A Single Side Priority Based GA Approach for 3D Printing Center Integration to Spare Part Supply Chain in Automotive Industry

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Abstract: Developments in manufacturing technologies and new opportunities lead to reconsider the design of the spare part supply chains. In this paper, 3D printing technology, which is one of the most critical applications of industry 4.0 has been studied for examining new opportunities. Manufacturing facilities, 3D printing centers, warehouses, distribution centers have been taken into account in supply chain. Quantity of products, timing, technology to be used, assigned facility, investments and warehouse for product storage are considered as decision variables. The output of this study is to propose a mathematical model that minimizes the sum of production, distribution, and inventory holding costs. The main constraints of the model are the capacity of the manufacturing facilities & 3D printing centers, warehouse areas, and demands. Inventory holding cost, unit transportation cost, production time and cost, needed space, distances between facilities, transportation time, bill of materials, demand in periods, and investment cost parameters have been used in a mathematical model and reached the optimum solution with branch and bound algorithm. Because of the nature of the problem, solution time takes longer when the problem size is larger. Therefore, in this paper, a unique Single Side Priority Based Algorithm (SSPBA) has been developed in genetic algorithm approach to find near optimum results.

Keywords: genetic algorithm; industry 4.0; spare part supply chain; 3D printing

1 INTRODUCTION

In 2017, the automotive sector accounted for about 5% of the world economy [1]. Again, according to 2017 data, 97 million vehicles were produced in the world. Approximately 1 250 000,000 vehicles are considered to be in use today [2]. High vehicle demand gives employment opportunity for millions of people in the world, clearly demonstrates the importance of the sector in different aspect. In the automotive sector, it has been revealed that after sales revenues have a significant effect on the company profits. In 2001, it was found that General Motors' profit after sales of $ 9 billion was more than the profit from regular vehicle sales (150 billion dollars) [3]. This shows how the spare parts in the automotive sector have an impact on operating profitability and sustainability. Also, the surveys revealed that approximately 23% of the spare parts remained without sales, and on time delivery performance is 85% [4]. This data allows us to think that effective spare part supply chain management can have a positive impact on the company's annual profits and create a competitive advantage.

The organization of production and post-production activities is crucial for the continuity of this system. The breadth and diversity of the customer and service network, high and increasing vehicle demand, and developing manufacturing technologies show that the spare part supply chain should be reconsidered. In this study, a unique solution methodology will be introduced in the spare parts production and distribution network design.

1.1 Literature Review

In order to understand new trends and past studies in spare part logistics, papers, and thesis on distribution systems and spare part logistics have been searched. Most of the proposed solutions in those fields include mathematical models. Emerging technologies such as 3D printers, industry 4.0 components lead to think about new perspectives in the supply chain. It has been seen that there are studies related to additive manufacturing technics and

applications in different fields, but there were limited studies on integration to supply chain.

An efficient 3D printed part ordering system has been presented. In the study, a cloud-based platform is used for analysing geometry of the part, preparing quotation, additive manufacturing and delivering the part [5]. The study is promising for advance industry 4.0 implementations.

Additive manufacturing has a positive effect of lead time reduction as well. It is reported that the 14-day period could be reduced to 3 days if the electronic components were repaired by the additive production method. Models of current and future situations are shared. Besides, a real case analysis was performed, and images were presented [6, 7].

Silva and Rezende evaluated the possible impact of additive production and 3D printers on production and their logistics. It was recommended to use the 3D printer to make prototypes, or for low volume production, instead of material movement, sending technical details will provide cost advantage in health industry. It was also mentioned that it would be more beneficial to carry out logistic activities without being exposed to environmental and restrictive procedures [8].

It has been stated that spare parts could be produced by means of rapid manufacturing techniques. In the study, production locations, storage areas, service points are shown in a network but it is limited. Although it is known that rapid manufacturing techniques allow for the production of spare parts, integrated supply chain work has not been done, and mathematical model has not been included to this work [9]

When the model size gets bigger, the elapsed time for the solution matters. In order to decrease solution time still having consistent results, there are many heuristic approaches that have been proposed in supply chain problems. One of them is the genetic algorithm (GA), which is used in this paper as well.

A heuristic approach based on a single-period, single-source, multi-product, multi-stage supply chain design problem has been proposed. In the model suggested, it is

not possible to see how the cost matrix has been created, its single period, and there is no backlog. In these conditions, it can be clearly seen that GA has the best performance indicators among heuristic methods in that study [10].

For new product development and management of the absolute inventory, a study has been published. In the paper, a priority-based algorithm has been implemented for small, medium, and large scales. The model is solved with Lingo and GA, and performance has been compared in order to overcome NP-hardness [11].

A mixed-integer linear programming (MILP) model is proposed for a multi-product four-stage flexible supply chain network design (SCND). This paper shows that GA is a useful tool when there is no other delivery mode in the supply chain [12].

