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ENHANCING RETAIL OPERATIONS: DYNAMIC FULFILMENT STRATEGIES IN OMNICHANNEL RETAIL

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Abstract

This study explores the trend of in-store fulfillment in omnichannel retail, where nearby store inventories are utilized for online order fulfillment. This model presents advantages such as faster delivery, cost reduction, improved stock management, increased sales, and enhanced customer satisfaction. Operational challenges include determining the optimal fulfillment location for online orders. Investigating a retailer with online and brick-and-mortar stores, this paper addresses dynamic order fulfillment decisions considering customer demand and shipping cost uncertainties. The study employs Stochastic Dynamic Programming for shorter periods and the Genetic Algorithm for longer periods, revealing that the Genetic Algorithm provides solutions closely approximating optimal.

Keywords: decision-making, dynamic programming, genetic algorithm, omnichannel marketing, order fulfillment

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1. INTRODUCTION

Omnichannel is the seamless and integrated use of all distribution and communication channels, such as websites, social media, email, physical stores, and more, to create a nearly flawless customer experience. The essence of the omnichannel marketing strategy is to unify all channels and engage customers through these integrated platforms (Lazaris & Vrechopoulos, 2014). Today, many prominent brands have adopted the omnichannel strategy as a foundational approach to enhance customer satisfaction, foster loyalty, and provide a distinctive shopping experience. In recent years, a significant portion of brands have transitioned from a multichannel to an omnichannel marketing strategy with the emergence of the concept of omnichannel marketing (OM) (Piotrowicz & Cuthbertson, 2014).

The omnichannel approach significantly contributes to the industry in three keyways. First, it eliminates the ambiguity surrounding the term "multichannel" by clearly distinguishing between multichannel, cross-channel, and omnichannel shopping. Second, it offers a long-term perspective on the customer experience envisioned by omnichannel marketing. Third, it paves the way for new research and development in examining marketing channels within the retail sector (Mosquera et al., 2017).

The omnichannel retail strategy provides numerous benefits for retailers, including rapid delivery, reduced shipping costs, a higher likelihood of maintaining optimal stock levels, increased sales, enhanced customer satisfaction, and more. However, it also presents certain challenges due to the variable circumstances involved. One such challenge is determining and optimizing order fulfillment policies that positively impact a retailer's profitability. This study focuses on a retailer operating both online and in-store operations, with the goal of assessing the profitability of shipping a product resulting from an online order from various locations, such as an e-commerce warehouse or physical stores.

The structure of the study is as follows: section 2 provides a literature review, while section 3, methodology, is further subdivided into subsections, including data acquisition (3.1), Stochastic Dynamic Programming (SDP) (3.2), and Genetic Algorithm (GA) (3.3). Section 4 is dedicated to presenting the results and discussion of the study. Lastly, section 5 contains the conclusion of the study. This section presents the final verdict on the research topic and provides recommendations for future research.

2. LITERATURE REVIEW

As part of our research, we conducted a comprehensive analysis of the existing studies on omnichannel marketing. Our focus was to provide a summary of the various studies related to the omnichannel marketing strategy available in the literature. We aimed to present a clear and concise overview of the most significant findings in this field.

Alptekinoğlu and Tang (2005) created a multichannel distribution system to investigate the most effective distribution network design strategy for firms in specific conditions. They focused on determining whether it is more effective to fulfill orders from a central location or from individual stores. Geng and Mallik (2007) created a two-tiered multichannel distribution system model using game theory. Their goal was to explore inventory competition and how manufacturers should distribute their stocks to competing channels. The study revealed that under mild capacity constraints, both manufacturers and retailers could benefit, leading to increased overall profit in the supply chain. However, when capacity constraints were highly severe, the study concluded that manufacturers would always keep all capacity for themselves. Under moderately tight capacity constraints, it was observed that manufacturers might not supply inventory to retailers while not fully utilizing their available capacity. Chen et al. (2009) concentrated on developing optimal delivery routes to guarantee the delivery of fresh and cost-effective perishable food products to customers. Their research underscored the significance of creating an integrated and well-designed production schedule and delivery routes for suppliers to ensure the provision of the freshest foods while meeting customer demands in a cost-efficient manner. Acimovic and Graves (2015) aimed to determine the most efficient method for fulfilling each customer's order while minimizing the average cost of outbound shipping. Their approach successfully reduced outbound shipping costs by 1% by using an intuitive method that considered both immediate outbound shipping costs and forecasts of future outbound shipping costs when making shipping decisions. Gao and Su (2017) conducted a study to examine the impact of the Buy Online, Pickup In-Store (BOPIS) strategy on store operations. They focused on determining which products should be targeted for BOPIS implementation and how the revenue generated through this strategy should be allocated across channels. Not all products are suitable for in-store pickup; in particular, applying BOPIS to products that perform well in stores may not be profitable. While it helps acquire new customers, encouraging existing customers to switch from online orders to BOPIS can reduce profit margins. In a decentralized retail system where store and online channels are managed separately, BOPIS revenue can be shared across channels to mitigate incentive issues. Ishfaq and Raja (2018) examined four different online order fulfillment techniques (from distribution centers, dedicated order fulfillment facilities, stores, and vendors) for omnichannel retailers. They compared these techniques and identified the best method, suggesting that retailers need to make certain changes in their order fulfillment and delivery processes to fulfill orders from stores at the minimum cost. Shi et al. (2018) examined the BOPIS strategy for a retailer that caters to both informed and uninformed consumers. They established thresholds for unit production costs and demand uncertainty, indicating when the BOPIS strategy is beneficial. Their study ultimately demonstrated that the BOPIS strategy is not universally advantageous for retailers. Furthermore, they showed that the BOPIS strategy can yield greater profits for the retailer as the proportion of informed consumers increases. Jin et al. (2018) examined how a retailer should optimally implement the BOPIS policy for fulfilling online orders. Ardjmand et al. (2018), proposed two discrete and integrated integer programming models to enhance and improve processes in the retail sector, including order cartonization, accurate product selection, and on-time order delivery. Additionally, they introduced a GA with the NSGA-II selection operator for the e-tail/retail industry.

