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paper text:

An inventory routing problem for deteriorating items with dynamic demand and spoilage rate I Gede Agus Widyadanaa, Krisna Wahyudib, I Nyoman Sutapac Master

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agede@petra.ac.id, bkrisnawahyudi17@gmail.com, cmantapa@petra.ac.id Abstract Inventory routing problems (IRP) are one of an important tool to be used for implementing vendor manage inventory. Many researchers try to develop methods for solving inventory routing problem, however, only a few of them develop methods for inventory routing problems for spoilage items. In reality, many items are deteriorated and spoil during transportation and storage period, but not many papers deal with them since they are hard to be modeled and solved.

15**In this paper, we** develop **a** model and methods **to solve the** inventory routing **problem**

for deteriorating items with dynamic demand and spoilage rate. Demand are varies and items spoil during planning periods. Those cases are more realistic since many commodities such as fruits and vegetables have dynamic demand and spoilage rate. A

3**Genetic Algorithm and Particle Swarm Optimization are** developed **to solve the problem**

with various demands in a specific planning period since the problem in an Np-hard problem. A numerical example and sensitivity analysis are conducted to verify the model and to get management insight into the model. The result is interesting and support general hypothesis that where dynamic demands result in higher inventory cost than static demands and increasing demand result in increasing inventory cost. The results show that increasing demand and deteriorating rates significantly affect the total cost, therefore the developed model is important and significantly useful to be used for solving IRP with dynamic demand and spoilage items. Keywords: Inventory, spoilage, dynamic demand, Genetic Algorithm, Particle Swarm Optimization MSC code: 65K10 INTRODUCTION Inventory Routing Problem deals with inventory and distribution issues since both costs are dominant cost in the supply chain ([4] and [12]), therefore many organizations try to streamline stock holding and transportation expenses. The IRP is an optimization inventory problem for some stores by considering transportation costs. The goal of IRP is transportation and inventory cost minimization [16]. For more than 30 years, many researchers have given attention to the IRP and there are many variations of models and solutions that have been studied [3]. The IRP model includes IRP with the continuous move was introduced by [14]. Aghezzaf and Landeghem [1] developed IRP with multi-tours, and then stochastic demand IRP was introduced by [6] and Liu et.al. [9] developed an IRP model with time windows. Recently many IRP models consider perishable items since perishable items are relevant for some important commodities such as fruits, vegetables, and meats. Perishable items have a random lifetime regarding environmental conditions such as temperature and humidity, the uncertainty of transportation time, and harvest time [8]. Hu et.al. [7] developed a simple IRP for perishable items and they developed decomposition and local search methods as efficient methods for solving the problem. The decomposition and local search is an efficient method, however to get more effective solution, metaheuristic methods can be applied. A Genetic Algorithm is used by [2] to solve an IRP problem with perishable items and single vendor. They extended IRP model by setting transshipment from one store to the other stores. A similar model and method for perishable items was developed by [5], however, they did not consider transshipment between stores. Widyadana and Irohara [15] extended IRP models for perishable items by considering deteriorated items and items are delivered under specific time windows. In the model, items are not only deteriorated during storing period in warehouses but the items are also deteriorating during the transportation period. The model are extended by [11], where they considered multi-objectives by regarding environmental issues in their model instead of one objective only. In this model, we developed an IRP great model developed by [2] and introduce a new model for solving more realistic condition. We use dynamic demand instead of static demand and dynamic spoilage rate since difficult to predict spoilage rate for agriculture commodities such as vegetables, meats and fruits. We develop a model that is more realistic to be applied for agriculture items. The problem is an NP-hard problem; therefore

3**Genetic algorithm and Particle Swarm Optimization are** used **to solve the problem. The**

Genetic Algorithm is one effective method to be used for solving IRP problems ([2] and [5]). The other effective metaheuristic method that is used

