69 - 77

Order Picking Problem in a Warehouse with Bi-Objective Genetic Algorithm Approach: Case Study[*]

İki Amaçlı Genetik Algoritma Yaklaşımı ile Bir Depoda Sipariş Toplama Problemi: Vaka Çalışması

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ABSTRACT: In this paper, an order picking problem with the capacitated forklift in a warehouse is studied by considering the total distance and the penalized earliness/tardiness. These objectives are important to reduce transportation costs and to satisfy customer expectations. Since this problem has been known as NP-hard, a genetic algorithm (GA) is proposed to solve the bi-objective order picking problem. The proposed approach is applied to auto components industry that produces wire harnesses responsible for all electrical functions in the vehicle. Experimental design is used for tuning the influential parameters of the proposed GA. The GA approach was solved by weighted sum scalarization.

Key words: Experimental design, Genetic algorithm, Order picking, weighted sum scalarization

Öz: *Bu çalışmada, toplam uzaklık ve cezalı erkenlik/gecikme durumlarını dikkate alan bir depoda kapasiteli forklift ile bir sipariş toplama problemi çalışılmıştır. Bu amaçlar, ulaşım maliyetlerini azaltmak ve müşteri beklentilerini* karşılamak için önemlidir. Bu problem NP-zor olarak *bilindiğinden iki amaçlı sipariş toplama problem çözümü için bir genetik algoritma önerilmiştir. Önerilen yaklaşım, araçtaki tüm elektriksel fonksiyonların çalışmasını sağlayan kablo demetleri üreten bir oto bileşenleri endüstrisine uygulanmıştır. Önerilen GA'nın etkili parametreleri için deney tasarımı kullanılmıştır. GA yaklaşımı ağırlıklı toplam skalerleştirme yöntemi ile çözülmüştür.*

Anahtar kelimeler: Deney tasarımı, Genetik Algoritma, Sipariş toplama, Ağırlıklı toplam skalerleştirme yöntemi

Jel Kodu: C61

1. Introduction

The firms have policies to gain a success in the market share competition. One of the goals to compete in the market is to minimize the total cost in the production system. Therefore, the firms try to minimize their costs such as minimizing work in process, finished goods inventory and their transportations in the shop floor. Holding inventory is often one of the most important problems in the success of a firm. Inventory cost consists of financing equipment, labour, protective issues and insurance requirements, handling, transporting, obsolescence, losses and the opportunity cost of choosing to deal with inventory. On the other hand, meeting the demand is the other important problem for the firms in the great competition. In this case, the firms have been studying on the strategy to meet the demand on time with sufficient inventory and

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[(*)] This paper was presented at the "The 15th International Logistics and Supply Chain Congress (LMSCM)" on October 19-20, 2017.

Geliş/Received: 09-12-2017, Kabul/Accepted: 25-01-2018

their transportations in the shop floors to minimize the total costs. In this situation, various problems to be optimized can be faced in the shop floors by the firms. Order picking can be defined as mostly labour-intensive and costly activity for warehouses, because the cost of order picking is predicted to be as much as 55% of the total warehouse operating expense (Koster, Le-Duc, and Roodbergen, 2007).

In this study, an order picking problem to determine the order list for a good route in a shop floor was analyzed. The problem is actually similar to a vehicle routing problems (VRP) with one warehouse and twelve workstations. In some studies, this problem type is considered as a Travelling Salesman Problem (TSP) (Lawler, Lenstra, Rinnooy Kan and Shmoys, 1995; Koster, Le-Duc, and Roodbergen, 2007). The VRP is also a generalization of the TSP. The goal in VRP is to find the optimal set of routes for a fleet of vehicles delivering goods various locations. Vehicle routing problems also have constraints as the following:

- Capacity constraints
- A maximum number of locations that each vehicle can visit.
- Time or distance constraints
- Time windows
- Precedence relations between pairs of locations

