Streamlined Supply Chain Operations: Leveraging Permutation-Based Genetic Algorithms for Production and Distribution

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Abstract: - Minimizing production and distribution costs by using resources in the most efficient way in supply chain management is among the most fundamental objectives. In increasingly competitive conditions, companies can act more strongly in market share with improvements in cost and efficiency factors. With the proposed Permutation Based Genetic Algorithm (PBGA) approach, the problem of optimizing the production and distribution line in the supply chain is addressed. The algorithm uses the processes of selection, crossover, and mutation to evolve the population in a permuted manner, taking into account multiple iterations, i.e. generation states. The results from the case studies also showed that resource utilization was realized efficiently with cost reductions and improvements in lead times. In this study, cost savings were achieved by applying the PBGA method, especially in information flow and process optimization between distribution and production. This can provide an advantage in a competitive environment.

Key-Words: - Supply Chain Management, Production and Distribution Model, Optimization, Permutation-Based Genetic Algorithm, Integrated Supply Networks, Mathematical Model.

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1 Introduction

In supply chain management, the effective coordination of production and distribution processes is crucial for the best adaptation to critical competitive conditions. In this context, optimization of production and distribution parameters is inevitable when factors such as variable customer demands and the need for efficient use of resources are taken into account. Since the traditional methods of supply chain optimization have disadvantages in terms of both cost and time, the PBGA method has been developed and applied in larger models, which gives result values very close to the optimum result in a shorter time. In the permutation-based genetic algorithm approach of the supply chain management model, all possible cases are analyzed by examining the crossover and population cases. The PBGA method can be easily applied to sequencing and scheduling problems that are frequently encountered in production and distribution problems.

Fast and accurate analysis of the dynamic variable structures in the model will facilitate dynamic information sharing with the proposed algorithm. In this context, it was aimed to analyze the obtained values and determine the appropriate solution and decision rules. In a continuous, changing, and uncertain environment, unpredictable demand and tight delivery times, short production cycles, and a wide range of products make decision-making in the production and distribution process difficult. In this study, an algorithm method is proposed and used to improve the dynamic decision-making process.

In this study, the PBGA method is used to determine the optimal task allocation of production and distribution tasks. This optimal sequencing also aims to minimize operational costs by considering parameters such as production capacity, available resource availability, and deadlines. With the PBGA method, genetic operators such as selection, crossover, and mutation are used over multiple iterations over multiple generations.

The remainder of this paper is structured as follows: Section 2 provides an overview of the pertinent literature. Section 3 delineates the model definition and formulation, encompassing the mathematical model of the production and distribution line model, while permutation-based genetic algorithms are detailed in subsequent subsections. Section 4 features a case study, summarizing the key results of our proposed approach in comparison to the current state of affairs. It also delivers a comprehensive analysis of the optimized schedules' robustness in the face of

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delivery delays. Finally, in Section 5, we present our concluding remarks.

2 Literature Survey

Supply chain management is an approach in which different processes, including procurement, production, inventory management, and distribution, are handled in an integrated manner. Reducing costs and improving customer service are among the main objectives. Therefore, there are extensive studies on supply chain management in the literature. The literature review in this paper focuses on SCM and genetic algorithms with a focus on PBGA implementation.

Some studies have grouped customers according to customer similarities and analyzed the profitability of the customer group with a genetic algorithm by taking into account the market dimension along with the quality function, [1], while a planning and scheduling model that takes into account order deadlines and outsourced operations in supply chain management has been discussed, [2]. At the same time, a mathematical model that takes into account supply chain dynamics was also studied, [3]. A genetic algorithm was used in this study where production processes and alternatives were considered. Reverse supply chain management and the adjustment of production parameters according to customer demands were also considered in this study. Supply chain management and genetic algorithm studies were also included in various studies, [4], [5], [6], [7].

The application of genetic algorithms to supply chain management has been explored from various angles. It has been used to develop integrated process planning, scheduling, and outsourcing supply chain models, distribution network design, multi-stage production, and hybrid genetic algorithms for production and distribution, [8], [9], [10], [11]. Researchers have also investigated lot and delivery scheduling, ready-mixed concrete delivery, and third-party logistic provider models using dynamic supply chain and distributed network approaches, [12], [13], [14], [15].

