Automatic pricing and replenishment decision of vegetable products based on heuristic optimization algorithm

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Abstract. This paper aims to investigate the application of heuristic algorithms to optimize pricing and replenishment strategies in retail markets, using vegetable products as an example. Traditional optimization methods are usually unable to solve complex real-world retail decision problems. Heuristic algorithms offer a promising solution by providing near-optimal results in a reasonable time. In this paper, the DPSO algorithm is combined with Genetic Algorithm (GA) and Simulated Annealing (SA) to create a comprehensive optimization framework. This hybrid optimization approach embodies the synergy among DPSO, GA and SA, and is able to dynamically adjust pricing and replenishment strategies. Experimental results demonstrate the effectiveness of this optimization strategy to maximize supermarket profitability while satisfying consumer and retailer demands. Finally, the transformative power of heuristic algorithms in retail management is exemplified and the utilization of data-driven strategies associated with them is advocated for better and sustainable development.

Keywords: Heuristic Algorithm, Decision Model, Big Data.

1. Introduction

Effective optimization of pricing and replenishment strategies for vegetable products can help improve the profitability of supermarkets in an increasingly competitive retail market. For complex decision-making problems in the real world, traditional optimization methods are difficult to obtain satisfactory results [1]. With the ability of heuristic algorithms to find near-optimal solutions in a reasonable time, the shortcomings of traditional optimization methods can be overcome. Therefore, the application of heuristic algorithms is seen as a promising way to solve complex decision problems in retail management [2].

Among the heuristic algorithms, the Discrete Particle Swarm Optimization (DPSO) algorithm has attracted significant attention in the field of computational intelligence due to its effectiveness in handling optimization problems with discrete decision variables [3]. For pricing and replenishment problems in retail markets, DPSO algorithms are the cornerstone for solving complex challenges.

In this paper, an integration of heuristic algorithms, including the DPSO algorithm, Genetic Algorithm (GA), and Simulated Annealing (SA), is intensively investigated to construct a comprehensive optimization framework for solving retail decision problems. Utilizing the collective power of these algorithms, pricing and replenishment strategies for various vegetable products can be effectively adjusted. The mixture of multiple algorithms can overcome the limitations of a single algorithm, explore richer solutions, and ultimately maximize profitability.

This paper outlines the fundamentals of the DPSO algorithm and discusses how it forms the core of the optimization framework. Based on it, the synergies between DPSO, Genetic Algorithm and Simulated Annealing are elucidated, as well as the specific roles of each algorithm in the hybrid optimization approach. In addition, the simulation modeling and corresponding experimental results exemplify the effective role of the synergistic approach in the process of optimizing pricing and replenishment strategies for vegetable products.

By harnessing the power of heuristic algorithms, a novel and data-driven approach to pricing and replenishment in the retail market is provided. This hybrid optimization approach has the potential to revolutionize the way retailers make decisions, thereby improving profitability, customer satisfaction, and overall competitiveness in a complex and ever-changing retail environment [4].

2. The basic fundamental of heuristic algorithm

2.1. The structure and principle of Discrete Particle Swarm Optimization

The Discrete Particle Swarm Optimization (DPSO) algorithm is a widely employed optimization technique that has gained considerable attention in the field of computational intelligence. The flowchart of DPSO model is shown in Figure 1 [5].

