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Optimization of Multi-Stage Distribution Process Using Improved Genetic Algorithm

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Abstract: A supply chain process in manufacturing industries involves a distribution process that ensures finished goods distribute to their customers properly. The process may involve several parties such as manufacturing plans, distributions centres, and retailers. To maximize profit, the companies need to optimize the distribution process by minimizing costs. The multi-stage distribution problem contains several constrains so obtaining optimum solution using exact methods may require excessive processing time. Genetic algorithm is proposed the solve the complex problem. The genetic algorithm is improved by modifying chromosome representation and related genetic reproduction operators. The new chromosome is designed to address different number of distribution stages in manufacturing industries. Thus, the proposed approach could be applied for various distribution problems. Several genetic operators are tested to obtain the most suitable reproduction operator for the multi-stage distribution process. The numerical experiments prove that the improved genetic algorithm is suitable for the optimization of the multi-stage distribution process and produce better result compare to those achieved by original genetic algorithm, simulated annealing, and random search as baseline method. The improved genetic algorithm produces solution with cost of Rp 20,167.8, lower than cost of Rp 21,860.4, Rp 23,354.30 and Rp 34,328.0 obtained by original genetic algorithm, simulated annealing, and random search, respectively.

Keywords: Genetic algorithm, Supply chain, Manufacturing, Cost optimization, Distribution process.

1. Introduction

Every manufacturing company is very familiar with the term distribution. Distribution is the delivery of production (finished products) from producers to customers [1, 2]. Wide area coverage in the distribution process resulting product must be delivered to some stage such as manufacturing plans, distribution centres, and retailers before it gets to the customer [3, 4]. The process is often referred to as multistage/multilevel distribution. In line with the opinion of Langroodi and Amiri [5] which states that the multilevel distribution is the delivery from the manufacturer/plant to the distributor and then underneath the distributor to the customer.

The number of levels used by the company's impact on the cost because it has a longer distribution network. This is contrary to the desire of companies that want to gain a lot in order to stay ahead when competing with other companies [3]. Therefore, minimizing the costs and also distribution time are very important in the distribution process [1]. A good distribution process may also increase company's service level [4].

The decision related to the distribution process should be frequently made as there is an increase of fluctuations in consumer demands. The demands should be fulfilled on time while considering manufacturer's inventory level [6]. Thus, an efficient approach is required to produce good solutions in reasonable amount of time [7].

In term number of stages, several types of the distribution network have been addressed in the previous studies. The related researches includes solving the problem by using two-stage distribution

[2, 8]. In the studies, there was central distributor located between producers and customers as an intermediary so that manufacturers were not directly sent to customers but through a distributor centre first. The other study [9] solved the problem of the distribution in three stages involving manufacturers, distributors, wholesalers and retailers.

In this study, rather than using a fixed number of distribution stages, we develop a flexible solution representation so it could be used to solve a problem that involves any level of distribution stages in manufacturing industries. The solution representation is then implemented as chromosome representation used by genetic algorithm to produce feasible solutions. This study is an extension of previous studies that also uses the genetic algorithm (GA) to find solutions of the problem [7]. The GA is chosen as it has been successfully applied for various complex combinatorial problems [10]. Several genetic operators are modified and tested to obtain the most suitable reproduction operator for the multi-stage distribution process. The numerical experiments are carried out to assess the effectiveness of the proposes approach. An original genetic algorithm and random search are used as baseline methods.

This paper consists of five sections. An introduction that contains the background problem and the need for a robust algorithm and flexible solutions are discussed Section 1. Section 2, literature review, explains related previous research. Section 3, methodology, explains the development of mathematical formulation and operators of the genetic algorithm. Presentation of computational experiment result is discussed in Section 4. Conclusions are presented at the last section.

2. Literature review

Some approaches to solve the distribution problems have been proposed. The approaches included mathematical modelling and fuzzy logic-based methods. To get good solutions in reasonable amount of time, several meta-heuristic algorithms such as simulated annealing, particle swarm optimization, and genetic algorithm were also implemented. Hybrid algorithms were also applied in several studies to address the complexity of the distribution problems.