This section also reviews studies that employ genetic algorithms to optimize product lot sizes within supply chain management. Some of these studies have focused on assembly line optimization, multi-staged distribution network production, demand allocation, transportation, and production scheduling. Others have examined the effects of components on flexible production system design.

In this paper, we develop an integrated inventory-production-distribution mathematical model. Extensive benchmark data, drawn from the literature and experimental results, have consistently shown that permutation-based genetic algorithms, as an optimization method, yield superior performance. As a result, we prefer the use of permutation-based genetic algorithms in this study, given their ability to provide optimal results quickly when analyzing large datasets

3 Model Definition and Formulation

This section is divided into two subsections: the first presents the mathematical model of the three-stage supply chain, while the second delves into the permutation-based genetic algorithm.

3.1 Production and Distribution Line Model

In the context of a three-stage production and distribution line, a linear program model has been formulated. This model is designed to identify and meet the demands of customers and warehouses efficiently. It comprises three interconnected stages where decisions made at each level hierarchically influence the subsequent stages (Figure 1). To clarify, the program, which shapes the distribution, production, and inventory plan, takes on the structure of a linear program, [16], [17], [18]. It starts by defining the set of variables, followed by the formulation of constraints and the objective function.

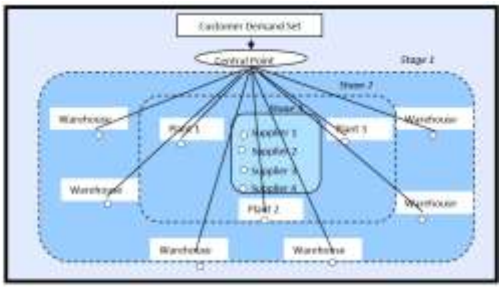

Fig. 1: Demonstration of problem structure

Index sets

n	set of customers
m	set of warehouse sites
l	set of plant sites
s	set of supplier sites

Decision Variables:

The decision variables involved in the minimization of the costs of the three-stage supply chain are as follows:

Z[i,m,t] the inventory level of i product in m warehouse in t period

P[i,l,t] the inventory level of i product in plant 1 in t period

W[i,s,t] the inventory level of raw material to be supplied from s supplier to produce i product at the end of t period

c[i,l,t] unit production cost of i product in plant 1 in t period

v[i,s,t] production cost of raw material to be supplied from s supplier to produce i product in t period

Ca[i,m,t] i product capacity of m warehouse in t period

Cb[i,l,t] i product capacity of plant 1 in t period

Cc[i,s,t] capacity of s supplier to hold raw material required by for i product in t period

Ta[i,m,t] transportation of i product in m warehouse to n customer in t period

Tb[i,l,t] transportation of i product in plant 1 to m warehouse in t period

Tc[i,s,t] transportation of s raw material from s supplier for production of i product in plant 1 in t period

Fa[i,m,t] transportation cost of i product in m warehouse to n customer in t period

Fb[i,l,t] transportation cost of i product in plant 1 to m warehouse in t period

Fc[i,s,t] transportation cost of necessary raw material from s supplier for production of i product in plant 1 in t period

Sa[i,m,t] safety stock of i product in m warehouse in t period

Sb[i.l.t] safety stock of i product in plant 1 in t period

Sc[i,s,t] safety stock of necessary raw material by s supplier for production of i product in plant 1 in t period

Ha[i,m,t] holding cost of i product in m warehouse in t period

Hb[i.l.t] holding cost of i product in plant 1 in t period

Hc[i,s,t] holding cost of necessary raw material by s supplier for production of i product in plant 1 in t period

Da[i,m,t]

$$\begin{cases} 1 & \text{if } i \text{ product is in } m \text{ warehouse during } t \text{ period} \\ 0 & \text{otherwise} \end{cases}$$

Db[i,l,t]

$$\begin{cases} 1 & \text{if } i \text{ product is in } l \text{ plant during } t \text{ period} \\ 0 & \text{otherwise} \end{cases}$$

Dc[i,s,t]

$$\begin{cases} 1 & \text{if the raw material necessary for } i \text{ product is in } s \text{ supplier during } t \text{ period} \\ 0 & \text{otherwise} \end{cases}$$

The primary goal of this function is to minimize the costs associated with distribution, production, and inventory management within the supply chain. Specifically, distribution costs are contingent on the mode of transportation, including factors like the cost per unit of time, lead time (comprising loading, travel, and unloading times), and the total number of shipments conducted. Production costs fluctuate based on the production levels at the various facilities. Additionally, holding costs are directly proportional to the quantities of products and raw materials held at all nodes throughout the supply chain. The objective function is expressed as follows:

Min (Production Cost+ Inventory Cost +Delivery Cost)

Production Cost:

$$Min\sum_{t=1}^{T}\sum_{i=1}^{I}((P[i,l,t])c[i,l,t])D_b[i,l,t]+((W[i,s,t])v[i,s,t])D_c[i,s,t]$$

Inventory Cost:

$$Min\sum_{t=1}^{T}\sum_{i=1}^{I}((Z[i,m,t])ha[i,m,t])D_a[i,m,t]+((P[i,l,t])hb[i,l,t])D_b[i,l,t]+((W[i,s,t])hc[i,s,t])D_c[i,s,t]$$

Delivery Cost:

$$Min\sum_{t=1}^{T}\sum_{i=1}^{I}((Ta[i,m,t])Fa[i,m,t])D_a[i,m,t]+((Tb[i,l,t])Fb[i,l,t])D_b[i,l,t]+((Tc[i,s,t])Fc[i,s,t])D_c[i,s,t]$$

Subject to

$$\sum_{n=1}^{N}\sum_{t=1}^{T}n_{it} \leq (Z[i,m,t]+P[i,l,t]+W[i,s,t]) \quad (1)$$

$$\left.\begin{aligned} Z[i,m,t] &\leq Ca[i,m,t] \\ P[i,l,t] &\leq Cb[i,l,t] \\ W[i,s,t] &\leq Cc[i,s,t] \end{aligned}\right\} \quad (2)$$

$$\left.\begin{aligned} Z[i,m,t] &\geq Sa[i,m,t] \\ P[i,l,t] &\geq Sb[i,l,t] \\ W[i,s,t] &\geq Sc[i,s,t] \end{aligned}\right\} \quad (3)$$

$$Z[i,m,t-1]+\sum_{l=1}^{L}Tb[i,l,t]=Z[i,m,t] \quad (4)$$

$$P[i,l,t-1]+\sum_{l=1}^{L}Tc[i,s,t]=P[i,l,t] \quad (5)$$

$$\sum_{n=1}^{N}n_{it}=Ta[i,m,t] \quad (6)$$

$$Da[i,m,t],Db[i,l,t],Dc[i,s,t] \in \{0,1\} \quad (7)$$

$$Ta[i,m,t],Tb[i,l,t],Tc[i,s,t] \geq 0 \quad (8)$$

This production planning model revolves around the dynamics of material flow, encompassing the movement of materials from suppliers to plants, then from plants to warehouses, and ultimately from warehouses to customers. To construct a model that accurately assesses this system, we considered the aforementioned characteristics while establishing connections with existing models in the literature, particularly in the domains of production and transportation. However, it's important to note that not all lot size models and material flow values were taken into account in this study. It aimed to scrutinize inventory flow by defining material flow variables within the system.

There are several constraints in place:

Constraint 1 ensures a balance between customer demand and total inventory.

Constraint 2 deals with production capacity and inventory limitations.

Constraint 3 focuses on safety stock levels.

Constraint 4 pertains to the ability to meet warehouse requirements from the plant for the upcoming period.

Constraint 5 relates to the plant's ability to fulfill its requirements from the supplier for the forthcoming period.

Constraint 6 involves the transport of customer demand from the warehouse to the customer.

Constraints 7 and 8 are associated with situational variables.

It's worth noting that conventional lot size models in the literature typically do not incorporate material flows between different points in the supply chain (e.g., from plants to warehouses and from warehouses to customers). Additionally, these models often consider a single plant supplying a single warehouse. However, the problem defined in this context considers variables such as the number of plants, warehouses, and the material flow, resulting in a more comprehensive analysis.

3.2 Permutation and Distribution Line Model

The Genetic Algorithm (GA) is a contemporary heuristic optimization method, drawing inspiration from the biological process of genetic operations. It employs chromosomes to represent potential solutions, with the initial solution pool typically consisting of a set number of chromosomes, [19], [20], [21], [22], [23]. The process of crossing and mutating ensures the generation of new chromosomes, each stronger than its predecessor. Permutation-based GA, such as in cases like the Traveling Salesman Problem and Vehicle Routing Problems, focuses on achieving optimal results by grouping similar features from repeated operational scenarios. Genetic control parameters, namely crossover and mutation rates, have a significant impact on population diversity.

