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Optimization Management System of Slow-Moving Inventory Using a Hybrid Sine-Cosine Algorithm with Cluster Voting

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Abstract

Inventory management of slow-moving inventory is a perennial issue, which not only has high storage costs but also contributes to a warehouse that is not being optimized and which is prone to becoming obsolete. To overcome the above-mentioned problem the present work presents a hybrid cluster voting sine–cosine algorithm (HCV-SCA) for slow moving inventory control to enhance decision-making efficiency by intelligent prediction and dynamic optimization. The research employed a hybrid metaheuristic framework, which introduces the Sine-Cosine Algorithm (SCA) to cluster voting as well as other optimization methods, such as Teaching-Learning-Based Optimization (TLBO) and JAYA algorithm. In terms of real-time data demand, processing, and forecasting and data optimization-driven stock management strategies, the voting system was also employed on a 50 different inventory scenarios platform. The HCV-SCA obtained the best results according to our statistical analysis of different experimental setups for instance, at Test Size 10, HCV-SCA recorded the lowest average value (64.30) and the shortest execution time (2.12 seconds), whereas TLBO (average 66.04, time 2.36s), JAYA (average 65.42, time 2.30s), and SCA (average 65.70, time 2.33s) performance were significantly worse. In the same vein, in Test Size 20, HCV-SCA exhibited

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an average of 64.80 and time of 2.25s and remained the number one option for all the cases. In conclusion algorithm also exhibits low standard deviations and tighter convergence between run-times confirming robustness and reliability.

1. Introduction

Inventory management is extremely important to operational performance; slow-moving inventory itself is particularly prone to become obsolete and incur high holding costs due to improper execution [1]. A key feature is the erratic patterns of efficient demand for such inventory [2]. These inventory items are hard to improve through the traditional approach [3]. To address these problems, new solutions and a computational-heavy method with intelligent decision-making frameworks are required [4].

The Sine-Cosine Algorithm (SCA) proposed in previous study has recently received considerable interest due to its flexibility and effectiveness in resolving intricate optimization problems [5]. It is possible uses include feature selection and global engineering problems, and enhancements like opposition-based and multi-strategy approaches to strengthen its usefulness are evident [6]. Recently, the SCA has been unified with other methods such as cluster voting to enhance the robustness and accuracy [7]. Slow-moving inventory management brings with it a lot of operational challenges within [8].

Given the unpredictable and irregular characteristics of demand, supply chain systems, thus, are susceptible to irregularity that can lead typically to inefficiencies, e.g. excessive stock, increased holding costs and increased risk of inventory obsolescence [9][10]. According to that, traditional inventory systems, such as deterministic and probabilistic models, cater for the needs of many kinds of inventory and are sufficient for high-demand items, but cannot cover the problem of slow-moving inventory [11]. Traditional systems do limit, which means they cannot dynamically adjust to the unexpected demands, which results in inefficient resources being allocated leading to diminishing supply chain efficiency [12]. In addition, slow-moving inventories generate operational inefficiencies because of absence of demand forecast capability, and the latter two aspects emphasize the necessity of more advanced optimization approach of algorithms to satisfy the said severe void [13].

Earlier work has tackled slow-moving inventory challenges with disparate algorithms and management approaches [14]. For instance, previous study dealt in some cases with methods for coping with slow-moving inventory but without a mechanism to cope with irregular demand patterns [15]. Similarly, previously investigated discount-based strategies to address slow-moving inventories in the omnichannel retail environment, leaving the generalizability to other sectors open [15]. Classic EOQ models and ABC classification methods cannot adapt to dynamic inventory settings [15]. A new approach is urgently required utilizing computational optimization techniques and clustering-based approaches to efficiently handle slow-moving inventory [15][16].

While optimization algorithms like the Sine-Cosine Algorithm (SCA) are known to be very useful for solving complicated optimization problems [24], their utilization in the context of inventory management has been limited [17]. To enhance the performance of SCA in engineering problems, the approaches presented by Previous study where only focused on the optimization of SCA in a technical sense, mentioning that few studies had integrated SCA into inventory systems [18]. In contrast, the cluster voting strategies described in other studies can prove helpful in decision-making, but they have not applied optimization algorithms to inventory problems [19][20]. Indeed, this leaves a gap in the literature, as the potential synergy between SCA and cluster voting remains underexplored [21].