After the literature search, it has been seen that there are combined studies in fields of the distribution systems & supply chains. There are also many studies using optimization technics such as mixed-integer programming and heuristics like genetic algorithms. However, we could not see any study that includes material planning, comparisons of emerging production methods such as 3D printing & conventional production systems, allocation of goods production, and storage possibilities in different facilities to minimize the total cost of operations in the automotive industry.

2 MODEL STUDY

Performance expectations from an excellent spare part supply chain in summary; 98% customer demand coverage (average 93%), 6 to 8 times inventory cycle per year (average 3-4), fulfil the order with 95% performance in a day or less than a day (average 3-5 days) and logistics costs (outbound and storage) not exceeding 5% of the selling price (average 8%) [13]. So that:
• In order not to lose the market share, the products must be ready in the required amount to respond to customer demand.
• Orders must be answered very quickly to ensure customer satisfaction.
• Shipment and storage costs should be minimized while the above items are met. A mathematical model has been developed with constraints, variables, and parameters in order to design a network that can provide improvements in these essential areas.

The automotive spare part supply chain starts with raw material producers and reaches to end-users with having various production centers, warehouses, and distribution centers. As can be seen in Figure 1, the model to be studied will be between additive manufacturing centers and distribution centers.

2.1 Mathematical Model

The notation, objective function, and constraints used in the developed model are given below. Seven sets used in the model:

Sets:
A: Set of additive manufacturing centers

I : Set of manufacturing centers

S : Set of warehouses

K : Set of distribution centers

J : Set of finished goods

Y : Set of semi-finished goods

T : Set of periods

The used parameters in the mathematical model are shown below.

Parameters:

$INV1_{JIT}$: Quantity of finished good "j" in manufacturing center "i" in t period

$INV2_{YIT}$: Quantity of semi-finished good "y" in manufacturing center "i" in t period

$INV3_{YAT}$: Quantity of semi-finished good "y" in the additive manufacturing center "a" in t period

$INV4_{JST}$: Quantity of finished good "j" in warehouse "s" in t period

$INV5_{YST}$: Quantity of semi-finished good "y" in warehouse "s" in t period

$CP1_I$: Production cost in manufacturing center "i"

$CP2_A$: Production cost in additive manufacturing center "a"

$CTRF_J$: Unit transportation cost of finished good "j"

$CTRS_Y$: Unit transportation cost of semi-finished good "y"

$CFXM_I$: Cost of opening a manufacturing center "i"

$CFXP_A$: Cost of opening an additive manufacturing center "a"

$CFXW_S$: Cost of opening a warehouse "s"

$CAPM_{IT}$: Capacity of manufacturing center "i" in t period

$CAPA_{AT}$: Capacity of additive manufacturing center "a" in t period

$CAPW_{ST}$: Capacity of warehouse "s" in t period

DEM_{JKT} : Demand of finished good "j" for distribution center "k" in t period

$TIMF_{JI}$: Production time of finished good "j" in manufacturing center "i"

$TIM1_{YI}$: Production time of semi-finished good "y" in manufacturing center "i"

$TIM2_{YA}$: Production time of semi-finished good "y" in additive manufacturing center "a"

$SPAF_J$: Needed space for finished good "j"

$SPAS_Y$: Needed space for semi-finished good "y"

$CIH1_I$: Inventory holding cost for manufacturing center "i"

$CIH2_A$: Inventory holding cost for the additive manufacturing center "a"

$CIH3_S$: Inventory holding cost in warehouse "s"

$DISl_{IS}$: Distance between manufacturing center "i" and warehouse "s"

$DIS2_{AI}$: Distance between additive manufacturing center "a" and manufacturing center "i"

$DIS3_{SK}$: Distance between warehouse "s" and distribution center "k"

$LT1_{IS}$: Lead time from manufacturing center "i" to warehouse "s"

$LT2_{AI}$: Lead time from additive manufacturing center "a" to manufacturing center "i"

$LT3_{SK}$: Lead time from warehouse "s" to distribution center "k"

BOM_{JY} : Needed quantity of semi-finished good "y" for finished good "j"

The variables of the model given below are related with the produced quantities, transported quantities, and opened facilities.

Variables:

XPF_{IJT}: Production quantity of finished good "j" in manufacturing center "i" in period "t"

$XPSl_{IYT}$: Production quantity of semi-finished good "y" produced in manufacturing center "i" in period "t"

$XPS2_{AYT}$: Production quantity of semi-finished good "y" produced in additi

$XLOG1_{JSKT}$: Transportation quantity of finished good "j" from warehouse "s" to distribution center "k" in period "t"

$XLOG2_{YAIT}$: Transportation quantity of semi finished good "y" from add. man. center "a" to manufacturing center "i" in period "t"

$XLOG3_{YIST}$: Transportation quantity of semi finished good "y" from manufacturing center "i" to warehouse "s" in period "t"

$XLOG4_{JIST}$: Transportation quantity of finished good "j" from manufacturing center "i" to warehouse "s" in t period

$XLOG5_{YSIT}$: Transportation quantity of semi-finished good "y" from warehouse "s" to manufacturing center "i" in t period