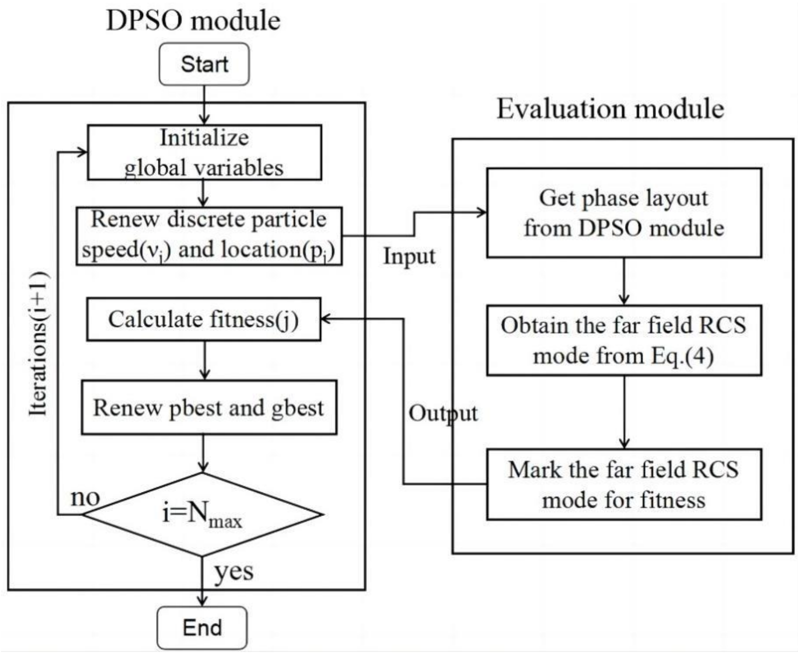

Figure 1. DPSO Model Structure

The general model of particle swarm optimization consists of four basic steps [6], which are:

(1) Initialize a swarm of particles, each representing a candidate solution with a position vector in the discrete solution space. Then assign random initial positions to each particle and initialize particle velocities.

(2) Define the objective function to be minimized or maximized.

(3) Optimization Process confines the position update equation and velocity update equation:

$$\mathbf{X}_{\mathbf{i}}^{(\mathbf{t+1})} = \mathbf{X}_{\mathbf{i}}^{(\mathbf{t})} + \mathbf{V}_{\mathbf{i}}^{(\mathbf{t+1})}, \tag{1}$$

$$\mathrm{V}_{\mathrm{i}}^{(\mathrm{t+1})} = \mathrm{w} \cdot \mathrm{V}_{\mathrm{i}}^{(\mathrm{t})} + \mathrm{c}_1 \cdot \mathrm{r}_1 \cdot \left(\mathrm{P}_{\mathrm{i}}^{(\mathrm{t})} - \mathrm{X}_{\mathrm{i}}^{(\mathrm{t})}\right) + \mathrm{c}_2 \cdot \mathrm{r}_2 \cdot \left(\mathrm{G}^{(\mathrm{t})} - \mathrm{X}_{\mathrm{i}}^{(\mathrm{t})}\right) \tag{2}$$

Where $\mathrm{X}_{\mathrm{i}}^{(\mathrm{t})}$ represents the position of particle i at iteration t, which corresponds to a candidate solution in the discrete search space. $\mathrm{V}_{\mathrm{i}}^{(\mathrm{t})}$ is the velocity of particle i at iteration t, which guides the movement of each particle, allowing them to explore the solution space and converge toward the optimal solution. w is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random vectors, $\mathrm{P}_{\mathrm{i}}^{(\mathrm{t})}$ denotes the personal best position of particle i found so far, $\mathrm{G}^{(\mathrm{t})}$ represents the global best position found by any particle in the swarm at iteration t.

(4) Specify a termination condition, in most cases by giving the maximum number of iterations or achieving a satisfactory solution quality.

(5) The best solution found by the DPSO algorithm is given by $\mathbf{G}^{(\mathbf{t})}$ at the end of the optimization process.

The core components and equations of the DPSO algorithm makes it suitable for solving combinatorial optimization problems with discrete decision variables.

2.2. The combinations of other heuristic algorithms

In the context of optimizing pricing and replenishment strategies for vegetable products in a retail market, a hybrid optimization approach is employed. This approach combines Discrete Particle Swarm Optimization (DPSO) with Genetic Algorithms (GAs) [7] and Simulated Annealing (SA) [8]. By doing so, it forges a robust and versatile framework tailored to surmount intricate optimization challenges. At its core, DPSO, as elucidated previously, forms the foundational optimization paradigm. It meticulously orchestrates the iterative adjustment of pricing and replenishment strategies for a diverse spectrum of vegetable products, ensuring a meticulous exploration of the solution space. However, the overarching objective is to transcend the limitations of conventional optimization paradigms and achieve heightened efficacy.