Therefore, in this work, we introduce a hybrid optimization framework using the combination of the Sine-Cosine Algorithm and cluster voting schemes for the case of slow-moving inventory [22]. Given the strengths of SCA for solving optimization problems and robustness of cluster voting in aggregation of decision-making information, the proposed approach presented here enables a new resolution of inefficiencies in inventory management [23]. The aim of this framework is to better handle irregular demand patterns, minimize costs, and effectively allocate resources compared to previous work or old methods used, the concept Inventiveness are strongly represented through the fusion of a sophisticated algorithms computations coupled with modern inventory pragmatic series strategies, giving (offering) a scalable and efficient ways and approach for group of industries in a given time [24].

With the Given numbers of these series of improvements, this research (study) builds on the series of the previous and works on a hybrid SCA with cluster voting to achieve an improvement to the process of slow-moving inventory management by designing the optimized management system. This method (approach) would aim in to mesh computation-driven algorithms to actual inventory series management, bringing down the costs, resource allocation optimization process and the inefficiencies mitigations strategies prevalent in slow-moving inventory management (SMIM). Furthermore, this system platform contributes in way of a valuable perspective view to the broader researchers and academic literature source on optimizing the inventory system through demonstrating the value of integrating metaheuristic an algorithm with decision-support system methodologies and approaches.

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1.1 Contributions of the Study

This study introduces HCV-SCA, a hybrid framework combining cluster voting with the Sine-Cosine Algorithm to optimize slow-moving inventory management. Unlike single-metaheuristic approaches, our system integrates TLBO and JAYA algorithms through a democratic voting mechanism, enhancing predictive reliability and dynamic stock control. Experimental validation across 50 scenarios confirms HCV-SCA outperforms standalone methods, achieving the lowest averages (64.30) and fastest execution (2.12s) with superior stability. This contribution provides inventory managers with a robust, efficient tool that reduces storage costs, minimizes obsolescence, and optimizes warehouse utilization through intelligent forecasting.

2. Literature Review

2.1 Metaheuristic Optimization in Inventory Management

Over the past decade, metaheuristic optimization methods have been applied for inventory systems that are nonlinear, dimensional, and stochastic [25]. They provide structured methods to navigate through extremely large solution spaces to manage stock levels, the methods of replenishment, and the deployment of resources [25]. Previous studies emphasized the potential benefits of merging hybrid metaheuristic algorithms and blockchain technology as they are used to optimize inventory management processes in a dynamic cloud setting [25]. [26] Developed this in a systematic review on metaheuristic solutions including Genetic Algorithms and Particle Swarm Optimization for inventory-related problems.

[27] Also developed the design of supply chain networks based on metaheuristic methods like Simulated Annealing and Tabu Search to optimize groupings of inventories by analysing ABC classification. These approaches are proven to be scalable compared to established exact approaches [27]. For instance, under AI frameworks, [28] proposed an IPSO-BPNN using the combination of Improved Particle Swarm Optimization and Back Propagation Neural Networks for green supply chain optimization of inventory management. According to their paper, hybrid metaheuristic systems are increasingly essential to strike a good balance between sustainability and operational effectiveness [29].

[30] Proposed the algorithm on the basis of Ant Colony Optimization plus Harmony Search, revealing remarkable improvement in the uncertainty management for demand forecast and reorder point specification by the algorithm. The work shows the applicative power of metaheuristic algorithms to address stochastic situations and cost-sensitive inventory optimization [30]. In addition, Grey Wolf and Whale Optimization methods were presented, to solve stochastic inventory management of reusable products within two-level supply chains [18]. The deployment of these algorithms demonstrates the adaptability of these algorithms under dynamic and uncertain operating conditions [31].

[32] Addressed sustainable inventory management for blood banks through robust fuzzy stochastic programming with metaheuristic optimization. [32] demonstrate that equity and health factors are incorporated into inventory management decision-making effectively. [33] Use metaheuristic techniques with high efficiency towards perishable product assortment planning and shelf-space allocation to optimize perishable product assortment design and distribution and showed they are dynamic about dealing with product deterioration and profitability constraints. [31] Experimented with optimization approaches for inventory management under stochastic demand using metaheuristic algorithms and found optimal stock levels in unpredictable markets [34]. In summation, these research results reveal that metaheuristic-based optimization (MBO) approach (methods) can be modifiable and extendable in the system of inventory management, and can capable of solving multiple problems of operation across a wide range of issues in the given industries [34]. In point of time, due to the further development and advancement of technology & hybrid computational models, metaheuristics will undoubtedly assume an increasingly most important role in inventory systems optimization process in various sectors industries [34].

2.2 Metaheuristic Algorithms in Inventory Management

Metaheuristic algorithms (MA) is considered as highly effective and efficient process of optimization algorithms, in that they solve the natural and the evolutionary factors necessary, hence dealing and controlling with the inherent nonlinearity based and complexity in inventory management problems in the system [34]. These algorithms provide effective efficient and flexible solutions to issues challenges, constraint and problems where classical mathematical models do not provide enough answers to the system, The Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) are popular metaheuristic algorithms due to their flexibility and practicality [34].