The objective of VRP is generally to design a set of minimum cost routes that serve a number of places. Since its first formulation in 1959, in the literature, there have been many studies (Ghannadpour, Noori, T.-Moghaddam and Ghoseiri, 2014). Lenstra and Rinnooy Kan (in 1981) have analyzed the complexity of the vehicle routing problem and they have concluded that practically all the vehicle routing problems are NP-hard because they are not solved in polynomial time. The VRP with time windows (VRPTW) is also NP-hard because of its extension structure of the VRP based on Solomon and Desrosiers (in 1988). An important extension of the classical vehicle routing problem is called capacitated vehicle routing problem. Wei, Zhang, Zhang and Lim (2015) proposed the capacitated vehicle routing problem with two-dimensional loading constraints, which is a generalized capacitated vehicle routing problem in which customer demand is a set of two-dimensional, rectangular, weighted items. Rubrico, Higashi, Tamura and Ota (2011) presented a solution for a dynamic rescheduling problem involving new orders arriving randomly while static orders have been given in advance in warehouse environments.

Serna, Uran, Cortes and Benitez (2014) studied a solution procedure for solving the vehicle routing problem with pick-up and delivery with multiple warehouses based on a hybrid metaheuristic. Nagy and Salhi (2005) proposed heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries. Rao, Wang, Wang and Wu (2013) focused on the scheduling of a single vehicle, which delivers parts from a storage centre to workstations in a mixed-model assembly line.

Gils, Ramaekers, Braekers, Depaire and Caris (2017) analyzed and statistically proved the relations between storage, batching, zoning, and routing by a full factorial ANOVA.

The detailed information related to VRP and order picking systems can be found in the studies of Tonci Caric and Gold (2008) and Gils, Ramaekers, Caris and Koster (2017).

The problem in this study is similar to VRP with one forklift, one warehouse and twelve workstations. One forklift is visiting each workstation and picking up the orders based on its capacity. Each workstation has one pallet to store the product and the forklift has a capacity of three pallets. In the existing system, the forklift is visiting the workstations randomly and does not consider any distance or repetition and the cost.

In the study, the order picking problem with the capacitated forklift in a warehouse was studied by considering two objectives such as the total distance and the penalized earliness and tardiness. A genetic algorithm (GA) approach is proposed to solve the bi-objective order picking problem and the proposed approach is applied to auto components industry that produces wire harnesses responsible for all electrical functions in the vehicle.

2. The Proposed Algorithm

The proposed algorithm is developed according to the concept of the genetic algorithm (GA). The detailed procedure of the proposed algorithm is as follows:
Step 1. Initial Population: As shown in Figure 1, the structure of the chromosome is designed by sequencing the workstations (k=1, 2,…,12) in the shop floor. An initial population of each chromosome is randomly created as shown in Figure 1. Each chromosome contains 14 genes. The component of the chromosome represents the sequence of workstations with the warehouse. The first and the last genes show the warehouse and are indicated as a value of 0. Thus, the beginning and ending node of the forklift should be the warehouse.

0	2	10	7	8	12	3	1	4	11	5	9	6	0

Figure 1. Schematic representation of the chromosome structure

Step 2. Fitness Evaluation: After obtaining the chromosome structure, the route is formed based on the capacity of the forklift. In this study, the current capacity of the forklift is three pallets. Each workstation has a pallet for storing the finished product. The route in Figure 2 is created according to these capacity values. Total distance objective value is computed by taking into account both of the route in given Figure 2 and the distance matrix between the workstations. In addition, earliness/tardiness cost objective value is also calculated by considering costs which arise because of the waiting of forklift’s operator and holding inventory. The bi-objective fitness value has obtained the sum of weighted total distance objective value and weighted earliness/tardiness cost objective value. Each weight for objectives is determined by decision-makers in the firm.