In Figure 2, the operational steps of the permutation-based genetic algorithm are outlined. Step 1 involves defining objective functions and variables, while Step 2 covers the definition of GA parameters like pop size, mutation rate, and selection criteria. Step 3 entails the creation of the initial population, and Step 4 involves iterating through generations to identify the best permutation. Step 5 encompasses pairing individuals and initiating the mating process, while Step 6 is dedicated to carrying out the mating. Step 7 includes mutation and population operations, and Step 8 deals with sorting costs. Finally, the results are displayed on the screen.

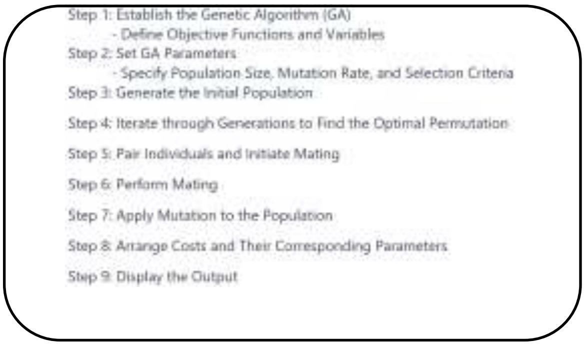

Fig. 2: Permutation based Genetic Algorithm Steps

4 Implementation

In this study, we examined a supply chain model in multiple stages and optimized the system using both a simple Genetic Algorithm (GA) and a permutation-based GA. In GA, we represent solutions, individuals, and chromosomes with indexes, typically composed of 0s and 1s, drawing inspiration from biology. Genetic algorithms assume that certain parts of the algorithm represent specific features or characteristics on a biological chromosome, ultimately aiming to find the optimal solution iteratively during recombination, [24], [25], [26], [27], [28], [29].

This section delves into a three-stage distribution network supply chain model, which comprises six warehouse distribution points, three plants, and four suppliers denoted as x, y, z, and t, each associated with a specific plant. Products are evaluated as U_i ($i=1,2,3,4$), warehouses as D_j ($j=1,2,3,4,5,6$), plants as F_k ($k=1,2,3$), and the number of customers varies from 10 to 200. The primary objective is to meet customer needs with minimal cost. This section also evaluates factors like determining transportation charges between warehouses, optimal stock levels in warehouses, and the relationship between the production rates of plants in the first stage and suppliers. Customer demands are initially addressed from warehouses; if the products are not available there, they are sourced from plants. The demand chain initiates from the customer and flows down to warehouses, plants, and suppliers. The optimization factors include customer demand sizes, warehouse and plant stock levels, plant production rates, and part supply speed. GA optimization typically does not rely on the analytical properties of the objective function. It mainly involves two fundamental operations: repeated iterations and the random generation of new solutions, followed by evaluating their optimality based on predefined fitness functions. These characteristics empower GA. Permutation-based GAs like Hu's and Haupt & Haupt's, as well as the improved program discussed here, are known for effectively finding solutions to complex problems, including those in mobile sales and tabulation domains. At the start of the GA process, each chromosome represents a potential optimal solution. The integrated supply chain management approach involves several stages: distribution, production, and contribution. In this study, we designed three different chromosome structures: Chromosome A for the first stage, Chromosome B for the second stage, and Chromosome C for the third stage. Table 1 details the reception of order data by the warehouses and provides data for the first stage. Table 2 shows materials that are unavailable in warehouses and need to be supplied by warehouses from plants. It also outlines the processing methods and how data is used in the second stage. Table 3 demonstrates the parts that are not provided by the plant and need to be produced and supplied by suppliers in this production stage. The data presented in Table 3 corresponds to the third stage. The related demand is primarily met by the permutation-based genetic algorithm at the warehouse level in the first stage. If the first stage cannot fulfill the demand, the second stage is activated, and if the second stage also falls short, the third stage comes into play.

The supply chain model's aim is to provide customers with products at a lower cost through faster service. Key factors affecting the system include production cost, supply, and transportation, as they contribute to the overall cost of the process. A faster system implies a shortened production cycle and quicker product delivery to customers. Additionally, the company seeks to reduce production costs and enhance the entire system's performance by accurately estimating the firm's cost status and customer demands in terms of timing and quantity.