Mathematical modelling-based methods were implemented in several studies. For example, min–max dynamic programming formulation was used to solve a two-echelon supply chain problem [11]. While the min–max dynamic programming was used for small size problem, they implemented a min–max matheuristic for larger problems. Similar approaches were applied in [12, 13] for optimization of inventory levels and transportation cost. The research [12] used non-integer linear optimization problems in the formulation to minimize inventory and transportation costs. To solve the formulated problem, Lagrangian approach was applied. Results of the study was the achievement of cost savings and profit improvement. Distribution issues raised in the study encouraged the non-linearity of inventory cost. The study [13] used max-min penalty approach to reducing the total cost of transportation.

Fuzzy logic based methods were also applied by researchers to solve the problems of fuzzy transportation and distribution with the function of ranking [14]. Trapezium fuzzy value represented distribution costs resulting in a ranking function. Once it is converted into crisp, which was solved easily using standard transport algorithm. The approach was still too classic to be easily understood and applied in the real world. The benefit was reduced computational complexity. However, the optimal solution produced had the possibility of the same value with standard transport algorithms without fuzzed. This shows that there was no change in the optimal solution of methods offered. While the study [15] used type-2 fuzzy parameters on the two problems fixed costs of transportation. Unit transportation cost and fixed cost in the first problem and the second problem was the unit transportation cost, fixed cost, supplies, and demands. As with previous studies [14], the study addressed the distribution problems only take two stages from multiple sources to multiple destinations (customer) without going through the distribution centre or retailer.

Artificial intelligence based methods were also implemented like in [16] which resulted in a three-stage distribution model so that it can generate a good simulation for distribution management. Meta-heuristic algorithms that belong to artificial intelligence-based methods were also implemented. For example, simulated annealing was used to solve the distribution problem in [17]. The transfer of the product to the customer used a cross-docking centre with a short storage time. Mix-integer programming was used to formulate the problems which were solved using simulated annealing. Based on that the proposed algorithm, the results obtained provide solutions that were effective and efficient in minimizing the total cost of transport in the cross-docking network. However, the study did not consider the distribution of multi-stage flexible distribution problems.

Population based meta-heuristic algorithms that have capability in exploring a wide search space were also implemented in several studies. For example, particle swarm optimization (PSO) was used to solve the distribution problem that exists in real-world [18]. The study had an objective determining the best reorder point of warehouses in supply chains.

A genetic algorithm (GA) is well known as a robust optimization tool has been successfully used for complex combinatorial problems [10]. Thus, the algorithm has been used for solving various cases related to the transportation problems. For example, the genetic algorithm in [2] was used to solve the distribution problems in two ways, namely by considering the transportation costs per unit, the fixed costs associated with the route and the infinite capacity of each distributor centre (DC) and the way followed was considering opening cost of distributor centres, per-unit transportation costs from plant to DC and DC to a customer. The benefit was that the proposed algorithm provides a better solution to the computational experiment than the respective best-existing algorithms for the two procedures. However, the research only applied two stages. Making it less flexible for multi-stage problems.

The mentioned previous studies mostly used a fixed number of distribution stages and also fixed number of vehicles used for transportation. The issue of multi-stage distribution using genetic algorithm was also presented in the study [7]. The results of GA were compared with the Random Search and found that the results of GA more qualified than random search. This research study conducted a flexible multi-stage distribution problems and also flexible number of vehicles. The GA with different operators is developed to obtain better results.

3. Methodology

The problem in this study is a multi-stage distribution and use one type of product. In the research process, based on a survey and interviews with experts in the distribution of the company where they work, this study used simulated data that has been designed according to the statistical distribution of the real data. The data has been designed and tailored to the problem so that the distribution data used in this study is the data capacity of the stock of each company, the capacity of the stock distributor at each stage, the number of vehicles, vehicle capacity, and costs that follow [7].