0	2	10	7	0	8	12	3	0	1	4	11	0	5	9	6	0

Figure 2. The route belonging to the defined chromosome structure

According to the chromosome structure in Figure 1, gen 0 is the beginning node for the operator of the forklift. Firstly, the forklift operator visits the second workstation and picks up a pallet for the forklift. The capacity of the forklift is reduced to 2 pallets from 3 pallets. The forklift operator visits the tenth and seventh workstations, respectively, until the forklift is full. And then, he visits the warehouse for unloading the forklift. Similarly, by following the rank in Figure 1 from left to right, the route is obtained as shown in Figure 2.

The fitness value of each chromosome is determined by evaluating objective functions. The objectives are defined as:

Total Distance: The capacitated forklift must start from the warehouse and goes to workstations for taking the ready pallet or pallets if the loading capacity is available. The forklift comes back to the warehouse when its capacity is full. Then this order picking process is repeated until all workstations are visited. The total travelling distance of the forklift should be minimized according to the distance matrix calculated by using the facility layout.

Penalized Earliness and Tardiness: Every workstation has minimum and maximum order picking times due to the production rate. Managers want to pick the ready pallets between the minimum and maximum times. If the forklift arrives a workstation before the minimum order picking times then the forklift operator waits for the minimum time to load the ready pallet. On the other hand, if the forklift arrives a workstation after the maximum time then it causes the inventory cost. We penalized both of them. The earliness cost is calculated by using the operator's hourly wage. Additionally, the tardiness cost is based on the cost of inventory area. The total earliness and tardiness cost should be minimized.

The fitness function = w_1×(Total Distance) + w_2×(Penalized Earliness and Tardiness)

Step 3. Selection: In the genetic algorithm, parent chromosomes are selected with a probability related to their fitness. Highly fit chromosomes have a higher probability of being selected for mating than fewer fit chromosomes. (Teekeng and Thammano, 2012: 124). Tournament selection method is proposed in this paper. In tournament selection, one tournament is performed for every non-elitist individual. The tournament size is a given parameter and tournament candidates are randomly chosen from the current population. (Bogdanović, 1989: 3035).

Step 4. Crossover: Crossover is the process that two parents chromosomes recombine to form a new offspring chromosomes. Two chromosomes are randomly chosen to behave as parents. In this study, it is used random keys representation for solving sequencing problems. (Bean, 1994: 155). Random-keys representation is an effective way to guarantee feasibility of all offspring for sequencing problems. For each gene, a real random number in the interval [0,1) is generated. If the random number obtained is smaller than the given crossover probability, then the allele of the first parent is used. Otherwise, the allele used is that of the second parent.

Step 5. Mutation: Mutation operation is applied to the population after performing crossover operation. Mutation operators provide the ability to overcome a local optimum point solution. (Chakrabortia, Biswasb and Palc, 2013: 508). Swap position mutation (SPM) is used in this paper. The SPM operator randomly selects two elements and swaps their positions if the probability is greater than the given mutation probability to produce new offspring with a randomly generated probability.

Step 6. Termination: In this study, termination criterion is the number of maximum iteration. This procedure continues until the number of maximum iteration is reached. The system is run 1000 times in the problem.

The pseudo code of the proposed genetic algorithm is presented as:

Randomly initialize a population of chromosomes ()
While i← i_{max} **do**
    i←i+1
    Fitness evaluation for each individual using an objective function ()
    Elitism ()
    Crossover ()
    Mutation ()
End While
Return the best objective function

3. Experimental Results

The parameters required to run the algorithm are population size, number of generations, number of iterations, crossover and mutation probabilities. These parameters have important roles in the performance of the genetic algorithm. The full factorial design approach is used for tuning the influential parameters of the proposed GA to obtain efficient solutions. Full factorial experiments are the only means to completely and systematically study interactions between factors in addition to identifying significant factors. After GA parameters are determined, in order to find the effectiveness of these parameters, 81 (3^4) different experiments are needed for each weight to solve the bi-objective problem. In addition, the number of experiments would be repeated five times to verify the accuracy of the solutions. Therefore, the number of the experiments required for each weighted problem is 405 (81x5). The number of the experiment is 4455 (405x11) for eleven different weights. GA parameters and their levels in Table 1 belong to eleven different weights that is shown in Table 2.