In this pursuit, Genetic Algorithms (GAs) are strategically interwoven into the DPSO model. These genetic operators, comprising mutation and crossover, are applied at selective intervals to inject diversification into the particle population. Mathematically, the mutation operation introduces diversity by perturbing a subset of particle solutions, represented as:

$$X_{\text{mutated}} = X_{\text{original}} + \delta, \tag{3}$$

Here, X_{mutated} signifies the mutated solution, X_{original} represents the original solution, and δ embodies a stochastic perturbation.

Conversely, the crossover operation blends solutions from distinct particles to spawn novel offspring solutions. Its mathematical instantiation reads as:

$$X_{\text{offspring}} = \alpha \cdot X_{\text{parent1}} + (1-\alpha) \cdot X_{\text{parent2}} \tag{4}$$

Where $X_{\text{offspring}}$ denotes the progeny solution, X_{parent1} and X_{parent2} are parent solutions, and α constitutes a crossover parameter.

Furthermore, the principles of simulated annealing are applied within the DPSO framework. SA introduces controlled stochasticity by sporadically accepting solutions that deviate from the current optimum. The probability of accepting such solutions is formally expressed as:

$$P(\text{Accept}) = \exp\left(\frac{E_{\text{new}} - E_{\text{current}}}{T}\right) \tag{5}$$

In this equation, $P(\text{Accept})$ symbolizes the likelihood of embracing the novel solution, E_{new} quantifies the energy (or cost) associated with the new solution, E_{current} embodies the energy of the prevailing solution, and T signifies the prevailing temperature parameter.

This stochastic optimization technique introduces controlled randomness by occasionally accepting solutions that deviate from the optimum. This randomness aids in escaping local optima, facilitating a more extensive exploration of the solution space.

The integration of genetic algorithms and simulated annealing within the DPSO model extends the algorithm's ability to address complex optimization challenges in the context of retail decision-making. This synergistic approach empowers retailers to make data-driven pricing and replenishment decisions for a diverse array of vegetable products, thereby maximizing the cumulative profitability of their offerings in a competitive market environment.

2.3. The preparation of data preprocessing

The dataset is derived from a sales data collection of a supermarket. It gives the commodity information of 6 vegetable categories distributed by a supermarket; It also respectively provides the sales details and wholesale price data of each commodity of the supermarket from July 1, 2020 to June 30, 2023; It also has the recent data of the loss rate of each commodity. Through analyzing these information, the eventual goal is to maximize the market's profit without suffering from goods shortage[9].

Commencing with data preprocessing, the initial phase encompasses the extraction of sales transaction details from Table 2 for the period spanning June 24th to June 30th, 2023. Subsequently, the daily sales quantities for each individual product are amalgamated, and the pinnacle day in terms of cumulative sales volume is ascertained. Additionally, the maximum unit price for each product on a daily basis is computed and recorded in the newly generated spreadsheet.

Following this, the product identifiers are employed to procure the corresponding wholesale prices from Table 3, specifically within the same temporal bounds. Furthermore, employing the product identifiers once more, the pertinent loss rates are mapped from Table 4 and associated with their corresponding products. These meticulous procedures culminate in the establishment of a comprehensive spreadsheet denominated "MergedData.xlsx."

This methodological approach entails data extraction, aggregation, and association to yield an integrated dataset, facilitating the following comprehensive academic investigation of product sales, wholesale pricing dynamics, and loss rates during the stipulated time frame.

3. Results

3.1. The establishment of simulation model

The large data determination model for the best supermarket profit for item choices of replenishment and price is implemented in python language.

3.2. Analysis of experimental results

According to the results of multiple iterations of the model, the best total profit of the supermarket in one day is up to 1603 yuan. The following is a map of product replenishment and pricing strategy distribution using python matplotlib library to visualize simulated annealing results., as shown in Figure 2.