Table 1. Data Representation in the First Stage (For a Customer Set of 5)

Customer Demands	A	C	B	D	A	
Gen Demonstration	1	2	3	4	5	
Supplier	D1	D2	D3	D4	D5	D6
Gen Demonstration	1	1	2	2	1	1

In the practical implementation of the system, optimization was carried out utilizing data from the Warehouse, Plant, and Supplier databases. The optimization process commenced by considering lot sizes ranging from 10 to 200 as data sets, and a permutation-based Genetic Algorithm (GA) was applied and assessed, with the system costs not yet factored in. The data contained in Table 2, Table 3 and Table 4, as shown in the operational columns of Figure 3, were leveraged to evaluate the overall system cost. Table 4 presents information from the warehouse database, housing data specific to the first stage. This database includes details such as product type, distance from the central point, and current stock status. Conversely, Table 5 provides insights regarding the plant database in the second stage, encompassing product types, stock status, production rates, and distances from the central point.

Table 2. Warehouse Database and Its Contents

Warehouse	Product Type	Distance from the center	Stock Status	Safety Stock	Unit Delivery Cost($)
D1	A B D	200	4 4 4	2 2 2	3 5 8
D2	A C D B	150	6 6 7 6	2 2 3 2	2 7 6 3
D3	A C D	300	6 6 4	2 2 2	3 4 7
D4	A B	100	7 5	2 2	6 2
D5	A D C B	400	6 6 6 6	2 3 2 2	3 8 6 2
D6	A C B	220	4 3 4	2 2 2	7 5 2

Table 3. Plant Database and Its Contents

Plant	Produced Product	Distance from the center	Stock Status	Safety Stock	Production Rate (Product/ Day)	Unit Produc. Cost ($)	Unit Deliv. Cost ($)
F1	A	100	3	2	2	40	3
	B		3	2	3	30	5
F2	A	190	3	2	1	38	2
	C		3	2	2	50	7
	D		3	2	4	70	6
F3	B	75	3	2	2	30	8
	D		3	2	4	65	6
	C		3	2	3	50	2

The data within the initial stage's database forms the system's primary decision-making mechanism. It should a product become unavailable in the warehouses, the plant information, which is part of the second stage's database, comes into play, triggering the system's decision-making mechanism.

Table 4. Supplier database and content

Supplier	Used Product	Distance from the center	Supply period (Part/Day)	Unit Delivery Cost ($)
T1(x,y)	A	100	1	3
	B		2	5
T2(x,t)	A	150	1,5	5
	D		2,25 – 3	4
T3(x,y,t)	B	75	1	7
	D		3	6
	C		2	5
T4(y,t)	A	90	2	7
	B		3	6
	C		2	5
	D		1,25	4

Table 6 encompasses a database containing supplier details relevant to the third stage. This information comprises elements like product components and supply lead time. Figure 3 displays the operational flow of the system's general functioning mechanism. The system operates by deducing the optimal operational pattern through the application of a genetic algorithm after receiving essential input data from the database module. Table 5 illustrates the product selection from various warehouses based on heuristically chosen x and y coordinates to satisfy the demands of a group of 10 customers. Meanwhile, Table 6 provides insight into the product quantities remaining in the warehouses after meeting these customer demands. The distribution of the leftover products following the fulfillment of all customer group requirements is detailed in Table 9.

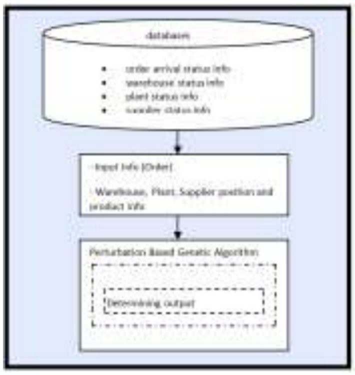

Fig. 3: Evaluation process of the supply chain with GA

Table 5. The amount of products in all warehouses after the demand of customer group of 10 persons are met