Table 1. GA parameters and their levels

Factors	Levels		
	Level 1	Level 2	Level 3
Population size	100	150	200
Crossover rate	0,1	0,5	0,9
Mutation rate	0,05	0,10	0,15
Tournament size	3	5	7

The ANOVA is calculated by using Minitab 17.0 software. The main effect plot and the interaction plot for the weights of w_1=0.5 and w_2=0.5 are given Figures 3 and 4, respectively as an example.

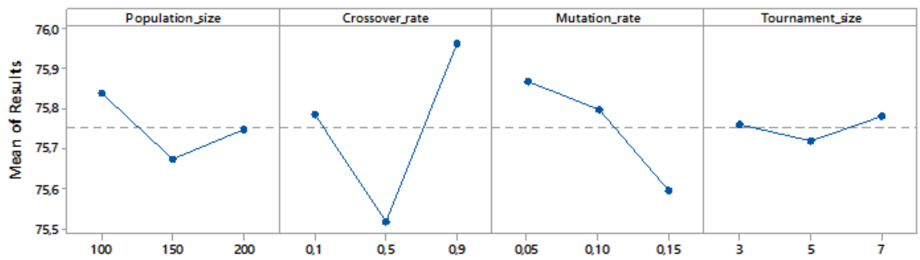

Figure 3. The main effects plot for bi-objective fitness value

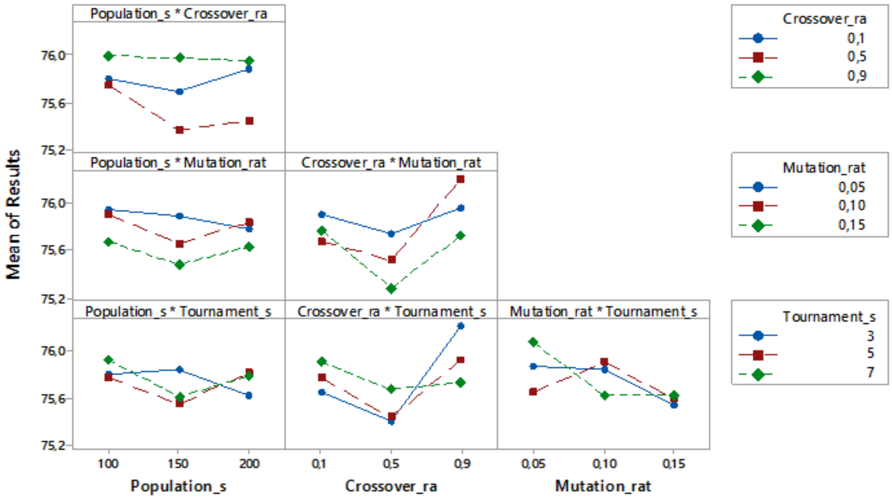

Figure 4. The interaction plot for bi-objective fitness value

GA parameters' levels of the weights of $w_1=0.5$ and $w_2=0.5$ were obtained from Figure 3 and 4. Therefore, these levels were defined as 150 for population size, 0.5 for crossover rate, 0.15 for mutation rate and 3 for tournament size as shown in Table 2.

Table 2. The most effective combination of factor levels

	Total distance objective weight (w_1)	Earliness/tardiness objective weight (w_2)	Population size	Crossover rate	Mutation rate	Tournament size
1	1,0	0,0	100	0,1	0,05	3
2	0,9	0,1	200	0,5	0,05	5
3	0,8	0,2	150	0,5	0,15	3
4	0,7	0,3	200	0,5	0,10	3
5	0,6	0,4	200	0,5	0,15	5
6	0,5	0,5	150	0,5	0,15	3
7	0,4	0,6	200	0,5	0,15	3
8	0,3	0,7	150	0,5	0,15	3
9	0,2	0,8	100	0,5	0,15	3
10	0,1	0,9	200	0,5	0,15	3
11	0,0	1,0	200	0,5	0,15	3

[*] All times are given in CPU seconds and the case study is solved by using Intel® Core™ i5-4460 CPU @ 3.20 GHz and 8.00 GB Ram.