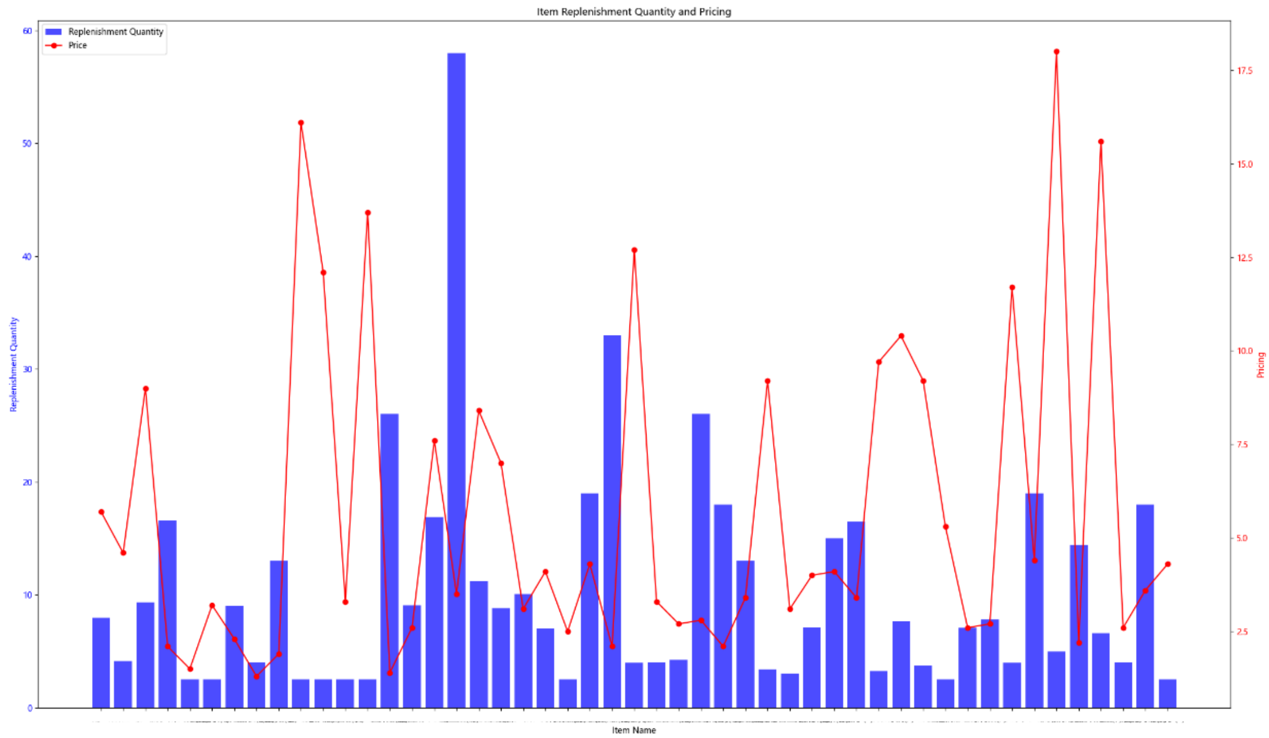

Figure 2. Predicted replenishment quantity and pricing

The following table uses the DataFrame function and custom CSS format to draw a single item replenishment pricing table, and only part of the table header is shown in Table 1.

Table 1. Concrete detail about item choices on Jul 1st of 2023

Sales date	Item number	Item name	Item replenishment quantity	Item price
2023-07-01	102900005115779	Yunnan lettuce	7.971	5.7
2023-07-01	102900005115908	Choi Sum	4.112	4.6
2023-07-01	102900011000328	Screw pepper	9.300	9
2023-07-01	102900005115786	Bamboo leaf vegetables	16.569	2.1
2023-07-01	102900011036686	Fungus(portion)	2.500	1.5
2023-07-01	102900051000463	Round eggplant(2)	2.500	3.2
2023-07-01	102900011030929	Fresh fungus(portion)	4.000	1.3
2023-07-01	106971533450003	Seafood Mushroom(pack)	13.000	1.9
2023-07-01	102900011018132	Wild pink lotus root	2.500	16.1
2023-07-01	102900011032343	Colorful pepper(2)	2.500	12.1
2023-07-01	102900011013274	White jade mushroom(pack)	2.500	3.3
2023-07-01	102900011032732	Gourd(2)	2.500	13.7
2023-07-01	106949711300259	Enoki mushroom(box)	26.000	1.4
2023-07-01	102900011008164	Milk cabbage	9.044	2.6
2023-07-01	102900005116714	Broccoli	16.900	7.6

From the continued iteration of optimal result, the choices of items is gradually fixed to around 33 types per day, which contents the consumer and the seller simultaneously.