The distribution problem is solved using genetic algorithm (GA). In GA, there are several steps that must be done starting from chromosome representation, reproduction, and selection in accordance with the principle of imitating the biological properties of individual natural selection [19]. As a potential solution, a chromosome/individual should be measured his ability to complete solutions with regard to the fitness value. The greater fitness that produced the better the chromosomes are selected in solving a problem [20].

3.1 Mathematical formulation

Mathematical formulation is used to describe the objectives and constraints of multi-stage distribution problem. There are I stages and every stage i has distributor unit j a number of J. Every unit distributor j has vehicle v with total V is used to send the items. Each distributor unit j has the capacity Cp to stock the item and any vehicle v has a capacity of V_{cp} and fixes cost Co.

Each distributor unit R that requests amounting Or serviced by distributor unit at the stage above and beyond also to know which the distributor stage that respond to the order indicated by the status of St. 1 on St indicates that the distributor stage respond the order and vice versa for 0.

In the distribution process, the objective function of the problems faced is to minimize the costs [21]. Because it minimizes the cost to be the solution to the problem of multi-stage distribution. The objective function is formulated in Eq. (1).

$$z = \sum_{i=0}^{I}\sum_{j=0}^{J}\sum_{r=0}^{R} X_{ijr} Co_{ijr} St_i \tag{1}$$

Where X_{ijr} represents the total of items unit sent from stage i by distributor unit j to distributor unit r. Then Co_{ijr} is fixed cost for the delivery of distributor unit j to distributor unit r. St_i is the status of the distributor stage i in the service request.

In this study, in addition to using equations to calculate the costs, there are also some equations which are used as constraint functions as a prerequisite to represent a chromosome. The constraint functions are used.

3.1.1. Constraints on the limits of the total order

This constraint relates to the limit of total orders from distributors customer unit so that the number of reservations of distributor customer unit should be the same as the items delivered by the sender distributor unit. If the sender distributor unit has less stock to serve an order, the system automatically takes the shortage of items on a stage above and beyond. The function of the constraints for the total order shown in Eq. (2).

$$\sum_{i=0}^{I}\sum_{j=0}^{J}\sum_{r=0}^{R} X_{ijr} = Or_r \tag{2}$$

Where Or_r is the total of order request to distributor r.

3.1.2. Constraints on the limits of the vehicle capacity

Every vehicle from a distributor unit sender used to send the items to customer distributor unit has a certain capacity limit. The number of delivered items may not exceed the capacity of a vehicle that has been determined. This is determined because it affects the quality of the delivered items and vehicle durability to prevent rapid deterioration. Constraint function is shown in Eq. (3).

$$\sum_{v=0}^{V} X_{irv} \le Vcp_v \tag{3}$$

Where X_{irv} is the total of items unit shipped from the distributor stage i to distributor r using vehicle v. Vcp_v is the capacity limit of vehicle v.

3.1.3. Constraints on the stock distributor unit sender

Last are the constraints stock distributor unit sender means each distributor unit sender always have inventory stock. When distributor units deliver the items then the number of delivered items may not exceed the stock distributor unit sender. Constraint function is shown in Eq. (4).

$$\sum_{j=0}^{J} X_{ij} \le Cp_j \tag{4}$$

Where X_{ij} is the total of items unit sent by distributor unit sender j and has inventory stock with total Cp_j.

3.2 Chromosome representation

The most important initial step in the process is to represent chromosomes of GA. Because the chromosome is used to encode a solution in the genetic algorithm [22]. The encoding genetic algorithm used in this study is a real coding. Table 1 shows a representation of the chromosome that is used in this study. Each chromosome is divided into several segments. The first segment represents distributors and substage below consecutive represent the distributor sender, the sender's vehicle from each distributor and the distributor customer. Each gene located on a chromosome is a representation of the number of items unit transported by any vehicle. The length of chromosomes in this study determined from the number of distributors who do order in every stage multiplied by the total number of vehicles owned by each distributor that serves the ordered items in each stage. Table 1 shows a representation of chromosomes for one stage or one segment.