After using the proposed GA approach for the analyses based on the experimental design parameters, the results were obtained as seen in Table 3. Three different situations for the capacity of forklift were evaluated to see the more accurate solutions. Sensitivity analysis based on the capacity of forklift is also given in Figure 5.

Table 3. The results of the proposed approach

	w1	w2	Capacity of forklift: 3 (Current)			Capacity of forklift: 4			Capacity of forklift: 2		
			Bi-objective value	Medium	Standard Deviation	Bi-objective value	Medium	Standard Deviation	Bi-objective value	Medium	Standard Deviation
1	1,0	0,0	110,4400	110,443000	0,009487	108,4400	109,440000	1,054093	113,4400	113,440000	0,000000
2	0,9	0,1	105,6838	107,075666	1,833748	105,6907	106,300852	1,222562	109,1283	109,546180	1,216176
3	0,8	0,2	100,5976	101,182811	1,233819	100,5814	101,761569	1,264242	102,4566	102,848457	0,572175
4	0,7	0,3	94,0657	94,159196	0,120689	94,0657	94,081526	0,049964	94,0792	94,117997	0,122806
5	0,6	0,4	84,6076	84,680014	0,120512	84,6068	84,700994	0,157542	84,6155	84,615549	0,000000
6	0,5	0,5	75,1495	75,225051	0,101617	75,1495	75,198717	0,079178	75,1519	75,151936	0,000000
7	0,4	0,6	65,6610	65,724220	0,110475	65,6610	65,711150	0,149180	65,6610	65,692620	0,066619
8	0,3	0,7	56,1379	56,285323	0,190379	56,1379	56,385342	0,467066	56,1379	56,183409	0,077997
9	0,2	0,8	46,6147	46,804293	0,209493	46,6147	46,728241	0,141508	46,6147	46,715389	0,090125
10	0,1	0,9	37,0915	37,233730	0,165712	37,0619	37,132863	0,095673	37,0915	37,162630	0,159963
11	0,0	1,0	27,5355	27,647367	0,190803	27,5355	27,588117	0,166547	27,5355	27,676992	0,194459

It can be seen from Table 3 and Figure 5 that the capacity affects the bi-objective fitness function for all weights of the objective functions. Managers can select the capacity of forklift due to the importance of the objectives.

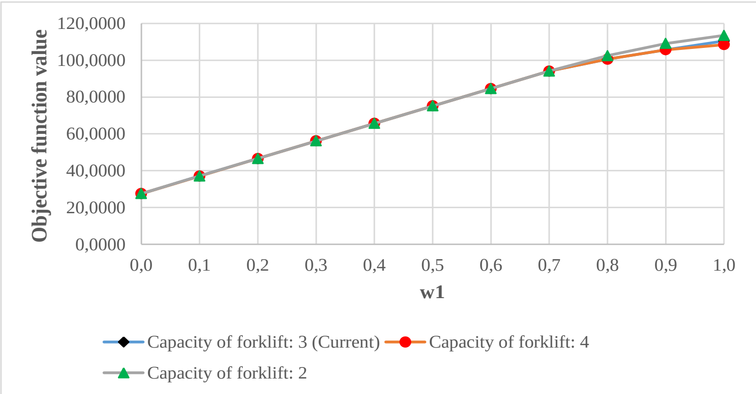

Figure 5. Sensitivity analysis based on the capacity of forklift

4. Conclusion

An order picking problem with the capacitated of three pallets of a forklift in a warehouse is studied by considering two objectives. The first objective is the total distance and the other is the penalized earliness and tardiness. A GA approach is proposed to solve this bi-objective order picking problem for a firm in auto components industry that produces wire harnesses responsible for all electrical functions in the vehicle. The problem is analysed as a VRP problem and different situations were also evaluated such as different weights and capacity of the forklift. The order picking problem is the main part of the production. Therefore, managers need efficient methods to evaluate order picking systems. The proposed approach can support to decide the capacity of the forklift and try to find the more accurate routes based on the objectives.