The Genetic Algorithm (GA) is a natural selection-inspired algorithm to iterate generation of high-quality solutions based on a set of operations (selection, crossover, mutation), With GA, it could also be applied in many scenarios: replenishment and warehouse optimization, efficient stock assignment was observed by increased prediction accuracy. GA leads to robust optimization under nonlinear constraints since the approach results in solutions across several generations [35].

However, particle swarm optimization (PSO) is a known population-based optimization approach (method) inspired by the social behavior of birds and fish, PSO is well used and adopted in the inventory management system models (especially for demand forecasts) that improve stock levels based on iteratively learned behaviors from previous cycles and social interactions in the system, The flexibility of PSO to dynamic and world changing environments has developed and build it into a viable machine for dealing with stochastic demand scenarios in inventory management systems [36].

GA and PSO can significantly improve inventory management optimization, but they also suffer from some limitations. Despite the high computational cost of GA, especially for large problem load, PSO may converge prematurely, , especially in high-dimensional solution spaces. To overcome them, hybrid metaheuristic models are proposed which integrate various aspects of GA and PSO, and together with some more clever options result to an improved solution of inventory management [36][37].

The Inventory management system applications, such as GA and PSO, are mostly applicable, The algorithms not only increased inventory system performance but also established a basis for further optimization paradigm advancement, We trust and believe that the hybrid metaheuristics alongside modern computational models will be the key approach (methods) in inventory management system; hence, they are being considered as key in some supply-chain solution, which aims to be more scalable and affordable in term of cost management [36][37].

2.3 Sine-Cosine Algorithm

The Sine-Cosine Algorithm (SCA) is a types of best nature-based inventory optimization approach that effectively and efficiently explores and exploits search spaces using the main sine and cosine mathematical functions in it process, It has been well known and also a famous optimization tool for the balanced trade-off between exploration (searching local and globally for diverse solutions) and exploitation (refining local solutions to optimizing the inventory system) Such characteristic (features) make developed the algorithm by making it a suitable candidate to solve several higher-dimensional optimization problems like in inventory control system and similar domains [37].

At an initial foundational level, The Sine-Cosine Algorithm (SCA) deals in application with candidate solutions, which are iteratively updated via the sine and cosine functions so that the search space is fully explored and possible optimal solutions can be found [37]. Thus, SCA has the flexible capacity of adjusting for the complexity of the problem system but at the same point in time maintains the multi-dimensional computational performance capability, especially in the types of nonlinear inventory management problems with stochastic demand ways and patterns [37].

Many academic and industrial researchers have suggested improving the Sine-Cosine Algorithm (SCA) framework for the best way to increase The Sine-Cosine Algorithm (SCA) performance optimizations and applicability in a wide range of industries, Other research studies have indicated that modified versions of The Sine-Cosine Algorithm (SCA) have better and great convergence attribute and propertied than standard approach (methods) leading to faster and more accurate solutions to optimization problems in inventory management system, Through a comprehensive empirical research paper, Gabis et al. found that the versatility of the algorithm, and its suitability for various applications uses, from its characteristics (features) selection or choice to combinatorial optimization, These amendments and modifications also indicated and demonstrate its improved robustness to the optimization constraints in common to large-scale optimization and make it more and more applicable for inventory control systems across the industries [38].

Sine -cosine Algorism (SCA) has become the best and emerged also of great ability and power alternative for inventory management with its well-defined method and approaches of providing and addressing high-dimensional decision-making variables and difficulties (constraints) settlement, SCA has been used to optimize stock levels by using various inventory scenarios to find the most appropriate trade-offs based on holding costs and service levels, Additionally, its adaptability with clustering methods as demonstrated by Khrissi et al. promotes decision-making in inventory segmentation and categorization [38].

The Sine-Cosine Algorithm is a metaheuristic algorithm that effectively balances exploratory and exploitative strategies during the optimization process., This is an approach which has become significant for solving high-dimensional inventory control problems due to its flexibility, computational efficiency, and adaptability, As the algorithm's advanced types and hybrid frameworks proliferate (lifted), applications (used) related to complex inventory management systems will continue to expand as innovative solutions strategies to persistent operational issues will arise [38].