Table 1. Chromosome representation in 1 segment

Level *i*													
Distributor Sender *j*						..	Distributor Sender *J*						
Vehicle *v*			Vehicle *V*			..	Vehicle *v*			Vehicle *V*			
r	…	*R*	*r*	..	*R*	..	*r*	..	*R*	*r*	…	*R*	
45	…	20	38	..	21	..	73	..	27	54	…	24	

In Table 1, Stage i is stage distributors that serve the request, but because of the stage of distributor exemplified only one segment, then i only equal to 1. However, if the case is multi-stage, the value of i equal to the number of stages required. At each stage has some distributor unit sender that serve the request order and expressed by j. While v state the vehicle of distributor unit sender j and distributor unit customer denoted by r.

On the first gene contains 45 which means it is at stage i, distributor unit sender j sent to distributor unit customer r using vehicle v and so on until the last gene in accordance with the structure of the image representation of chromosomes.

3.3 Fitness function

Each chromosome is represented to have a value called the fitness function. The value obtained from this fitness function which is used as a comparison between one chromosome to another. Higher fitness value which gives the possibility of chromosomes is selected as the solution. This is what makes the representation of chromosomes and the fitness function as the main key in the evaluation of GA process [23]. Calculations used to obtain fitness values shown in Eq. (5).

$$Fitness = \frac{1}{Z} \tag{5}$$

Where Z is total cost from distribution process regarding Eq. (1).

After the calculation of fitness was done, it is necessary to collect chromosome / individual as many as the population size to the population pool. When the population size is 10 then the population pool must contain 10 individuals.

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3.4 Reproduction

The next steps in the genetic algorithm after initialization population is the reproduction. There are two operators in the reproduction process including crossover and mutation. Additionally, the reproduction process has parameters that determine how large the number of children generated, namely crossover rate (*cr*) in the crossover process and mutation rate (*mr*) in the process of mutation. The number of children resulting from the reproduction process is collected in a separate pool called children's pool. The purpose in the reproductive process is the number of children produced diverse because through the process of exploration and exploitation of the parent who elected to produce children [24].

3.4.1. Crossover

Crossover operator is the core and unique operator in GA. This crossover method is a method of reproduction that involves two parents from population pool hat selected randomly. This method is used to get the child with chromosome more varied because it is derived from two parents. There are several kinds of methods of crossover in genetic algorithm, but in this study only uses one cut point crossover (OCP). These models do a crossover on each segment or at the level of each individual. So, if there are more than one stage, the crossover process on each chromosome will do as much as n stage. In Fig. 1 is shown the crossover process using one cut point.

OCP crossover process is shown in Fig. 1. In the left figure, there are some initials of the individual such as P1, P2, and C1. P1 which means Parent 1, P2 describe Parent 2, and C1 is the result of the first child of the crossover between P1 and P2. Every individual has a chromosome that consists of several genes that are shown in the columns after each initial. C1 is the result of the crossover process and it can be seen that the genes possessed a cutting at point 3rd of the gene on the figure. Gen 1 and 2 of the C1 is the same as the gene from P1, the 3rd gene until the end of the same gene from gene P2.

cutting point

P1	45	20	38	21	73	27	54	24
P2	52	12	37	31	66	34	62	32
C1	45	20	38	31	66	34	62	32

Figure. 1 Crossover process using one cut point

3.4.2. Mutation

Mutation is another operator of the reproductive process. This method performs the reproduction process involving only one chromosome. There are several methods of mutations that exist in genetic algorithm. This research will use the method of random exchange mutations. Mutations of this model using a random number r as a trigger the amount of change in genes value. Random value r has a range 0 to 1 assuming that the exploitation of r did not exceed the limit range of genes when generated. The limit range of gene intended is the difference between the maximum and minimum limits so that the value generated when r multiplied by the difference between the limit range is a variation of the portion. The results obtained are summed with the value of the parent gene so that the changes are not too far away. It is based on the principle of a possible child has a gene that is not too far from its parent. Eq. (6) is a function of the random process of mutation for each gene exchange.

$$g'_a = g_a + r(\max - \min) \tag{6}$$

Where g_a is an original value of the a-th gene before mutated and g'_a is the resulting gene after mutated. Same as the crossover process, mutation process is also done at each stage as a segment in a chromosome. So, if there is I stage on each chromosome, the mutation process is done as many as I stage.