The proposed GA can be compared with the other meta-heuristics such as simulated annealing, tabu search, ant colony optimization, particle swarm optimization, etc. The bi-objective GA approach is solved by the weighted sum scalarization. It can be compared with the ε-constraint method, the Tchebycheff scalarization method, the conic scalarization method for the bi-objective problem in the future.

5. References

Bean, J.C. (1994). Genetic algorithms and random keys for sequencing and optimization. *ORSA Journal on Computing*, 6, 2, 154-160.

Bogdanović, M. (1989). An ILP formulation and genetic algorithm for the Maximum Degree-Bounded Connected Subgraph problem. *Computers & Mathematics with Applications*, 59(9), 3029-3038.

Chakrabortia, D., Biswasb, P. and Palc, B.B. (2013). FGP Approach for solving fractional Multiobjective Decision Making Problems using GA with Tournament Selection and Arithmetic Crossover. *Procedia Technology*, 10, 505–514.

Ghannadpour, S. F., Noori, S., T.-Moghaddam R. and Ghoseiri, K. (2014). A multi-objective dynamic vehicle routing problem with fuzzy time windows: Model, solution and application. *Applied Soft Computing*, 14, Part C, 504-527.

Gils, T., Ramaekers, K., Braekers, K., Depaire, B. and Caris, A. (2017). Increasing order picking efficiency by integrating storage, batching, zone picking, and routing policy decisions. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2017.11.021

Gils,T., Ramaekers, K., Caris,A. and Koster, R.B.M. (2017). Designing efficient order picking systems by combining planning problems: State-of-the-art classification and review. *European Journal of Operational Research*, 1–15. https://doi.org/10.1016/j.ejor.2017.09.002

Goldberg, D.E. (1989). *Genetic algorithms in search, optimization & machine learning.* MA: Addison-Wesley, Reading.

Koster, R., Le-Duc, T. and Roodbergen, K.J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, 182, 481–501.

Lawler, E.L., Lenstra, J.K., Rinnooy Kan, A.H.G. and Shmoys, D.B. (1995). *The Traveling Salesman Problem.* Chicheste: Wiley.

Lenstra, J.K. and Rinnooy Kan, A.H.G. (1981). Complexity of Vehicle and Scheduling Problems. *Networks*, 11, 221-227.

Nagy,G. and Salhi, S. (2005). Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries, *European Journal of Operational Research*, 162, 126–141.

Rao, Y.Q., Meng-Chang Wang, M.C., Wang, K.P. and Wu, T.M. (2013). Scheduling a single vehicle in the just-in-time part supply for a mixed-model assembly line, *Computers & Operations Research*, 40, 2599–2610.

Rubrico J.I.U., Higashi, T., Tamura, H. and Ota, J. (2011). Online rescheduling of multiple picking agents for warehouse management. *Robotics and Computer-Integrated Manufacturing*, 27, 62–71.

Serna, M.D.A., Uran, C.A.S., Cortes, J.A.Z. and Benitez, A.F.A. (2014). Vehicle routing to multiple warehouses using a memetic algorithm, *Procedia - Social and Behavioral Sciences*, 160, 587 – 596.

Solomon, M.M. and Desrosiers, J. (1988). Time Window Constrained Routing and Scheduling Problem. *Transportation Science*, 22, 1-13.

Teekeng, W. and Thammano, A. (2012). Modified Genetic Algorithm for Flexible Job-Shop Scheduling Problems. *Procedia Computer Science*, 12, 122-128.

Tonci Caric, T., and Gold, H. (Eds.) (2008). *Vehicle Routing Problem*. Austria: In-The.

Wei, L., Zhang,Z., Zhang, D. and Lim, A. (2015). A variable neighborhood search for the capacitated vehicle routing problem with two-dimensional loading constraints. *European Journal of Operational Research*, 243, 798–814.