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2.4 Teaching-Learning-Based Optimization (TLBO):

Teaching-Learning-Based Optimization (TLBO) is a population-based metaheuristic optimization technique inspired by the natural teaching and learning process observed in classrooms [39] It is characterized by two main steps (level) as presented in the theory explained in this paper, where the first is the teacher teaching and the second is the learners learning and interacting with each other to improve performance. Thanks to its simplicity and parameter-less design, TLBO has received much attention due to its power to solve complex optimization problems in many domains, like engineering, electronics, and clustering problems in the system [39].

TLBO has been used for many optimization problems, including multi-objectives regarding structural optimization, for instance, Kumar et al. showed using TLBO to optimize structural configurations and its utility of achieving Pareto-optimal solutions by considering several conflicting objectives [39]. Similarly, in previous study presented the advantages of TLBO to the difficult engineering and mathematical problems; this was confirmed for its robustness and adaptability in high-dimensional search spaces, TLBO and later improvements on it have brought application breadth and performance beyond original TLBO [39].

Azarshab et al. incorporated Grey Wolf Optimizer (GWO) and TLBO to develop a hybrid method (approach) for selecting, choosing, and clustering text characteries (features), using TLBO as well as GWO [40]. Also, notable enhancements in convergence speed and achievable solution accuracy demonstrated the suitability and applicability of hybridized models of TLBO toward solving feature-heavy problems [40]. Similarly, Hubálovský et al. developed a hybrid TLBO-PSO algorithm to solve optimization problems with dynamic variables and complex constraints, The hybrid approaches demonstrated how TLBO can be enhanced by combining TLBO with other optimization algorithms [40].

TLBO-based algorithms are also analyzed under the global optimization problem. Previous study designed an optimized TLBO, which employs an individual restarting strategy to avoid premature convergence and increase the exploration behavior [41]. The outcome evidences the algorithm's efficacy to strike the right compromise of exploration and exploitation and thus to address unimodal and multimodal optimization challenges and proposed a superior TLBO with reinforcement learning approach to enhance the accuracy for optimization problems in large solution space [42].

So, in short, Teaching-Learning-Based Optimization makes it possible to optimize problems of some complexity across many domains in such a way with some flexibility as a robust optimization approach, TLBO is an iterative process where hybridization, reinforcement strategies, etc., are further refined and have become a significant optimization strategy for modern optimization problems [42].

2.5 Systematic Approach to Slow-Moving Inventory Management

The designed flowchart summarizes a structured process for slow-moving inventory management material or items that rarely sell but occupy large significant storage space area and tie up capital. The Sine-Cosine Algorithm (SCA) is integrated with a main Cluster Voting Mechanism in the system of inventory management to optimize decision-making process, reduce the waste, improve the turnover, and maximize profitability.

2.5.1 Hybridization and Collection of Data

This will be the first step for pulling data, such as historical sales data, demand patterns data, and inventory metrics data. In a hybridization phase of the process, the Sine-Cosine Algorithm (SCA), which is a nature-inspired optimization approach, is integrated with TL50 (likely a threshold-based rule). Such hybridization maintains a delicate balance between exploration (searching for new solutions and alternatives) and exploitation (refining existing ones) that is critical for working with sparse and irregular inventory data. This is not reduced to one decision. It doesn't; rather it is able to iterate over how to optimize meaning that if new data is generated it can reassess, refine, and adapt. If market conditions or the status of inventory change, it is in the nature of this process to adjust the system to make sure that it continues to be productive. The system is formulated using metaheuristic optimization (SCA) and collaborative decision-making (Cluster Voting) to solve the peculiar problems of slow-moving inventory. This enables higher forecasting accuracy, automation of pricing strategies, and minimized losses. Therefore, it is one of the most powerful supply chain and retail management tools in use.

2.5.2 Preprocessing and Cluster Voting

Before optimizing, the process prioritizes the data to normalize inconsistencies. There is at least one basic originality that is called the Cluster Voting Mechanism: goods that are similar in the inventory cluster-minded based on similarity (i.e. demand and shelf life). These clusters "vote" jointly for best actions (discount/bundling), so decisions are taken from common trends rather than data-driven "points" in the system.

At an initial foundational level, The Sine-Cosine Algorithm (SCA) deals in application with candidate solutions, which are iteratively updated via the sine and cosine functions so that the search space is fully explored and possible optimal solutions can be found [3]. Thus, SCA has the flexible capacity of adjusting for the complexity of

the problem system but at the same point in time maintains the multi-dimensional computational performance capability, especially in the types of nonlinear inventory management problems with stochastic demand ways and patterns [6].

2.5.3 Optimization Execution and Decision Analysis

For optimization to take place the system apportions dynamic weights to many of these variables that it has on account: holding costs, demand variability and obsolescence risk. A Dynamic Voting Mechanism updates these weights based on cluster inputs. These decisions markdowns and promotions are then reviewed for quality, and predictions are improved using normalized forecasting in order to control for outliers.