OPM_I: If the manufacturing center i is opened 1, otherwise 0

OPA_A: If the additive manufacturing center is opened 1, otherwise 0

OPW_S: If the warehouse s is opened 1, otherwise 0
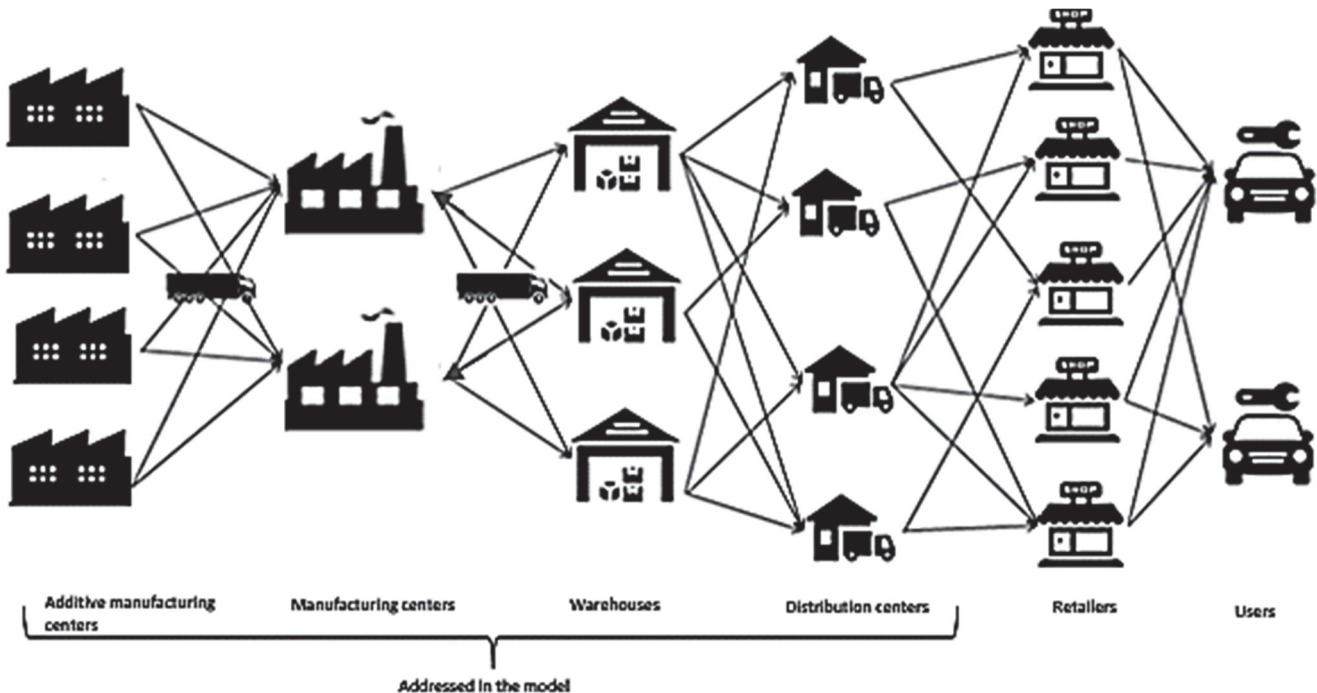
Figure 1 Spare parts distribution network

Objective function:
Min. Prod. cost + Tran. cost + Inv hold. cost + + Investing cost (1)

$$\text{Prod. cost} = \left(CP1_I \times TIMF_{JI} \times XPF_{IJT} \right) + \\ + (CP1_I \times TIM1_{YI} \times XPSl_{IYT}) + \\ + (CP2_A \times TIM2_{YA} \times XPS2_{AYT})$$ (2)

$$\text{Tran. cost} = \left(DISl_{IS} \times XLOG4_{JIST} \times CTRF_J \right) + \\ \left(DIS2_{AI} \times XLOG2_{YAIT} \times CTRS_Y \right) + \\ + \left(DIS3_{SK} \times XLOG1_{JSKT} \times CTRF_J \right) + \\ + \left(DISl_{IS} \times CTRS_Y \times \left(XLOG3_{YIST} + XLOG5_{YSIT} \right) \right)$$ (3)

Inv hold. cost =

$$\begin{aligned} &\left(CIH1_I\left(INV1_{JIT}\times SPAF_J + INV2_{YIT}\times SPAS_Y\right)\right)+ \\ &+\left(CIH2_A \times INV3_{YAT}\times SPAS_Y\right)+ \\ &+\left(CIH3_S \times\left(INV4_{JST}\times SPAF_J + INV5_{YST}\times SPAS_Y\right)\right) \end{aligned} \quad (4)$$

$$\begin{aligned} Investing\ cost =&\left(CFXM_I \times OPM_I\right)+ \\ &+\left(CFXP_A \times OPA_A\right)+\left(CFXW_S \times OPW_S\right) \end{aligned} \quad (5)$$