3.5 Selection

Besides there is a method of reproduction used to produce a child, the genetic algorithm also has a selection process in which this selection process evaluates each chromosome parent and child to get a new population that contains new individual qualified. Before entering the selection process, GA works by evaluating each chromosome using a fitness function. The value generated by the fitness function which is on each chromosome that is used as a benchmark in the selection process. There are various methods used. In this study, the selection method used is elitism which this method works by sorting in descending based on the fitness value so that only individuals with the greatest fitness will be selected. The GA process is continued until the limits that have been determined [25].

4. Experimental result

A genetic algorithm is an algorithm that works by using multiple parameters as input. Genetic algorithm

Table 2. Testing result of population size

No	Population size	Average cost	Average fitness
1	10	6270	0.0001684984
2	20	5080	0.0001995103
3	30	4775	0.0002126277
4	40	4955	0.0002048416
5	50	4375	0.0002346217
6	60	4700	0.0002188333
7	70	4285	0.0002389802
8	80	4190	0.0002386630
9	90	4290	0.0002331000
10	100	3910	0.0002559861

Table 4. Result testing of *crossover rate* and *mutation rate* combination

Crossover rate (*cr*)	Mutation rate (*mr*)	Average cost	Average fitness
0.1	0.9	4550	0.0002398221
0.2	0.8	4285	0.0002398221
0.3	0.7	3945	0.0002593855
0.4	0.6	3955	0.0002586965
0.5	0.5	3910	0.0002639413
0.6	0.4	3925	0.0002627761
0.7	0.3	4070	0.000250042
0.8	0.2	4145	0.0002478912
0.9	0.1	4430	0.0002336377

parameters have an influence on the optimal solution given. Therefore, in this study conducted some tests to get the best parameters of the genetic algorithm of distribution problems with the model of crossover, mutation and selection that has been chosen to give the best solution. The best solution to the stochastic algorithms such as GA is seen by the average fitness to test the stability of the solutions obtained.

4.1 Testing of population size

The size of the population contained in the genetic algorithm is one of the parameters which have an influence on a given solution. The larger the size of the population, the more varied solutions that can be given to the genetic algorithm so the impact on the possibility to get a better solution. In testing the size of the population uses the population size in the range between 10 to 100 by 10 times of execution for each population size. Table 2 shows the test result of population size.

The test results to determine the appropriate size of the population are shown in Table 2. From the results obtained the population is able to provide the best solutions are the size of 100.

4.2 Testing number of generations

By testing the number of generations is expected to get the optimal solution. In general, genetic algorithms provide a better solution if the number of generations is greater. However, in some cases did not affect the number of generations to get a better solution. In this study, testing the number of generations is done by a range between 100 to 1000. The population size used based on the best fitness value of previous tests, 100. The test results of the number of generations are shown in Table 3.

Table 3. Testing result of the number of generations

No	Generation Number	Average cost	Average fitness
1	100	3945	0.0002579337
2	200	4200	0.0002434614
3	300	3685	0.0002761948
4	400	4125	0.0002488171
5	500	4440	0.0002330662
6	600	4105	0.0002478166
7	700	4090	0.0002472525
8	800	4245	0.0002424727
9	900	4190	0.0002484967
10	1000	3910	0.0002559861

The test results to find the right the number of generations are shown in Table 3. From the test results obtained that number of generations with the best fitness value of 300.

4.3 Testing combination of crossover rate (cr) and mutation rate (mr)

Testing combination of cr and mr also used to get a combination that can provide optimal solutions. In this test using the combination of cr and mr between 0.1 to 0.9 for each combination. Population size and the number of generations used by 100 for population size and 300 for generation number based on the best results of the previous test. Table 4 shows the result of the testing combination of *cr* and *mr*.