15**to solve NP-hard problems such as** IRP **problem**

is Particle Swarm Optimization ([14] and [10]). MODEL DEVELOPMENT We developed the Inventory routing model in this paper using on [2] with dynamic demand and spoilage rate. Some assumptions that are used in this model are: ? Demand rate distribution during the replenishment period (T) is known. ? Deteriorating rate during replenishment period (T) is known In this model we assume there is one product, one vendor and one delivery player with multi- period. Notations that are used in this paper are: Parameters: hi T M : Inventory cost at store I ($) : Replenishment period : Numbers of store di (t) Sri (t) Spi (t) Q cij Ci Pr Ii (0) Variables Li Hi Xij (t) qi (t) : Delivery volume from store i at period t : Deteriorating rate in store i at period t : Number of reject in store i at period t : Delivery capacity (unit) : Delivery cost from store i to store j ($) : warehouse capacity at store i : Product price ($) : Initial stock in store i : Minimum stock in store i : Maximum stock in store i : { 1, $iZ\ llZlZl\ ZZlilZlZZ\ Zlll\ lllZ\ i\ ll\ llllZ\ i$ 0, $llhZllilZ$: Product quantity delivered to store i at period

15**t** $T\ M\ T\ M\ T\ M\ M$

$LilZ= \sum\sum hiHi(l)+Pl \sum\sum Sli(l)+ \sum\sum \sum ZiiXii(l)$ t=1 i=1 t=1 i=1 t=1 i=1 i=i+1 (1) $Hi(l)= Hi(l-1)-Sli(l-1)+ li(l)-$ $Zi($

12l**)** i**=1..**L;l=**1..**S (2) $Sli(l$

) = $Sli(l)Hi(l)$ i = 1 . . L ; l = 1 . . S (3) $Hi(l) \leq Ci$ i = 1 . . L ; l = 1 . . S (4) $Hi(l) \geq Li$ i = 1 . . L ; l = 1 . . S (5) $M \sum$ $li(l) \leq P$ l = 1 . . S i=1 (6) Constraints: $M\ M \sum Xii(l) = \sum Xii($

12l**)** i **= 1 . .** L ; l = **1 . .** S i

=0 i=0 (7) $li(l)= Hi-(Hi(l-1)- Sli($

12l**−1**)− $Zi(l)$**)** i**=1..**L;l=**1**

..S ((81)2) $Xii(l) \in \{0,1\}$ i = 1 . . L ; i = 1 . . L ; $i \neq i$; l = 1 . . S (9) $Sli(l) \in \{0\%, \ldots ,100\%\}$