Constraints:

$$INV1_{JIT} = INV1_{JIT-1} + XPF_{IJT} - \sum_1^s XLOG4_{JIST}, \ \forall j,i,t \quad (6)$$

$$\begin{aligned} INV2_{YIT} =\ & INV2_{YIT-1} + XPS1_{YIT} - \sum_1^s XLOG3_{YIST} - \\ &-\sum_1^j\left(XPF_{IJT}\times BOM_{JY}\right)+\sum_1^s XLOG5_{YSIT-LT1_{IS}} + \\ &+\sum_1^a XLOG2_{YAIT+LT2_{AI}}, \ \forall y,i,t \end{aligned} \quad (7)$$

$$\begin{aligned} INV3_{YAT} = & INV3_{YAT-1} + XPS2_{YAT} - \\ &-\sum_1^i XLOG2_{YAIT}, \ \forall y,a,t \end{aligned} \quad (8)$$

$$\begin{aligned} INV4_{JST} = & INV4_{JST-1} + \sum_1^i XLOG4_{JIST-LT1_{IS}} - \\ &-\sum_1^k XLOG1_{JSKT}, \ \forall j,s,t \end{aligned} \quad (9)$$

$$\begin{aligned} INV5_{YST} = & INV5_{YST-1} + \sum_1^i XLOG3_{YIST-LT1_{IS}} - \\ &-\sum_1^i XLOG5_{YSIT}, \ \forall y,s,t \end{aligned} \quad (10)$$

$$DEM_{JKT} \le \sum_1^s XLOG1_{JSKT-LT3_{SK}}, \ \forall j,k,t \quad (11)$$

$$\left(CAPM_{IT}\times OPM_I\right) \ge \left(\begin{aligned} &\sum_1^j\left(XPF_{IJT}\times TIMF_{JI}\right)+ \\ &+\sum_1^y\left(XPS1_{IYT}\times TIM1_{YI}\right) \end{aligned}\right), \ \forall i,t \quad (12)$$

$$\left(CAPW_{ST}\times OPW_S\right) \ge \left(\begin{aligned} &\sum_1^j\left(INV4_{JST}\times SPAF_J\right)+ \\ &+\sum_1^y\left(INV5_{YST}\times SPAS_Y\right) \end{aligned}\right), \ \forall s,t \quad (13)$$

$$\left(CAPA_{AT}\times OPA_A\right) \ge \sum_1^y\left(XPS2_{AYT}\times TIM2_{YA}\right), \ \forall a,t \quad (14)$$

$$OPM_I, OPA_A, OPW_S \in\{0,1\} \quad (15)$$

The first five (1-5) of the above equations are related to the objective function and components of the model. Subsequent equations are constraints, (6) total inventory equilibrium in the production plant, (7) total inventory equilibrium in the production plant, (8) total inventory equilibrium in the additive production facility, (9) equality of finished product inventory held in warehouse, (10) equality of the semi-inventory kept in the warehouse, (11) limitation of the demand, (12) production capacity constraint of manufacturing centers, (13) warehouse space constraint, (14) production capacity constraint of additive Manufacturing centers, decision to open or not to open facilities (15) 0-1 constraint.

3 APPLICATION OF THE MODEL

The sample network in the implementation of the model is shown in Fig. 2. In this lay-out, distribution centers, warehouses, manufacturing centers and additive manufacturing centers are demonstrated considering their approximate locations on the map. The mathematical model is used for designing the supply chain to meet customer demands on time, in order to minimize total operational costs under constraints which are shown in Section 2.1.

Figure 2 Location of manufacturing center, additive manufacturing center, warehouse and distribution centers

3.1 Gathering the Model Data

The data has been taken from a company operating in the automotive supply chain and the model is inspired by its current operations. Parameters related to the model, such as distances, product types, are also introduced in this section. Distances between facilities have been summarized in Tab. 1, the bill of materials has been summarized in Tab. 2.

Table 1 Distances between facilities

$DIS1_{IS}$	1	2	3	$DIS2_{AI}$	1	2	3	$DIS3_{SK}$	1	2	3
1	4	13	7,5	1	2	10,5	11	1	3,5	3,5	15
2	8	5,5	9	2	11,5	7	2	2	11	6	5,5
3	9	5,5	4,5	3	9	9	2,5	3	5	4,55	11,5

Table 2 Quantities of semi-finished parts per products

BOM_{JY}	1	2	3	4	5
1	1	1	1	0	0
2	1	1	0	0	0
3	0	0	1	1	1

The data belonging to parameters described under Section 2.1 are shown in Tab. 3 to Tab. 10. Process data are in minutes; demand values are in quantities, area data are in square meter, the currency is taken as Euro.