Product A	Product B	Product C	Product D
43	32	28	27

Table 6. Distribution of products selection by a customer group of 10 persons

x	y	Warehouse	D1	D2	D3	D4	D5	D6
9501293	6154324	D6	-	-	-	-	-	D6B
2311385	7919370	D4	-	-	-	D4B	-	-
6068426	9218130	D5	-	-	-	-	D5B	-
4859825	7382073	D5	-	-	-	-	D5D	-
8912990	1762661	D3	-	-	D3D	-	-	-
7620968	4057062	D3	-	-	D3A	-	-	-
4564677	9354697	D5	-	-	-	-	D5D	-
185036,4	9169044	D4	-	-	-	D4A	-	-
8214072	4102702	D3	-	-	D3C	-	-	-
4447034	8936495	D5	-	-	-	-	D5D	-

As indicated in Table 7, customer demand is fulfilled at Level 1, corresponding to the warehouse level, when it falls within the range of 10-110. In the case of demand ranging from 120-140, it is addressed at Level 2, which represents the plant level. For demand falling within the range of 150-200, fulfillment occurs at Level 3, denoting the supplier level. This implies that customer demand is promptly satisfied when the first two levels are involved. However, the system requires a certain response time to fulfill the demand when it falls between 150-200.

Table 7. Inventory Status in Response to Product Demand from Customers

Customer Demand	Product A	Product B	Product C	Product D	
10	43	32	28	27	Meeting the demand at warehouse level
20	35	25	29	31	
30	37	24	22	27	
40	33	24	19	24	
50	26	22	21	21	
60	25	21	21	13	
70	27	11	18	14	
80	21	15	10	14	
90	19	9	10	13	
100	12	9	6	13	
110	2	8	13	7	Meeting the demand at plant level
120	10	-5	1	10	
130	-2	3	0	9	
140	-8	7	2	-1	Meeting the demand at supplier level
150	3	-13	2	-2	
160	0	-12	-3	8	
170	-8	-6	5	1	
180	-13	-9	-8	-10	
190	-22	-20	-3	-5	
200	-17	-23	-13	-7	

5 Results

Table 8 presents CPU time (in seconds) and cost values derived from three programs. When considering customer demand in the range of 10-110, Hu's program demonstrates remarkable efficiency, completing operations swiftly, while Haupt & Haupt's program delivers cost savings of nearly 40%. Notably, as customer demand increases over time in Haupt & Haupt's programs, the operational duration also extends, as visually represented in Figure 4. Especially when customer demand stands at 40, Haupt & Haupt's program stands out, offering a solution at a substantial 86% cost reduction. Consequently, Haupt & Haupt's program appears well-suited for Stage 1 customer demands.

For customer demand levels ranging from 120 to 140, the improved program emerges as an attractive option, providing cost-efficient solutions with a 25% reduction, albeit at the expense of a 3-5 second increase in operational time compared to Hu's program. Similarly, when the demand falls within the 150-200 range and is addressed at the third level, the improved program may be the preferred choice. Although the improved program does entail an 18% higher cost than Haupt & Haupt's program for customer demands at this stage, it offers specific advantages. A detailed breakdown of solution costs provided by the three programs is available in Figure 5.

Table 8. Contrasting CPU Time (in seconds) and Cost Results of Hu's, Haupt & Haupt's Permutation-Based Genetic Algorithm Program, and the Enhanced Program.

Time				Cost			
Customer demand	Hu's program	Haupt&Haupt program	Improved program	Customer demand	Hu's program	Haupt&Haupt program	Improved program
10	0,01	10,886	4,126	10	4,4431	2,7675	4,4371
20	0,371	17,425	8,222	20	5,7124	4,9736	7,5523
30	0,32	30,935	4,737	30	7,5716	6,6676	11,0131
40	0,391	48,58	5,838	40	18,3032	9,8429	17,4107
50	0,34	76,23	6,269	50	14,4417	14,2202	23,7393
60	0,46	102,337	6,56	60	29,2335	17,8624	28,2775
70	0,471	144,087	10,996	70	34,0517	22,2479	33,5243
80	0,511	193,278	7,52	80	39,2303	27,269	36,5909
90	0,56	247,717	7,941	90	42,7152	28,9809	39,1516
100	0,54	328,803	7,09	100	48,2069	36,6896	46,8824
110	0,681	422,968	6,93	110	51,3723	37,0028	50,6283
120	0,681	506,188	7,941	120	57,7785	44,3837	57,7608
130	1,101	649,324	9,184	130	64,6015	49,6422	59,1106
140	1,192	811,607	9,594	140	62,045	52,111	62,1572
150	0,851	992,507	9,724	150	75,8208	60,4887	71,9964
160	1,372	1194,137	9,023	160	75,1576	60,7198	71,8089
170	1,051	1427,483	11,276	170	80,7484	66,712	79,1177
180	1,592	1667,919	10,104	180	86,5319	72,009	85,2672
190	1,222	1951,486	11,186	190	92,1246	77,0603	89,9424
200	1,843	2261,392	12,368	200	99,4272	81,8837	95,3638