4. Conclusion

The effectiveness of the application of heuristic algorithms in solving vegetable product pricing and replenishment strategies is demonstrated in the modeling and analysis of the results, in particular the integration of the DPSO algorithm, Genetic Algorithm and Simulated Annealing. Through a comprehensive optimization framework, the synergy between these heuristic algorithms is able to provide near-optimal solutions that maximize the profitability of supermarkets and satisfy both consumers and retailers. Based on the experimental results of the model's multiple iteration outputs, the maximum daily profit can reach 1603 yuan, demonstrating the tangible benefits of the hybrid optimization approach in real-world scenarios.

The journey from traditional retail management strategies to the application of heuristic algorithms represents a significant paradigm shift. Heuristic algorithms have the potential to revolutionize the retail industry, enabling retailers to make optimal decisions that strike a harmonious balance between profitability and customer satisfaction. In a dynamic and competitive retail environment, the application of heuristic algorithms opens the door to innovation and improved decision-making [10]. In the future, it is clear that heuristic algorithms will continue to play an important role in optimizing retail management decisions, providing a well-established framework for solving complex challenges. This paper demonstrates the potential of heuristic algorithms in optimizing decision-making problems and suggests data-driven strategies for retailers to achieve better and more sustainable growth.

References

[1] Sohangir, Wang, D., Pomeranets, A., & Khoshgoftaar, T. M. (2018). Big Data: Deep Learning for financial sentiment analysis. Journal of Big Data, 5(1), 1–25. https://doi.org/10.1186/s40537-017-0111-6

[2] Talla Nobibon, Leus, R., & Spieksma, F. C. R. (2011). Optimization models for targeted offers in direct marketing: Exact and heuristic algorithms. European Journal of Operational Research, 210(3), 670–683. https://doi.org/10.1016/j.ejor.2010.10.019

[3] Yu, Wang, S., & Xi, L. (2008). Evolving artificial neural networks using an improved PSO and DPSO. Neurocomputing (Amsterdam), 71(4), 1054–1060. https://doi.org/10.1016/j.neucom.2007.10.013

[4] Hansen, Raut, S., & Swami, S. (2010). Retail Shelf Allocation: A Comparative Analysis of Heuristic and Meta-Heuristic Approaches. Journal of Retailing, 86(1), 94–105. https://doi.org/10.1016/j.jretai.2010.01.004

[5] Wu, Guozhang & Yu, Wenqi & Lin, Tao & Deng, Yangyang & Liu, Jianguo. (2020). Ultra-Wideband RCS Reduction Based on Non-Planar Coding Diffusive Metasurface. Materials. 13. 4773. 10.3390/ma13214773.

[6] Rameshkumar, K., Suresh, R. K., & Mohanasundaram, K. M. (2005, August). Discrete particle swarm optimization (DPSO) algorithm for permutation flowshop scheduling to minimize makespan. In International Conference on Natural Computation (pp. 572-581). Berlin, Heidelberg: Springer Berlin Heidelberg.

[7] Garg, H. (2016). A hybrid PSO-GA algorithm for constrained optimization problems. Applied Mathematics and Computation, 274, 292-305.

[8] Kathpal, S., Vohra, R., Singh, J., & Sawhney, R. S. (2012). Hybrid PSO–SA algorithm for achieving partitioning optimization in various network applications. Procedia engineering, 38, 1728-1734.

[9] China Undergraduate Mathematical Contest in Modeling Organizing Committee. (2023). China Undergraduate Mathematical Contest in Modeling. https://cumcm.cnki.net

[10] Camacho-Vallejo, Muñoz-Sánchez, R., & González-Velarde, J. L. (2015). A heuristic algorithm for a supply chain′s production-distribution planning. Computers & Operations Research, 61, 110–121. https://doi.org/10.1016/j.cor.2015.03.004.