Table 3 Weekly demands for products

DEM_{JKT}	1	2	3	4	5	6
K:1	0	0	1500	2000	500	2000
K:1	0	0	1000	1000	1000	1000
K:1	0	0	1000	2000	2000	2000
K:2	0	0	2000	3000	1000	3000
K:2	0	0	1000	2000	500	2000
K:2	0	0	1000	3000	1000	3000
K:3	0	0	500	1000	1000	1000
K:3	0	0	2000	1000	1000	1000
K:3	0	0	1000	1000	1000	1000

Table 4 Plant capacities

$CAPM_{IT}$	20000	8000	2000
$CAPW_{ST}$	5000	15000	5000
$CAPA_{AT}$	400	800	1000

Table 5 Investment cost

$CFXM_I$	10000	2000	8000
$CFXP_A$	200	100	100
$CFXW_S$	7000	1000	2000

Table 6 Inventory holding cost

$CIH1_I$	2
$CIH2_A$	50000
$CIH3_S$	1

Table 7 Finished product and semi-finished production cycle times

$TIM1_{YI}$	0,1	0,2	0,1	11	0,3
$TIM2_{YA}$	1	2	1	1	3
$TIM3_{JI}$	1	0,5	1	-	-

Table 8 Shipping costs per piece

$CTRS_Y$	0,1	0,2	0,1	0,1	0,3
$CTRF_J$	2	1	3	-	-

Table 9 Unit production costs in facilities

$CP1_I$	10	5	7
$CP2_A$	7	5	5

Table 10 Areas covered by products

$SPAS_Y$	0,1	0,2	0,1	0,1	0,3
$SPAF_J$	2	1	3	-	-

Fig. 3 shows the connections between semi-finished goods and finished goods, which are inspired by their drawings. For example, finished good 1 is constituted from semi-finished goods 1, 2, and 3.

Figure 3 2D illustration finished products and semi-finished products

Table 11 Stage-1 in sub-chromosome

3.2 Alternative Solution Method

The introduced integrated model for the proposed supply chain network is a mixed-integer programming model with several constraints. Solving these models in a reasonable time, especially in real-world instances, is the main challenge in most researches. When the model size is getting larger, it is hard to solve with applying exact solution algorithms. In this paper, we propose to use a genetic algorithm (GA) solution method to reach near optimum results.

3.2.1 Representation of GA Approach

One of the earliest and simplest representations has been made by G. A. Vignaux and Z. Michalewicz considering a genetic algorithm for the linear transportation problem [14]. They used edge-based encoding and binary system for assignments [10]. In both studies, total facility capacities and demand are equal. If there is a deviation, it is covered by a dummy facility or demand, which is different from the model we propose. In order not to use dummy facility or demand, there is

supposed to be a backlog in the supply chain when there is more than one period if total capacity is sufficient to cover whole demand in the supply chain. In our study, there is no priority for customer demand satisfying; both of them have the top priority equally, which is different from other studies. Another difference, using zeros for genes on the left section of the sub-chromosomes, which helps the algorithm to find the possible lowest cost for the customer in case of demand & capacity inequality. The mentioned supply chain design in the previous section must be eligible to use genetic algorithm, so that it needs to be converted to a transportation tree in this specific case. Because there is more than one possible place to produce semi-finished goods, this is why M1, M2, and M3 are shared for both stages, and their capacities need to be updated in each iteration. The converted supply chain illustration can be seen in Fig. 4.

The sub-chromosome for one period consists of three stages in this case, which can be seen in Tab. 11, Tab. 12, and Tab. 13. So that the whole sub-chromosome can be multiplied for six periods.

Figure 4 Transportation tree for GA

Table 12 Stage-2 in sub-chromosome

t=6	STAGE-2																
J	FG 1						FG 2						FG 3					
I,S	Plant			Warehouse			Plant			Warehouse			Plant			Warehouse		
#	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
R	0	0	0	2	3	1	0	0	0	4	6	5	0	0	0	9	8	7

Table 13 Stage-3 in sub-chromosome

t=6	STAGE-3																
J	FG 1						FG 2						FG 3					
S,K	Warehouse			D.Center			Warehouse			D.Center			Warehouse			D.Center		
#	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
R	0	0	0	2	1	3	0	0	0	4	6	5	0	0	0	7	9	8

The length of the sub-chromosome is equal to the sum of Stage-1 $|Y| \cdot (|A| + |I|)$, Stage-2 $|J| \cdot (|I| + |S|)$ and Stage-3 $|J| \cdot (|S| + |K|)$. And the whole chromosome's length can be formulated as $|T| \cdot (|Y| \cdot (|A| + |I|) + |J| \cdot (|I| + |S|) + |J| \cdot (|S| + |K|))$.

To implement an encoding & decoding methodology, the cost calculation for each allocation becomes essential. The cost matrix needs to be accurate to find out the best matches. The best and most suitable matches in cost matrix help to minimize total cost. Cost matrix can be calculated in different ways if there is a certain break-even point when there are fixed costs. In our case, the volume is quite enough to distribute fixed costs among the demanded parts. So that total costs must be calculated, including fixed and variable costs, which are derived from parameters given. The cost matrix for each stage can be seen in Tab. 14, Tab. 15, and Tab. 16.