12i **= 1 . .** L ; l = **1 . .** S (10) S, L

∈ {0, 1, 2, 3, … } (11) $hi,Zi(l),P,Ci,Hi(l),Li,Li,li(l) \geq 0$ (12) The objective function is shown in Eq. 1, where the total cost consist of inventory cost, reject cost and delivery cost. Equations 2 to 12 show the model constraints. Stock quantity in period t depend on quantity of stock from previous period, number of rejected stock, incoming and outgoing product (Eq. 2). Eq. 3 shows rejected quantity is equal to rejected rate times quantity of stock. Maximum stock quantity every period cannot overcome store capacity (eq. 4). Stock quantity in every store every period must be bigger than minimum stock (5). Delivery quantity of each vendor is equal to capacity delivery to all store (6). Whenever there is delivery from i to j, then the vehicle will outbound from j (7). Eq. 8 shows delivery quantity when number of stock less than the maximum stock. Genetic Algorithm Genetic algorithm used in this paper is a simple GA with: a. Chromosome representation Chromosome represents three variables which are minimum stock, maximum stock, and routing for each period. Minimum and maximum stocks are represented using integer values as shown in Figure 1. Notation for the minimum stock is Li and the maximum stock is Mi. Figure 1. Minimum and maximum stock chromosome The third variable is delivery routing for each period. A chromosome is represented by integer values that show the sequence of the store that are visited by the vehicle. When one store is not visited due to enough stock, then the chromosome is represented by zero (0). Chromosome for vehicle routing can be seen in Figure 2. Figure 2. Chromosome representation for vehicle routing b. Fitness function and selection The GA fitness function is derived from equation 1 and parents selection is using roulette wheel rule where chromosome with less fitness value has a higher possibility to be chosen as parents. c. Crossover The Crossover method that is used in this paper is a one-point crossover. d. Mutation The Mutation process is done inside of one chromosome where each cell has 40% possibility to be mutated. When a cell is chosen to be mutated, it changes randomly between a specific minimum and maximum values. e. Elitism Elitism is a process to keep the best chromosome in each generation automatically become an offspring in the next generation. f. Stopping criteria Stopping criteria set the GA method to be stopped. In this paper stopping criteria is using a predetermined number of generations. Particle Swarm Optimization Particle Swarm Optimization algorithm works as particles move together to follow the positions that have been found so far. Some important things that have to be set up to get good PSO are particle representation, position, velocity, fitness function, global best, and local best. a. Particle representation Particle representation for minimum and maximum stock is similar to chromosome representation in GA, however, vehicle routing representation is different. PSO uses float values instead of the sequence as shown in GA. Particle representation for vehicle routing is shown in Figure 3. The sequence of the vehicle will follow the particle from the lowest to the highest values where value 0 shows that the retail is not visited at that period. For example route for the vehicle in period one in Figure 3 is from the vendor to stores 4-2-5 and return to vendor. Figure 3. Particle representation of vehicle routing b. Particle velocity Particle velocity will be updated at every iteration to move every particle closer to the best particle in local and global position. The velocity for each particle can be updated using equation 12. $lii+1 = llii + Z1lZlZ1 \times (lZZlli - lii) + Z2lZlZ2 \times (ZZZll - lii)$ (12) Where the gbest is the best particle position for all previous iteration and pbest is the position of a particle from the previous iteration. c. Particle position The later position of each particle is moved with his velocity as shown in equation 13.Particle position Later position of each particle is moved with his own velocity as shown in equation 13. $lii+1 = lii + lii+1$ (13) d. Fitness value The fitness value is similar to the GA fitness value, where the fitness value is derived from equation 1. e. The best solution and stopping criteria The best solution is derived form the best solution from the last iteration where the number of iteration is determined at advanced. A NUMERICAL EXAMPLE AND RESULT The numerical example uses the main data from data generation. There are two types of demand, the first case is dynamic demand and the second case is static demand. Demand data is generated uniformly from 20-60. The other data such as distance, inventory cost, warehouse capacity at each store, initial stock, delivery capacity, and product price are generated consecutively 10, 5, uniform [20 - 50], uniform [10 - 25], uniform [60 - 100], uniform [60 - 100], 750, and 40. we use PSO to get management insight of static and dynamic demand. that the PSO outperforms GA in terms of the best fitness value and computation time, therefore The best solution for case 1 and case 2 for GA and PSO are shown in Table 1. The table shows Figure 5. The PSO best fitness value for case 1 with 250 Iteration and 140 population Fitnes Value ($) 43000 48000 53000 58000 63000 0 14 28 42 56 Best Fitness Value 70 84 Iteration 98 112 126 140 154 168 182 196 210 224 238 initial solution. the best fitness value has been convergent. The best fitness value of PSO is 32.14% better than the values convergent is 198 iteration, therefore we set the number of iteration is 250 to guarantee that case 1 is shown in Figure 5. The solutions show that the longest iteration for getting the best fitness solution for case 1 is derived from 250 iterations and 140 population. The best fitness values for For the PSO there are 32 combinations of the population (P), iteration (G), and cases. The best solution. initial fitness value. Therefore the GA result in significant improvement compares to the initial to guarantee that the solution has been convergent and the best solution is 18.65% less than the the solutions convergent at the 200th generation. We set the number of generations is equal to 250 Figure 4 shows that the GA is not trapped to local optimal easily. The two cases show that at least Figure 4. The best fitness value for case 2 with 250 Iteration and 140 population Best Fitness Value Iteration Fitness Value ($) 40000 45000 50000 0 11 22 33 44 55 66 77 88 99 110 121 132 143 154 165 176 187 198 209 220 231 242 Genetic Algorithm for both cases. The best fitness function for case 2 is shown in Figure 4. We set varies of population size and the number of iterations to get the best parameter for the Table 1. The optimal values and running time of GA and PSO Optimal Cost ($) Running Time (S) GA PSO GA PSO Case 1 45123 44296.6 3311 2850 Case 2 41297.2 41058.6 3281 2659 Table 2 shows a comparison between case 1 with dynamic demand and case 2 with static demand. The table shows that dynamic static has less inventory cost but higher spoilage cost and delivery cost, however, the spoilage and delivery cost is not significantly. Case 1 has a higher cost than case 2 since stores have to keep more stocks to prevent lost sales. The dynamic demand results in a 9.1% higher inventory cost than static demand. Therefore, important for organizations to keep demand as stable as possible in each period to reduce inventory cost. Table 2. Fitness values for case 1 and case 2 Case 1 Case 2 Holding cost Spoilage Cost Transportation Cost Penalty Cost Total cost $ 35362.6 Holding cost $ 8032.0 Spoilage Cost $ 737.8 Transportation Cost $ 0.0 Penalty Cost $ 44132.4 Total cost $ $ $ $ $ 32421.4 8096.0 795.0 0.0 41312.4 A sensitivity analysis is used to evaluate the effect of spoilage rate to the total cost. We use spoilage rate 5%, 7%, and 9% and keep all parameters at the same values. The sensitivity analysis result is shown in Table 3.