From the test results combined crossover rate and mutation rate shown in Table 4 obtained that best fitness value when using a combination of 0.5 for crossover rate and 0.5 for mutation rate.

4.4 Result analysis

After testing the parameters of GA, based on the average cost and average fitness obtained best GA parameters shown in Table 5.

The parameters of GA in Table 5 are able to provide near optimal solution to the problem of multi-

Table 5. Result of the best GA parameters

Parameter of GA	Value
Population size	100
Number of generations	300
Crossover rate	0.5
Mutation rate	0.5

stage distribution. Using the same data, solutions using improved genetic algorithm (IGA) is compared to a solution on previous studies that are random search (RS) algorithm as a baseline method and previous version of genetic algorithm (GA) using an extended-intermediate crossover, insertion mutation and elitism selection. A simulated annealing that has been known as popular optimization method is also used as a comparison method.

We focus on comparing the improved GA with the previous version of GA as the GA has been proved as a superior method for complex problems such as the product distribution problem. For example, the GA produced better results than simulated annealing for network design problem that is considered as large-scale optimization problem [26]. A similar finding was also proved in the chemical composition optimization that is considered as a complex problem [27].

The random search (RS) algorithm has two main processes to enable exploiting and exploring the search space of the distribution problem. The first process works by randomly exchange number of items unit transported by any vehicle within a distribution stage. The second process exchange the number of items between two different distribution stages.

The simulated annealing (SA) has three main processes to solve the distribution problem as follows:

- Generating a random initial solution.
- Producing an alternative solution by using two main processes as applied in the RS.
- Applying a function to reduce the probability of accepting a new worse solution. This mechanism enables the SA to escape local optimum areas.

Computational experiments of SA, RS, GA and IGA are performed 10 times and the results are shown in Fig. 2.

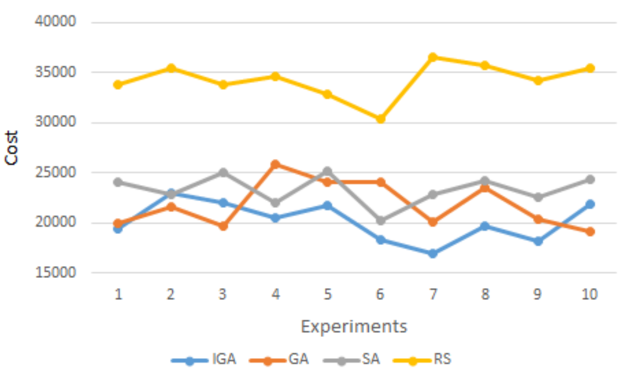

Figure. 2 Comparison cost of all methods

Table 6. Comparison of average cost and fitness

Methods	Average Fitness	Average Cost (Rp)
Improved GA (IGA)	0.000050	20,167.80
Genetic Algorithm (GA)	0.000046	21,860.40
Simulated Annealing (SA)	0.000043	23,354.30
Random Search (RS)	0.000029	34,328.00

Based on the line chart in Fig. 2 it, can be seen that IGA provides superior results (the lower cost) comparable to those achieved by other methods. The random search (RS) as a baseline method gives the worst results (the higher cost). The simulated annealing (SA) has better results than RS but its performance is still bellow than the previous version of GA.

Experiments performed 10 times considering GA and SA are stochastic algorithms that gives different results when executed [25]. Because of the stochastic nature of GA, the results that can be used as a benchmark is the average value. The average fitness and distribution costs of all methods are shown in Table 6.

According to Table 6, the improved genetic algorithm produces better results in the average cost and fitness in comparable to those achieved by the previous version of the genetic algorithm. These results prove that the improvisation of the genetic operators of GA is effective to provide a lower cost of distribution process.

5. Conclusion

Multi-stage distribution problems can be solved using the genetic algorithm with the proposed operator models that are extended-intermediate crossover, the insertion mutation and elitism selection.

To produce a near optimal solution, GA parameter testing performed and resulted in the best parameters GA including the population size of 100, the number of generations 300, and a suitable combination of cr of 0.5 and mr of 0.5.