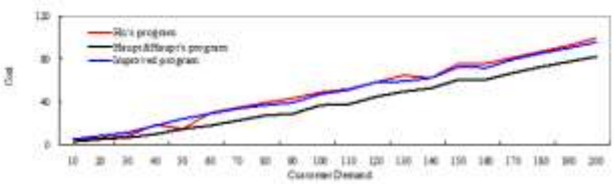

Fig. 4: Contrasting CPU Time (in seconds) Values for Customer Demand - A Comparative Examination of Hu, Haupt & Haupt, and Enhanced Permutation-Based Genetic Algorithm Programs

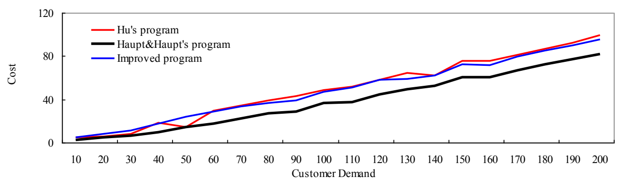

Fig. 5: Comparison of cost values among the Hu method, Haupt & Haupt method, and an enhanced Permutation-Based Genetic Algorithm program in response to customer demand.

6 Conclusion

In supply chain management, operational efficiency and customer satisfaction are the key factors in ensuring production and distribution coordination. Permutation-based Based Genetic Algorithm (PBGA) was used to reduce cost and improve lead time. With the results obtained, the effectiveness of the optimization technique applied in supply chain management was tested.

The implementation of the PBGA method resulted in a 15% improvement in production costs and a 12% improvement in distribution costs. This improvement was achieved through efficient use of resources and effective task sequencing. These factors also contribute to a direct increase in the profitability of the model considered.

It also contributes directly to customer satisfaction with a 20% reduction in delivery times. These improvements also strengthen the competitive position in the market. It is seen that the PBGA method gives a better result compared to the basic GA method. As a result, the PBGA method can be preferred as a method that can be used effectively in such models.

Effective resource allocation is crucial for cost control and operational efficiency. By optimizing the allocation of production and distribution resources, PBGA reduced idle time at production facilities by 25% and vehicle idle time for distribution activities by 15%. These improvements underline the algorithm's ability to maximize the use of available resources.

In comparison with the classical GA method, the proposed PBGA method shows a higher performance in terms of both cost and time parameters. Therefore, the use of this method should be preferred for such model structures in terms of analyzing results closer to the actual optimal result value in a shorter time.

In conclusion, the Permutation-Based Genetic Algorithm has proven to be a powerful tool to address the challenges of supply chain optimization. Its adaptability, robustness, and ability to deliver substantial cost reductions and lead time improvements make it a valuable asset for modern supply chain management. The results obtained from this research have direct and tangible implications for our business, including improved profitability, heightened customer satisfaction, and enhanced operational efficiency.

Within the scope of the next study, taking into account the following parameters in the performance analysis process, consistent predictions can be realized by using machine learning approaches, especially deep learning, in the clustering of data and prediction processes with Artificial Intelligence / ML Based algorithms. At the same time, by developing a digital twin approach in the AI-based production planning and scheduling process, instantaneous changes in the system can be easily observed with an equivalent simulation approach.

SCM KPIs: Typical KPIs used to monitor SCM improvements:
- Demand fulfillment index
- Inventory Supply Days (average)
- Forecast Accuracy (weighted average)
- Delivery Performance/shipment compliance
- Commitment to production
- Supply alignment
- End-to-end cycle time (from procurement to sale)

As we move forward, it is important to acknowledge that the field of supply chain management is dynamic, and future challenges and opportunities will continue to emerge. This research lays the foundation for further exploration, including multi-objective optimization, sustainability considerations, and real-time adaptation to dynamic supply chain conditions. By embracing innovation and advanced optimization techniques, we position ourselves to meet these challenges head-on and sustain our leadership in the ever-evolving landscape of supply chain management.

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