Paul et al. (2019) investigated the benefits of using the idle capacities of restocking vehicles to fulfill online orders in order to minimize order fulfillment costs. They found that the benefits of capacity sharing can be significant, particularly when the volume of goods to be delivered to store delivery points is small compared to the volume needed for restocking store inventories. Having several stores with sufficient transfer space is enough to reap the benefits of capacity sharing. The advantages of capacity sharing depend on the initial potential transfer locations and timing, making it location-dependent for store restocking and online order fulfillment. If the vehicle feeding the in-store pickup points cannot leave the depot earlier or later than the vehicle restocking store inventories, the benefits of capacity sharing will be more pronounced. Furthermore, the benefits of capacity sharing are not highly contingent on the capacity of the vehicle restocking store inventories. Kong et al. (2020) investigated the impact of BOPIS implementation under different pricing strategies for a retailer. They found that it is not always beneficial for the retailer and that under inconsistent pricing, it can be more profitable when the per-unit operational cost in the BOPIS channel is low. However, it's worth noting that the study did not take inventory issues into account. Yang and Zhang (2020) analyzed how in-store pickup affects the seller's profit. They found that on one hand, in-store pickup speeds up the delivery of online orders, enhances the retailer's brand awareness, and thus expands the firm's customer base. On the other hand, it encourages shoppers to shift from offline to online purchasing, and this shift negatively impacts the retailer's performance. They noted that when the positive aspect of expanding the customer base is overshadowed by the negative impact of consumer migration, the adoption of in-store pickup can lead to a decrease in the retailer's profit. Shin et al. (2020) utilized a stochastic model within a closed-loop supply chain framework to address the uncertainty of demand in the context of mobile phone trade-in and refurbishment services. This study conducted a detailed analysis of system behavior within the proposed model. Abouelrous and Gabor (2021) addressed an inventory optimization problem for a retailer facing stochastic online and in-store demand in a fixed-length sales season. Compared to the state-of-the-art algorithm developed by Govindarajan et al. (2021), the algorithm shows an average improvement of 6.2% in expected total costs and a maximum gain of 28.6%. The algorithm performs particularly well for shorter time intervals and relatively high in-store demand rates compared to Govindarajan et al. (2021). Bayram and Cesaret (2021) focused on a retailer selling a seasonal product through both online and offline (brick-and-mortar) channels. The study centered around a specific problem scenario involving multiple stores, each serving a different region, and a Distribution Center (DC). To determine the optimal order fulfillment decisions, they created a discrete-time, finite-horizon Markov decision process (MDP) model. They also developed a dynamic solution methodology to determine the optimal cross-channel fulfillment decisions for a retailer facing independent demand classes. Difrancesco et al. (2021) proposed a model for the problem of fulfilling online orders from stores, considering performance metrics such as optimal picking time, separation time, packing time, the number of pickers, and the number of packers, which sets it apart from other articles. However, it is not applicable to perishable goods, and it is designed for a single store, excluding the allocation of orders to stores. They found that the increasing arrival rate of in-store customers negatively impacts the online order service level, encouraging shorter online order delivery interruption times. Zhou et al. (2021) addressed the joint dynamic pricing and cross-channel fulfillment problem for omnichannel retailers with limited initial inventory and no opportunity for product replenishment within the season. The model characterized by the classic multinomial logit (MNL) choice model was used to capture customer demands, comparing it with omni-channel alternatives. A dynamic pricing policy was developed methodologically, taking into account the probability distribution structure. Momen and Torabi (2021), proposed a demand function that takes into account retailer pricing and product delivery time for a model that provides integrated fulfillment services considering different order channels. The