Using the best parameters GA of the test, the improved GA provides superior results from all methods when viewed from the average cost and fitness obtained. The improved genetic algorithm produces solution with the average cost of Rp 20,167.8, lower than cost of Rp 21,860.4, Rp 23,354.3 and Rp 34,328.0 obtained by original genetic algorithm, simulated annealing, and random search, respectively. For stochastic algorithm such as GA, the average fitness becomes a reference to determine the solution. This describes that the multi-stage distribution problems highly recommended solved using the improved genetic algorithm in combination with the OCP crossover operator, RE mutation, and elitism selection.

Conflicts of Interest

The authors declare no conflict of interest

Author Contributions

Conceptualization, Wayan Firdaus Mahmudy; methodology, Wayan Firdaus Mahmudy and Mohammad Zoqi Sarwani; software, Mohammad Zoqi Sarwani and Asyrofa Rahmi; validation, Wayan Firdaus Mahmudy and Agus Wahyu Widodo; investigation, Wayan Firdaus Mahmudy and Mohammad Zoqi Sarwani; writing—original draft preparation, Mohammad Zoqi Sarwani and Asyrofa Rahmi; writing—review and editing, Wayan Firdaus Mahmudy and Mohammad Zoqi Sarwani.

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References

[1] M. A. M. Ali and Y. H. Sik, "Transportation problem: A special case for linear programing problems in mining engineering", *International Journal of Mining Science and Technology*, Vol. 22, No. 3, pp. 371–377, 2012.

[2] K. Antony Arokia Durai Raj and C. Rajendran, "A genetic algorithm for solving the fixed-charge transportation model: Two-stage problem", *Computers and Operations Research*, Vol. 39, No. 9, pp. 2016–2032, 2012.

[3] F. Ghassemi Tari and Z. Hashemi, "A priority based genetic algorithm for nonlinear transportation costs problems", *Computers & Industrial Engineering*, Vol. 96, No. 1, pp. 86–95, 2016.

[4] R. Nourifar, I. Mahdavi, N. Mahdavi-Amiri, and M. M. Paydar, "Optimizing decentralized production–distribution planning problem in a multi-period supply chain network under uncertainty", *Journal of Industrial Engineering International*, Vol. 14, No. 2, pp. 367–382, 2018.

[5] R. R. P. Langroodi and M. Amiri, "A system dynamics modeling approach for a multi-level, multi-product, multi-region supply chain under demand uncertainty", *Expert Systems with Applications*, Vol. 51, No. 1, pp. 231–244, 2016.

[6] S.-Z. Lou and X.-C. Tian, "Inventory control in a fluctuating demand and return environment", *Control Theory and Applications*, Vol. 32, No. 1, pp. 934–941, 2015.

[7] A. Rahmi, W. F. Mahmudy, and M. Z. Sarwani, "Genetic Algorithms for Optimization of Multi-Level Product Distribution", *International Journal of Artificial Intelligence*, Vol. 18, No. 1, pp. 135–147, 2020.

[8] R. Masson, N. Lahrichi, and L. M. Rousseau, "A two-stage solution method for the annual dairy transportation problem", *European Journal of Operational Research*, Vol. 251, No. 1, pp. 36–43, 2016.

[9] Z. Indra and Subanar, "Optimization of Supply Chain Distribution Costs Three Levels Using Adaptive Genetic Algorithm and Distributed", *Indonesian Journal of Computing and Cybernetics Systems*, Vol. 8, No. 2, pp. 189–200, 2014.

[10] A. Syarif, D. Anggraini, K. Muludi, W. Wamiliana, and M. Gen, "Comparing Various Genetic Algorithm Approaches for Multiple-choice Multi-dimensional Knapsack Problem (mm-KP)", *International Journal of Intelligent Engineering and Systems*, Vol. 13, No. 5, pp. 455–462, 2020.

[11] L. Bertazzi, A. Bosco, and D. Laganà, "Min–Max exact and heuristic policies for a two-echelon supply chain with inventory and transportation procurement decisions", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 93, No. 1, pp. 57–70, 2016.