Table 14 Cost matrix between add.mancenters and manufacturing centers

I-A	1	2	3	4	5	6
1	10,1	17,0	19,2	12,3	18,8	16,3
2	22,1	5,0	16,4	20,8	14,3	16,3
3	21,6	13,7	7,7	21,3	9,3	9,8

Table 15 Cost matrix between manufacturing centers and warehouses

I-S	1	2	3
1	14,1	23,1	17,6
2	13,0	10,5	14,0
3	16,7	13,2	12,2

Table 16 Cost matrix between warehouses and distribution centers

S-K	1	2	3
1	3,7	3,7	15,2
2	11,0	6,0	5,5
3	5,1	4,6	11,6

3.2.2 Single Side Priority Based Algorithm

Priority based decoding algorithm is used for defining the allocations between depots and sources for one period when capacity and demand are equal in each echelon [11].

The same method can be seen in a genetic algorithm application for supply chain configuration with new product development [15]. In both papers, because of no restriction with periods and backlog coverage, priority based encoding & decoding algorithm enables initialization from any point of the arc in the transportation tree. But that can be criticized, in real cases in the automotive industry, backlog needs to be considered, and capacity needs to be managed for the whole time horizon which is ideally three months, in order to put action plans in place. To adapt priority based encoding & decoding methodology into this form of supply chain, demand and backlog can be managed from a single side when allocations are done to minimize solution time. So, we propose a different solution system that is triggered by the demand to find the best supplier for itself in each iteration. And we call this algorithm Single Side Priority Based Algorithm, shortly SSPBA. General solving procedure and of sub-procedures can be seen in Fig. 5, Fig. 6, Fig. 7, and Fig. 8.

```
General Solving Procedure: Main steps in one epoch
1:  Generate all chromosomes according to population size
2:  For Epoch 1 to 50
3:      For chromosome 1 to 100
4:          For t=T to 1
5:          Apply procedure 1, calculate stage 1 value
6:          Apply procedure 2, calculate stage 2 value
7:          Apply procedure 3, calculate stage 3 value
8:      Calculate the value of the objective function
9:      Sort chromosomes according to fitness, do selection
10:     Apply crossover process
11:     Apply mutation process
12:     Finalize new population for next epoch
13: End
```

Figure 5 Decoding of SSPBA for multi-period & product

```
Prodecure 1: Decoding of the stage 3
Input: Demand, capacity, sub-chromosome, M(very big value)
Output: Amount of product shipped to DC
1:  Find max. random value(R) for distributers
2:  Use cost matrix to find most suitable warehouse
3:  Assign XLOG1_JSKT, min(CAPW_ST, DEM_JKT)
4:  Update CAPW_ST, DEM_JKT
5:  If demand is satisfied, R value=0
6:  If there is no capacity/demand left for any, put M into related
    cost matrix items to avoid mismatches in next iteration
7:  If total ∑DEM_JKT>∑CAPW_ST, assign backlog
8:  Add backlog to DEM_JKT-1
9:  Calculate the cost
10: End
```

Figure 6 Procedure 1

```
Procedure 2: Decoding of the stage 2
Input: Demand, capacity, sub-chromosome, M(very big value)
Output: Amount of product shipped to WH
1:  Find max. random value(R) for warehouses
2:  Use cost matrix to find most suitable manufacturing center
3:  Assign XLOG4_JIST, min(CAPM_IT, DEM_JST)
4:  Update CAPM_IT, DEM_JST
5:  If demand is satisfied, R value=0
6:  If there is no capacity/demand left for any, put M into related
    cost matrix items to avoid mismatches in next iteration
7:  If total ∑DEM_JST>∑CAPM_IT, assign backlog
8:  Add backlog to DEM_JST-1
9:  Calculate the cost
10: End
```

Figure 7 Procedure 2

```
Procedure 3: Decoding of the stage 1
Input: Demand, capacity, sub-chromosome, M(very big value)
Output: Amount of semi-finished good shipped to MC
1:  Find max. random value(R) for manufacturing centers
2:  Use cost matrix to find best additiveman.&manufacturing center
3:  Assign XLOG3_YIST, min. (∑DEM_YIT, ∑(CAPM_IT + CAPA_AT))
4:  Update ∑(CAPM_IT + CAPA_AT), ∑DEM_YIT
5:  If demand is satisfied, R value=0
6:  If there is no capacity/demand left for any, put M into related
    cost matrix items to avoid mismatches in next iteration
7:  If ∑DEM_YIT>∑(CAPM_IT + CAPA_AT), assign backlog
8:  Add backlog to DEM_YIT-1
9:  Calculate the cost
10: End
```

Figure 8 Procedure 3

3.2.3 Solution Procedure

Initial Population is randomly created in the proposed model. Various initializations can be seen in papers if the idea cuts solution time relatively depending on the problem. Size and initializations need to be tailored for the problems. In our work, the population is consisting of 100 individuals and the size remains the same through iterations.

Fitness Function gives tracking and progressing opportunities for better results in heuristic approaches. It can be either targeted for cost reduction/minimization or profit maximization. In GA, when the initial population is created, chromosomes are calculated as designed in the math model to see which parents are most adaptive in its environment and eligible for the creation of the next generation. In our case, the algorithm is looking to minimize the total cost of the chain. So, chromosomes that are creating the lowest costs in fitness function tend to carry on their genes for the next generations.