research examined the dynamic competitive situation using a Nash-Stackelberg game approach, considering demand uncertainty under a probability framework. Gabor et al. (2022) worked on an inventory model for a multichannel retailer, i.e., a retailer that sells products both through physical stores and online. Their aim was to address the situation where inventory in a store falls below a certain level by offering discounts to customers for online purchases, ensuring that products are available for customers in urgent need, thereby preventing sales loss. These discounts provide an opportunity to carry less stock in stores while directing customers towards online purchases, reducing customer loss and total costs. With the adoption of this policy, there was an average decrease of 8.5% in total costs, with a maximum reduction of 19.5%. Yang et al. (2022) examined the value and timing of adopting a mixed omnichannel strategy, comprising BOPIS and Buy Online, Ship to Store (BOSS), and how these strategies impact retailers' inventory management. They found that omnichannel marketing strategies significantly influence customers' channel choices through the convenience variable (e.g., shopping inconvenience costs). It was concluded that retailers selling time-sensitive or experiential products might benefit more from the mixed strategy. Lastly, they determined that different omnichannel marketing strategies interact and vary in their effects on retailers' store operations and customers' channel choices depending on the product type. Quach et al. (2022) examined the effects of omnichannel retailing on customer experience and relationship outcomes. They collected data through an online survey with 786 available responses. Their findings revealed that the showroom approach (where stores are used for product showcasing and order placement) and the use of location-based services regulated the relationship between service consistency and privacy risk. Dethlefs et al. (2022) focused on the order fulfillment problem by addressing the multichannel approach where distribution centers and local stores are integrated into a holistic fulfillment concept. Additionally, they presented a decision model that combines the location assignment problem with the multi-depot vehicle routing problem to assess when rapid integrated order fulfillment would be beneficial for retailers engaged in multichannel sales. As a result, they showed that integrated rapid order fulfillment could reduce costs by an average of 7.4% compared to order fulfillment solely from distribution centers. Jiu (2022) examined how a retailer should allocate replenishments to each product for each distribution center (DC) in the initial period and how to allocate inventory from DCs to different stores. In the final period, the study explored which DCs and/or stores should fulfill the realized online demands. The numerical results of the study demonstrate that separating binary decisions from continuous decisions creates significant value compared to existing approaches. Dynamic programming is a method of breaking down a complex problem into recurring sub-problems, solving each sub-problem only once and storing the solution for later use in solving the complex problem. Pichka et al. (2022) proposed two mixed-integer nonlinear programming (MINLP) methods for the multinomial logit (MNL) choice model to develop a pricing structure for omni-channel retailers, taking into account e-channel structures. This study also examined the pricing structure while considering shipment processes for omni-channel retailers. Liu et al. (2022) addressed the Omni-channel retailing problem in conjunction with the Vehicle Routing Problem and employed the Grey Wolf Optimization approach to solve the optimization problem. Particularly in the case of large companies with numerous warehouses, delivery points, and retail stores, the efficient distribution of products based on demand poses a significant challenge. This study utilized two metaheuristic approaches, namely MOGWO and NSGA-II, to tackle the problem. Liu et al. (2023) compared the omnichannel order fulfillment strategies of BOPIS and BOSS through a model they developed. Additionally, they found that cross-selling benefits and offline search costs had a significant impact on the optimal strategies they were comparing. Ouyang et al. (2023) addressed the modeling and optimization of a dynamic structure considering the last-mile delivery system in e-commerce. The problem was modeled and solved using a Markov decision structure. Additionally, time window constraints were taken into account when determining delivery strategies.