Table 3. Fitness values for varies of spoilage rate Spoilage Rate 5% Spoilage Rate 7% Spoilage Rate 9% Holding cost $ 23382.4 Holding cost $ 24292.0 Holding cost $ 25069.6 Spoilage Cost $ 3840.0 Spoilage Cost $ 4824.0 Spoilage Cost $ 5376.0 Transportation $ 808.0 Transportation $ 902.0 Transportation $ 699.0 Cost Cost Cost Total cost $ 28030.4 Total cost $ 30028.0 Total cost $ 31144.6 Table 3 shows an increasing 2% spoilage rate form 5% to 7% result in increasing holding costs from 3% to 4%, and increasing the total cost from 3.7% to 7.2%. It shows that the spoilage rate significantly affect holding cost and spoilage cost, therefore this model is suitable to be used for items with high spoilage cost such as vegetables, fruits, and meats. For the set parameter values determined in this numerical example, the holding cost is the highest cost for the fitness values. This model shows that spoilage rate has high contribution to the total cost, therefore management has to keep spoilage rate as low as possible. Tools or machines for keeping low spoilage rate and variation such as refrigerator, refrigeration truck, vacuum packaging and drying machine are important to be applied for all business related with spoilage items. This finding is useful to support decisions and strategies for some business in countries like Indonesia where managements resistance to invest in machines and technologies. They think total inventory cost for spoilage items are not too significant compare investment cost. CONCLUSION Inventory routing problem is one important model to be used in the vendor manage inventory scheme, where the vendor delivers and keeps his stock to some retail stores. In this paper, an IRP for spoilage items is developed since spoilage items such as fruits and vegetables are common and reality. Instead of considering static demand, this paper considers dynamic demand. The model is an NP-hard problem therefore

3**Genetic Algorithm and Particle Swarm Optimization are** developed **to solve the problem**

. Both methods are effective to solve IRP problems. A numerical example is used to compare the performance of both methods. The results show that the PSO outperforms

3**GA in terms of solution quality and** computation **time** and **the**

total cost for dynamic demand is 9% higher than the total cost of static demand. A sensitivity analysis is conducted to analyst the effect of spoilage rate to the total cost. The sensitivity analysis shows that the spoilage rate significantly affects the total cost. The numerical example and sensitivity analysis show that this model is very important to be used to handle spoilage items and dynamic demand. Increasing of spoilage rate is significantly affect total inventory cost, therefore it is important for business to invest in some tools or machine too keep low spoilage rate and variation. Savings on inventory cost could be higher than machines investment cost on plausible time. This paper assumes that there is no transshipment between stores, therefore the next research can consider transshipment since transshipment is common to be used by some retail stores to reduce costs. The other future research by considering environmental issues for delivering items.

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