The Selection process directly effects solution time in GA. Once the initial population is created, the quality of the chromosome needs to be checked with fitness function and sorted. In the selection process, we propose elitism ratio is 4% so that the best four chromosomes can be picked for next-generation, and we set 10% spare places for having a chance to create random chromosomes in the next generation. The rest of the places in the next generation is filled with children which are coming from paired parents. Parents are matched with the ranking method considering Pareto rule. The parent has a higher rank (top 20%), gets a much bigger chance to match with other chromosomes.

Crossover is a tool to enlarge solution clusters to find global optimum results in the defined model once parents are selected in the current population. It enables to mix specified segments or sub-segments in chromosomes to inject possible good genes to others. The mixing ratio or strategy is depending on population size. To optimize crossover process, it is important to utilize chromosomes that have better rank right after fitness function evaluation, as mentioned in the selection process. In our methodology, differently from other studies, we propose a two-level crossover process; firstly, applying crossover in between segments and secondly applying it in periods to ensure if the characters of the assignments are similar between periods due to the nature of the problem. Since each period's genes are independent, in case of good sort the genes are accumulated in one period; this can be tested by means of global crossover operator via applying the same formations for other periods as well. Crossover possibilities can be seen in Fig. 9.

Global Chromosome:

P1: $G_1 - t_1, G_2\_t_2, G_3 - t_3, G_4 - t_4, G_5 - t_5, G_6 - t_6$

P2: $G_7 - t_1, G_8 - t_2, G_9 - t_3, G_{10} - t_4, G_{11} - t_5, G_{12} - t_6$

Global Crossover:

$G_2 - t_1, G_2 - t_2, G_2 - t_3, G_2 - t_4, G_2 - t_5, G_2 - t_6$

$G_3 - t_1, G_3 - t_2, G_3 - t_3, G_3 - t_4, G_3 - t_5, G_3 - t_6$

$G_4 - t_1, G_4 - t_2, G_4 - t_3, G_4 - t_4, G_4 - t_5, G_4 - t_6$

$G_5 - t_1, G_5 - t_2, G_5 - t_3, G_5 - t_4, G_5 - t_5, G_5 - t_6$

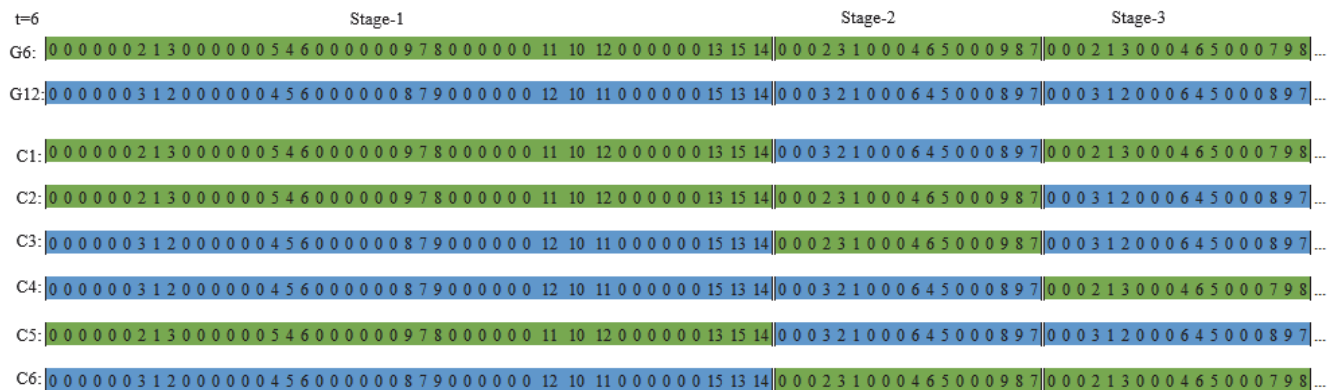$G_6 - t_1, G_6 - t_2, G_6 - t_3, G_6 - t_4, G_6 - t_5, G_6 - t_6$

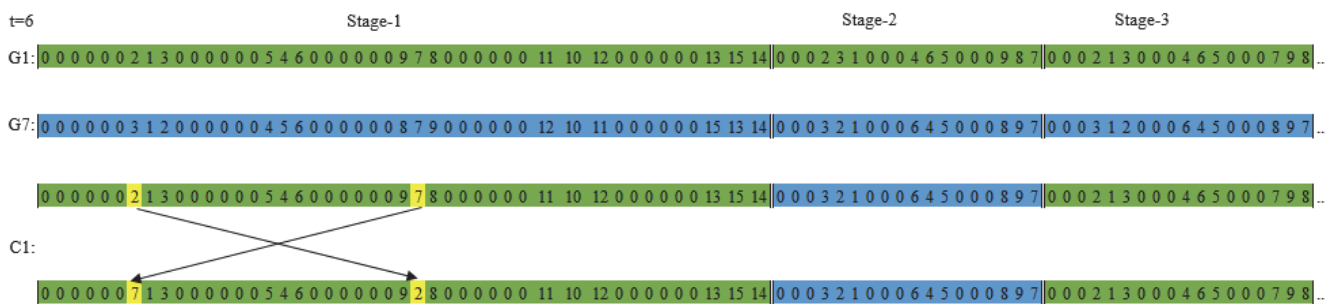**Figure 9** An illustration of crossover operator