The literature reviews various aspects of distribution and fulfillment strategies in the retail sector. Alptekinoğlu and Tang (2005) and Geng and Mallik (2007) focus on multichannel distribution systems, examining optimal network designs, and inventory competition under different conditions. Chen et al. (2009) highlight the importance of integrated production schedules and delivery routes for perishable food products. Gao and Su (2017) explore the impact of the Buy Online, Pickup In-Store (BOPIS) strategy on store operations, including product suitability, and revenue allocation considerations. Other studies investigate capacity sharing benefits (Paul et al., 2019), the impact of omnichannel strategies on retailer profit (Yang and Zhang, 2020), and inventory optimization (Abouelrous and Gabor, 2021). Various models and methodologies are applied in the literature such as game theory, stochastic modeling, and dynamic programming to analyze and optimize distribution processes. Common goal is enhancing efficiency, reducing costs, and maximizing profitability in a dynamic retail landscape.

3. METHODOLOGY

3.1. Data Acquisition

Our study focuses on a retail company that operates both online and brick-and-mortar stores. Figure 1 summarizes the omnichannel retail process discussed in the study. When an order is placed by a customer, the process follows different paths depending on whether the order is made online or in-store. If the order is placed online, the optimal fulfillment location (either a warehouse or a store) is determined using Stochastic Dynamic Programming and a Genetic Algorithm. If the order is placed in-store, the availability of the product in stock is checked. If stock is available, the order is fulfilled from the store; otherwise, the customer is directed to place the order online. The company has 30 stores situated in Istanbul and an e-commerce warehouse. For our analysis, we have chosen to examine the demand rates (λ), unit operational costs, unit processing costs, and unit shipping costs associated with the product "Brown Men's Jacket", as presented in Table 1. These costs are used in our calculations.

Table 1. Store information

Store No	λ	Unit Operational Cost	Unit Processing Cost	Unit Shipping Cost
0	0.02	200	10	9.10
1	0.005	300	20	8.05
2	0.03	300	20	6.72
3	0.04	300	20	7.30
4	0.015	300	20	9.19
5	0.005	300	20	5.50
6	0.09	300	20	6.77
7	0.035	300	20	6.41
8	0.035	300	20	6.41
9	0.035	300	20	6.11
10	0.005	300	20	6.95
11	0.005	300	20	10.31
12	0.005	300	20	6.08
13	0.015	300	20	6.48
14	0.01	300	20	6.06
15	0.01	300	20	7.77
16	0.02	300	20	9.00
17	0.02	300	20	10.31
18	0.02	300	20	9.03
19	0.015	300	20	7.21
20	0.02	300	20	6.51
21	0.005	300	20	4.68
22	0.005	300	20	18.09
23	0.01	300	20	7.72
24	0.005	300	20	7.88
25	0.02	300	20	8.50
26	0.005	300	20	17.39
27	0.01	300	20	5.89
28	0.03	300	20	17.39
29	0.005	300	20	7.04
30	0.01	300	20	8.11

3.2. Stochastic Dynamic Programming (SDP)

In the study, Bayram and Cesaret's (2021) mathematical model was used as a reference to determine the optimal solution for cross-channel fulfillment decisions. A dynamic approach is used to determine the optimal cross-channel fulfillment decisions of a retailer that is faced with independent demand classes. In Figure 2, in the final stage where the solution process begins, the state of the system is represented as S_N, and at this stage, the output of the final step, which is the decision variable X_N, is obtained through the transformation Sn function. X_N, along with the decision made, is also represented as $f_N(S_N,X_N)$, indicating the return that will be obtained upon making the decision. The process is continued in this manner from the final stage to the initial stage.

The profit from a sale at store i is given by $p_i - c_i^p$, whereas the net profit of a sale occurring online differs depending on from where this order is fulfilled and is denoted by $p_0 \quad c_j^p \quad c_j^h \quad c_j^s$, given that the online order is fulfilled from location j. It is assumed that selling the product in-store is more profitable than selling the product

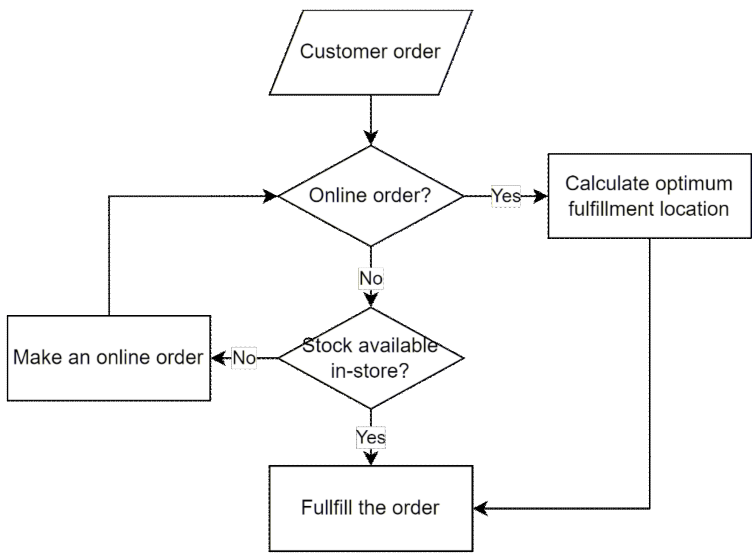

Figure 1. Overview of the Omnichannel Retail Process with Dynamic Fulfillment Optimization

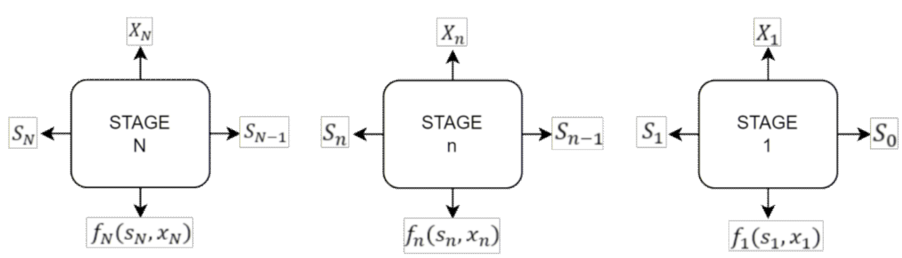

Figure 2. The Backward Recursion Process of an N-Stage Problem

online via any fulfillment option. Thus, a store customer will always be fulfilled as long as the corresponding store inventory is positive. The retailer's problem is whether to accept or reject an online customer and, if accepted, from which location to fulfill this customer.