[12] N. S. Dhakry and P. A. Bangar, "Minimization of Inventory & Transportation Cost Of an Industry" -A Supply Chain Optimization", *International Journal of Engineering Research and Applications*, Vol. 3, No. 5, pp. 96–101, 2013.

[13] S. Rekha, B. Srividhya, and S. Vidya, "Transportation Cost Minimization : Max Min Penalty Approach", *IOSR Journal of Mathematics (IOSR-JM)*, Vol. 10, No. 2, pp. 6–8, 2014.

[14] A. Ebrahimnejad, "A simplified new approach for solving fuzzy transportation problems with generalized trapezoidal fuzzy numbers", *Applied Soft Computing Journal*, Vol. 19, No. 1, pp. 171–176, 2014.

[15] P. Kundu, S. Kar, and M. Maiti, "Fixed charge transportation problem with type-2 fuzzy variables", *Information Sciences*, Vol. 255, No. 1, pp. 170–186, 2014.

[16] J. C. P. Yu, Y. S. Lin, K. J. Wang, and H. M. Wee, "Using AI Approach to Solve an Integrated Three-Echelon Supply Chain Model

with Strategic Alliances", In: *Proc. of First Asian Conf. on Intelligent Information and Database Systems*, Dong Hoi, Vietnam, pp. 259-264, 2009.

[17] İ. Küçükoğlu and N. Öztürk, "Simulated Annealing Approach for Transportation Problem of Cross-docking Network Design", *Procedia - Social and Behavioral Sciences*, Vol. 109, No. 2012, pp. 1180–1184, 2014.

[18] A. Király, T. Varga, and J. Abonyi, "Constrained Particle Swarm Optimization of Supply Chains", Vol. 6, No. 7, pp. 1113–1121, 2012.

[19] Z. Qiongbing, "A New Crossover Mechanism for Genetic Algorithms with Variable-length Chromosomes for Path Optimization Problems", *Expert Systems With Applications*, Vol. 60, No. 1, pp. 183-189, 2016.

[20] M. Thakur and A. Kumar, "Electrical Power and Energy Systems Optimal coordination of directional over current relays using a modified real coded genetic algorithm : A comparative study", *International Journal of Electrical Power and Energy Systems*, Vol. 82, No. 1, pp. 484–495, 2016.

[21] H. Guo, X. Wang, and S. Zhou, "A Transportation Problem with Uncertain Costs and Random Supplies", *International Journal of e-Navigation and Maritime Economy*, Vol. 2, No. 1, pp. 1–11, 2015.

[22] W. F. Mahmudy, R. M. Marian, and L. H. S. Luong, "Hybrid genetic algorithms for multi-period part type selection and machine loading problems in flexible manufacturing system", In: *Proc. of IEEE International Conf. on Computational Intelligence and Cybernetics*, Jakarta, Indonesia, pp. 126-130, 2013.

[23] Z.-Q. Chen and R.-L. Wang, "Solving the m-way graph partitioning problem using a genetic algorithm", *IEEJ Transactions on Electrical and Electronic Engineering*, Vol. 6, No. 5, pp. 483–489, 2011.

[24] R. Jiao, Z. Yang, R. Shi, and B. Lin, "A Multistage Multiobjective Substation Siting and Sizing Model Based on Operator-Repair Genetic Algorithm", *IEEJ Transactions on Electrical and Electronic Engineering*, Vol. 9, No. 1, pp. 28--36, 2014.

[25] V. N. Wijayaningrum and W. F. Mahmudy, "Optimization of ship's route scheduling using genetic algorithm", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 2, No. 1, 2016.

[26] F. Jia and D. Lichti, "A comparison of simulated annealing, genetic algorithm and particle swarm optimization in optimal first-order design of indoor tls networks", *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 4, No. 1, pp. 75–82, 2017.

[27] A. Kerr and K. Mullen, "A comparison of genetic algorithms and simulated annealing in maximizing the thermal conductance of harmonic lattices", *Computational Materials Science*, Vol. 157, No. 1, pp. 31–36, 2019.