Figure 10 An illustration of mutation process

Mutation is used for swapping genes in defined sub-segments after the crossover process in order to increase finding better solutions in the next generations. It generally does not give a more significant effect than other searching methods because of the limited ratio it has. When the priority is low in the selected genes exchanged, the possibility of the big chance gets smaller. Therefore, we use the 6% mutation ratio in our study in order not to miss

better fitness. The mutation process is illustrated in Fig. 10. The mutation is only done in the stage with swapping similar genes that affect the same variable.

3.3 Computational Results

The utilization rates of manufacturing centers determined by the solution of the model, amount of flow between the products held in the warehouse and the facilities are shown in Fig. 11.
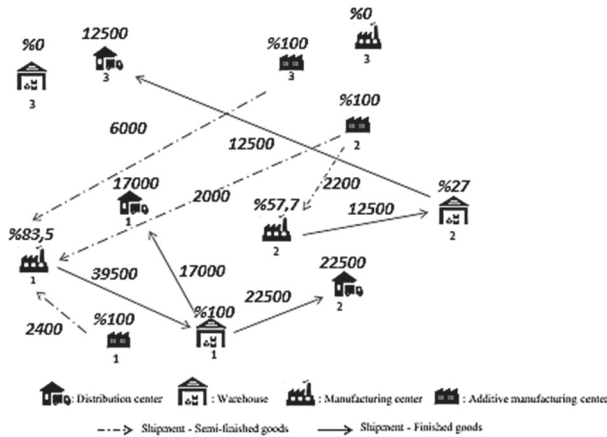

Figure 11 Post solution review with utilization rates

Lingo 11 and Matlab has been used for solving the problem. With SSPBA methodology, solution time has been decreased significantly.

When the results are analysed, it is observed that the investment facilities 1 and 2 are used actively, and no investment has been made to the third facility. When the warehouse preferences are examined, it is seen that although the cost of investment is higher than the others, warehouse 1 is in use because it is close to distribution centers. Due to the high preparation time and low demand for semi-finished goods, products have been assigned to additive manufacturing centers in order to minimize production costs. The semi-finished products produced were sent directly to production plants 1 and 2 for the assembly process. In addition, no semi-finished goods were sent to the warehouses, which indicates that the cost of shipping has been eliminated, the capacity is effectively used, and the semi-finished product is manufactured as needed.

3.4 Scenario Analyses

Scenario analyses have been done with changing some of the parameters, such as demand, production costs, and capacity. Cancellation of the semi-finished good flows between manufacturing centers and warehouses has been studied as well.

Scenario-I: Semi-finished good transportation between manufacturing centers and warehouses has been eliminated. The total cost has been decreased by 14%.

Scenario-II: The size of the variables has been increased. When the problem size gets larger, ILP could not be used for the solution method any more for the model defined. So, GA is the tool for near-optimal results for bigger models, and performance comparison can be seen in Tab. 17.

Table 17 Performance comparison between ILP and GA

Size	Variables							Lingo	Time	GA	Time	Gap
	A	I	S	K	J	Y	T					
	3	3	3	3	3	5	1	3405	00:00:01	3405	00:01:08	100,00%
Small	3	3	3	3	3	5	6	4015,3	00:00:02	4017	00:04:48	99,96%
	3	3	3	3	20	35	6	x	x	28263	00:06:10	x
Medium	10	3	3	3	80	100	6	x	x	105547	00:15:18	x
Large	10	3	3	3	100	120	6	x	x	103280	00:23:18	x

4 CONCLUSIONS

In this study, it is aimed to design a spare part distribution system in the automotive sector. It has been shown that by eliminating some transport activities by electronic data transfer, time and cost can be saved. It is emphasized that the positive effects of this way on the distribution of automotive services in which distributed end-to-end distribution activities are frequently experienced and distributed in the form of dispersed activities on efficiency and customer satisfaction. Addition to concept, SSPBA methodology has been developed to reduce solution time in GA approach differently from other studies as a contribution to literature.

Additive manufacturing facilities used with 100% efficiency shows that these facilities become a bottleneck, and the investment in these facilities will be in return. Especially in the production of products with low demand, the need for requirements such as mold, stock, process information makes the use of 3D printers attractive. 3D printers can be integrated into production facilities and investment decisions can be made in accordance with production volume. 3D printers create a room for low cost manufacturing, R&D and that will enable different options in the supply chain. The technical drawings, suppliers, customer databases and systems in which the data are processed dynamically will be essential for the sustainability.

Future studies on project management may also be evaluated, in which the parameters and cost items are diversified. From a sectoral perspective, these solutions are considered to be of great value.

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