The optimal value function in period *t* is given as Equation 1.

$$V^*(t,x_0,x_1,\ldots,x_i,\ldots,x_I) = \lambda' V*(t+1,x_0,\ldots,x_i,\ldots,x_I)$$
$$+\lambda_0 E_{pj}\left[max_{j\in J}\begin{pmatrix} y_jD_j + V^*(t+1,x0,\ldots,x_i - y_i,\ldots,x_I), \\ V^*(t+1,x_0,\ldots,x_j\ldots,x_I)\end{pmatrix}\right]$$
$$+\sum_{i\in I}\lambda_i((y_i(p_i - c_i^p) + V^*(t+1,x_0,\ldots,x_i - y_i,\ldots,x_I)) \quad (1)$$

The optimal value function in the last period is given as Equation 2.

$$V^*(T,x_0,x_1,\ldots\ldots,x_I)$$
$$= \lambda_0 E_{c_j^s}[max_{j\in J}](y_j(p_0 - c_i^p - c_i^h - c_i^s),0)] \quad (2)$$
$$+\sum_{i\in I}\lambda_i(y_i(p_i - c_i^p)$$

Here $V^*(t,x_0,x_1,\ldots,x_i,\ldots,x_I)$ represents the expected maximum profit of the retailer from time *t* to the end of period *T*.

$x_i(0)$ is the inventory at store (i) at time t=0.

$x_0(0)$ is the online (0) inventory at time t=0.

λ_j is the total demand arrival rate to all stores and warehouse centers (j) over the period from t to the end of T.

λ' is the total demand non-arrival rate over the period from t to the end of T.

E_{pj} is the expected maximum profit for all stores and warehouse center (j) (p).

p_j is the selling prices of all stores and warehouse centers (j).

c_j^p is the operational cost per unit for all stores and warehouse centers (j) (cost of goods sold, rent, labor, overhead, etc.) (p).

c_j^h is the processing cost per unit for all stores and warehouse centers (j) (picking, handling, packaging at the store).

c_j^s the shipping cost per unit for all stores and warehouse centers (j).

D_j is the total profit for all stores and warehouse centers (j) $\left(p_{j-}c_j^p - c_j^h - c_j^s\right)$.

y_i indicates whether the inventory at all stores and warehouse center (j) is positive or not.

Three different conditions were considered in the model. In the first case, if demand does not occur with probability λ', the expected profit is calculated as in Equation 3.

$$V*(t+1,x_0,\ldots,x_i,\ldots,x_I) \quad (3)$$

In the second case, if an online demand occurs with probability λ_0, then three possibilities will arise:

(i) The request is rejected, and the corresponding expected profit is calculated as in Equation 4.

$$V*(t+1,x_0,\ldots,x_j\ldots,x_I) \quad (4)$$

(ii) The demand from the warehouse center is met and the corresponding expected profit is calculated as in Equation 5.

$$y_0D_0 + V*(t+1,x_0 - y_0,\ldots,x_i,\ldots,x_I) \quad (5)$$

(iii) The demand is satisfied from store i and the corresponding expected profit is calculated as in Equation 6.

$$y_iD_i + V*(t+1,x_0,\ldots,x_i - y_i,\ldots,x_I) \quad (6)$$

In the third case, the retailer's expected (current and future) profit for the customer who comes to store i with probability λ_i in period t is calculated as in Equation 7.

$$(y_i(p_i - c_i^p) + V * (t + 1, x\_0, \ldots, x\_i - y\_i, \ldots, x\_I)) \quad (7)$$

3.3. Genetic Algorithm (GA)

Due to the limitations of SDP for long-term problems, a heuristic method has been proposed. Using the heuristic method of GA, it was possible to relieve the excessive computational burden and achieve results that are close to optimal. MATLAB's GA toolbox was utilized for the solution. The solution methodology of the GA is depicted in Figure 3.

To begin the solution, an initial population is created. The inventory of the store or e-commerce depot fulfilling the order is reduced, and the individual's status is instantly checked and included in the population if appropriate.

With a population size of 4 and the number of periods set at 5, a sample population is presented in Table 2, where C indicates chromosomes and D represents depots. A chromosome represents when and from which store or e-commerce depot the retailer should fulfill the online order. Permutation encoding was employed as the coding method.

The profit of each chromosome in the generated population is calculated using the objective function. Chromosomes survive or perish based on their calculated profit using the Roulette Selection method. It is assumed that C1 and C2 are survived and C3 and C4 perished in this selection. The surviving chromosomes are presented in Table 3.

Randomly selected pairs have been determined among the surviving chromosomes, and a random point has been selected again, and two chromosomes have been crossed. In Figure 4, the first chromosome (C1) and the second chromosome (C2) have been crossed, and

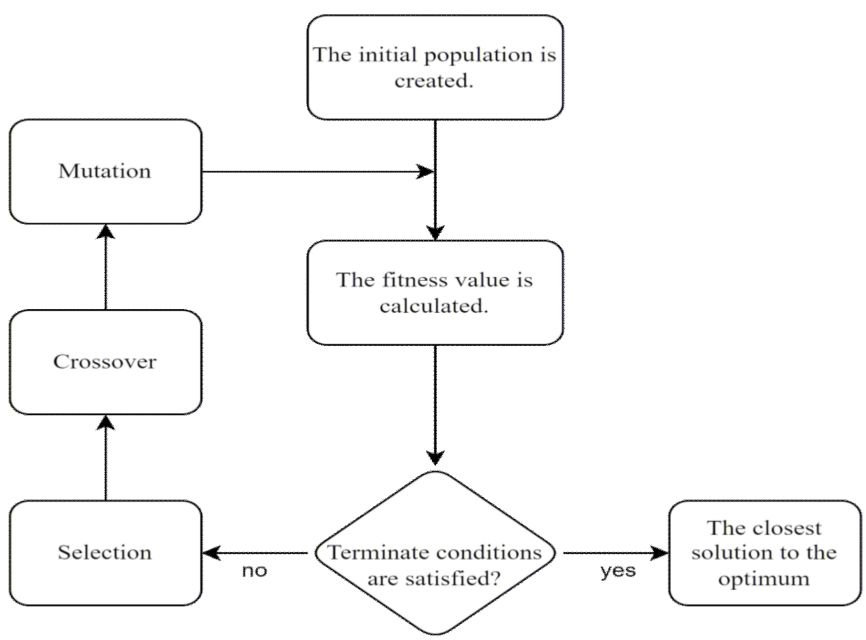

Figure 3. GA steps utilized in the study

new chromosomes (NC1, NC2) have been created.

The crossover probability is set to 0.95. As a result of crossover, the newly formed population is shown in Table 4.

The newly formed chromosomes undergo mutation with a probability of 0.005. The new value of the mutated gene is randomly selected from the gene pool. It is assumed that first depot (D1) of the fourth chromosome (C4) is selected for mutation. The resulting new population is presented in Table 5.

Table 2. Initial Population Matrix

	D1	D2	D3	D4	D5
C1	7	16	27	18	28
C2	30	12	26	21	6
C3	20	6	2	21	20
C4	16	23	6	28	15

Table 3. Surviving Chromosomes Matrix After Natural Selection

	D1	D2	D3	D4	D5
C1	7	16	27	18	28
C2	30	12	26	21	6

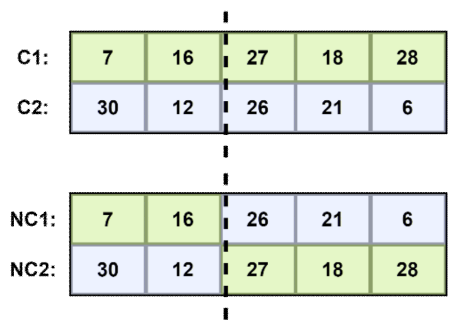

Figure 4. Crossover Example

Table 4. Matrix of the Population Formed as a Result of Crossover Operation

	D1	D2	D3	D4	D5
C1	7	16	27	18	28
C2	30	12	26	21	6
C3	7	16	26	21	6
C4	30	12	27	18	28

Table 5. The Population Resulting from Mutation Operation

	D1	D2	D3	D4	D5
C1	7	16	27	18	28
C2	30	12	26	21	6
C3	7	16	26	21	6
C4	**27**	12	27	18	28

Finally, after each iteration, the program provides output, indicating where the orders should be fulfilled during the period and the corresponding profit when fulfilled. GA yields results close to optimal.

4. RESULTS AND DISCUSSION

Exploring the comparative performance of SDP and GA in the context of store assignment and profit optimization, Table 6 and Table 7 present a detailed examination of their respective outcomes over six periods. Table 6 provides a side-by-side comparison of store assignment results, illustrating the store numbers designated by each method in each period. Meanwhile, Table 7 delves into the profit results, highlighting the financial outcomes generated by SDP and GA across the same six periods. Notably, the tables reveal subtle differences between the algorithms in terms of store assignments and profits.

In addition, in our study, the GA was run for d=2, d=3, d=4, d=5, d=10, d=15, d=20, d=50, d=100, d=150 and d=200 periods. The output results are given in Table 8.

SDP yields optimal results but falls short for long-term scenarios. To address the limitations of SDP, a sample size of 6 was chosen. When dealing with a small sample size, the sampling distribution of statistics does not tend to follow a normal distribution. In such cases, a non-parametric technique becomes necessary (Karagöz, 2010). To assess the disparity between the outcomes obtained through SDP and the GA, the Mann-Whitney U Test was employed.

Table 9 and Table 10 present the outcomes of the statistical analysis conducted to compare the results obtained from SDP and GA using the Mann Whitney U Test. Table 9 provides rank values for both SDP and GA in terms of their average results and the sum of these results across multiple iterations. It offers insights into the performance of these methods and their relative rankings. Meanwhile, Table 10 offers the results of the Mann-Whitney U Test, which was employed

Table 6. SDP and GA Results for Store Orders

Period	Store No in SDP	Store No in GA
1st	21	27
2nd	5	13
3rd	5	7
4th	27	29
5th	27	29
6th	21	8

Table 7. Six Period Profit Results of SDP and GA

Period	SDP	GA
1st	3693	3692.8
2nd	3077.5	3077.3
3rd	2461.98	2461.8
4th	1846.46	1846.4
5th	1230.98	1230.9
6th	615.5	615.5

Table 8. GA Results for 2, 3, 4, 5, 10, 15, 20, 50, 100, 150, 200 Periods

Periods (N)	Optimal Profit Value	Stores/E-commerce warehouse where the order is sent
2	1231	14 30
3	1846.4	10-10-5
4	2461.8	10-7-19-14
5	3077.3	19-27-13-27-24
10	6154.6	2-4-14-10-12-19-12-10-15-7
15	9231.9	28-17-9-30-18-18-10-22-25-14-14-15-9-21-28
20	12309	20-9-4-17-14-22-24-13-18-7-29-16-9-8-30-22-22-21-24-18
50	30771	24–28- 8-29-2 – 3-2-21 -19-4-25-20-3-3-9-25-4-6-8-4-12-22-14-21-16-11-21-5-5- 2-26-30-15-15-19-10-24-18-10-9-30-28-15-31-29-9-15-30-9-9
100	61543	21-4-3-2-18-26-24-31-19-12-2-8-21-14-6-17-19-25-15-29-27-17-17-21-21-7-15-20-29-6-27-9-18-5-17-3-12-21-2-21-28-15-27-24-14-19-22-8-15-2-19-2-20-7-16-15-22-22-23-14-11-17-27-28-20-17-17-6-5-19-19-20-3-3-19-13-14-3-13-4-31-22-15-5-24-30-27-27-6-10-27-15-31-9-12-23-17-18-3-3
150	92315	3-16-20-8-26-30-26-16-9-23-8-30-20-19-6-4-9-27-28-22-23-8-18-25-13- 31-4-11-16-3-23-18-17-26-27-25-11-15-24-4-4-9-17-30-22-10-10-27-28-20- 9-4-26-19-29-3-19-10-26-7-14-13-26-21-7-11-5-21-18-6-5-15-28-18-2- 3-25-15-12-25-12-17-22-27-11-21-30-3-19-13-10-9-24-31-7-24-7-31-25-14- 23-16-25-12-31-9-28-7-14-23-2-29-24-18-7-16-17-31-27-30-21-13-29-15-8- 13-22-18-24-31-30-17-30-4-3-10-18-17-28-17-14-17-22-2-25-5-15-9-12-21
200	123090	27-20-28-20-23-17-30-19-4-7-25-3-18-22-6-28-14-18-2-3-11-17-8-26-22- 1-23-11-15-18-30-13-4-29-29-27-17-22-27-11-29-11-26-6-25-1-20-14-30-8- 4-23-25-7-17-21-18-1-24-4-21-8-21-26-13-15-7-7-19-20-3-25-14-17-2- 28-3-6-27-20-28-20-23-17-30-19-4-7-25-3-18-22-6-28-14-18-5-23-30-13- 7-9-22-26-2-7-19-3-17-4-19-1-10-9-25-20-22-15-22-4-26-18-17-21-3- 29-23-21-1-30-21-4-16-26-16-28-25-7-1-18-22-9-16-21-20-9-25-10-20-21-2- 7-19-20-15-27-5-26-20-21-5-10-12-4-2-12-19-2-2-1-28-28-25-13-30-11- 16-14-3-11-29-19-8-26-12-1-1-22-8-3-23-7-26-2-12-9-2-18-16-8-6- 4-29-22-3-13-10-7-28-6-19-25-28-23-11-17-8-11

Table 9. Rank Values of Mann-Whitney U Test

	N	Average of Rows	Sum of Rows
SDP	6	6.92	41.5
GA	6	6.08	36.5

Table 10. Results of Mann-Whitney U Test

Mann-Whitney U	15.5
Z	-0.401
p	0.699

to evaluate the statistical significance of the disparities between the two techniques. The higher p-value (0.699>0.05). suggests that there might not be a substantial statistical distinction between the outcomes achieved using SDP and GA. These findings collectively emphasize that, in the context of the study, both SDP and GA yield comparable results. This suggests that not only can GA deliver solutions on an extended period, but it can also do so without compromising the quality of results when compared to SDP.

Table 11 provides a detailed comparison of the running times (in seconds) between SDP and the GA for different time periods (D). It is evident from the data that GA consistently outperforms SDP in terms of computational efficiency across all examined time periods. For short time horizons (P=3 to P=7), both SDP and GA exhibit rapid execution times, with GA generally being slightly faster. However, as the time horizon increases, SDP's computational demands escalate significantly, exceeding 10,800 seconds (or 3 hours) for P=7 and becoming impractical for longer periods (P=10, P=50, P=100, P=200). In contrast, GA maintains its efficiency, consistently completing the optimization tasks in less than one second. This substantial difference in running times underscores GA's advantage in handling extensive and complex optimization problems over extended time frames.

5. CONCLUSION

Economics encompasses human activities involving production, trade, distribution, consumption, import, and export. It encompasses all kinds of activities aimed at meeting human needs. When companies determine their order fulfillment policies, they should take into account the economic contribution of the chosen policy within their own organization. In case of incorrect decision-making regarding this policy, companies may face significant economic challenges internally. The multi-channel order management policy we have addressed in our study is crucial in terms of customer satisfaction, company profit, and brand reputation. Results obtained in numerous studies indicate that multi-channel order fulfillment leads to an increase in market share, improvement in profits and profitability, an increase in distribution levels, and an increase in return on investment for companies from an economic perspective.

In the realm of omnichannel retailing, the in-store order fulfillment policy stands out as a widely adopted strategy. This policy treats physical stores as mini-distribution centers, facilitating quicker deliveries and reduced shipping costs. Moreover, it offers a spectrum of advantages to retailers, including a heightened probability of maintaining larger inventories, an upswing in sales, and an enhanced level of customer satisfaction, which in turn leads to increased profitability. Presently, many retailers in Türkiye have enthusiastically embraced omnichannel retailing, recognizing its potential to revolutionize their operations.

Within the scope of our study, we introduce the in-store order fulfillment policy to omnichannel retailers using various methods. As evidenced by our research, the

Table 11. Comparison of Running Times (Seconds) of SDP and GA Per Period for 30 Stores and 1 Warehouse Center

Method	**Period (P)**								
	P=3	P=4	P=5	P=6	P=7	P=10	P=50	P=100	P=200
SDP	<1	2	9	450	>10800	>10800	>10800	>10800	>10800
GA	<1	<1	<1	<1	<1	<1	<1	<1	<1

SDP approach excels in delivering optimal results for the dynamic order fulfillment challenge. It equips decision-makers with crucial insights to pinpoint the most profitable locations for order fulfillment, whether in physical stores or distribution centers. Additionally, it aids in forward-looking inventory management by calculating potential profits. However, SDP reveals its limitations when applied over extended time periods. To mitigate this issue, our study incorporates GA. Remarkably, even when dealing with period sizes of 200 or more, the program runs in less than a second. Furthermore, the statistical tests we conducted indicate that there is no statistically significant difference between the results obtained from SDP and GA. This means that retailers can receive real-time information on the most profitable location for fulfilling dynamic orders, ensuring sustained profitability.

It's important to acknowledge that our study does not encompass channel switching scenarios, such as customers transitioning from physical store visits to online orders, or vice versa. The inclusion of channel switching dynamics could further enhance the study's applicability and precision.

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УНАПРЕЂЕЊЕ МАЛОПРОДАЈНИХ ОПЕРАЦИЈА: ДИНАМИЧКЕ СТРАТЕГИЈЕ ИСПУЊЕЊА У ОМНИКАНАЛНОЈ МАЛОПРОДАЈИ

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Извод

Ова студија истражује тренд допуњавања у продавницама у омниканалној малопродаји, где се залихе оближњих продавница користе за испуњавање онлајн поруџбина. Овај модел представља предности као што су бржа испорука, смањење трошкова, побољшано управљање залихама, повећана продаја и повећано задовољство купаца. Оперативни изазови укључују одређивање оптималне локације за испуњавање онлајн поруџбина. Истражујући малопродају са онлајн и класичним продавницама, овај рад се бави одлукама о динамичком испуњавању поруџбина с обзиром на неизвесност потражње купаца и трошкова испоруке. Студија користи стохастичко динамичко програмирање за краће периоде и генетски алгоритам за дуже периоде, откривајући да генетски алгоритам пружа решења која се блиско приближавају оптималним.

Кључне речи: одлучивање, динамичко програмирање, генетски алгоритам, омниканални маркетинг, испуњење наруџби

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