Sine -cosine Algorism (SCA) has become the best and emerged also of great ability and power alternative for inventory management with its well-defined method and approaches of providing and addressing high-dimensional decision-making variables and difficulties (constraints) settlement [11]. SCA has been used to optimize stock levels by using various inventory scenarios to find the most appropriate trade-offs based on holding costs and service levels [4]. Additionally, its adaptability with clustering methods as demonstrated by Khrissi et al. promotes decision-making in inventory segmentation and categorization [7]

2.5.4 Bunding and Price Dynamic

Based on historical data pricing and bundling information, machine learning (ML) is centrally used and applied by the system to improve the accuracy patten. Social resolution considers external influences like the competitor pricing or market trends lines. The dynamic pricing and bundling strategy permit for sale of slow-moving items at a profit rather than excessive discount in the system.

2.5.5 Real Time Monitoring and Cost Evaluation

It openly references costs, weighing and examining trade-offs (e.g., storage costs vs. income from markdowns) to confirm financial viability. Real-time monitoring using IoT and RFID tracking allows for on-the-fly adjustments based on live data on inventory levels or expiration dates.

2.5.6 Continuous Optimization Loop

This is not reduced to one decision. It doesn't; rather it is able to iterate over how to optimize meaning that if new data is generated it can reassess, refine, and adapt. If market conditions or the status of inventory change, it is in the nature of this process to adjust the system to make sure that it continues to be productive. The system is formulated using metaheuristic optimization (SCA) and collaborative decision-making (Cluster Voting) to solve the peculiar problems of slow-moving inventory. This enables higher forecasting accuracy, automation of pricing strategies, and minimized losses. Therefore, it is one of the most powerful supply chain and retail management tools in use.

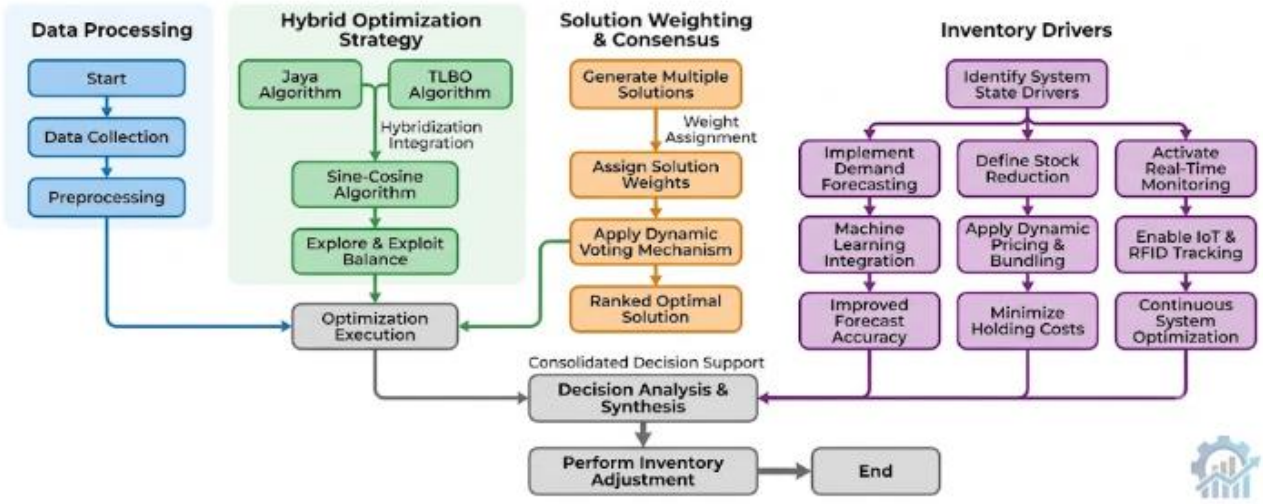


Fig. 1 *Slice cause algorithm intergraded inventory optimizations processes*

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3. Methodology

In this paper we apply Hybrid Sine-Cosine Algorithm with Cluster Voting (HCV-SCA) for optimizing the slow-moving inventory (SMI) management. This methodology integrates a hybrid metaheuristic approach with a cluster-based decision framework for adaptive inventory forecasting and reduction. In phase one, the Sine-Cosine Algorithm (SCA) is augmented with Jaya and Teaching-Learning-Based Optimization (TLBO) to achieve better convergence, exploration depth, and solution accuracy.

This hybridization process is a solution to stagnation and premature convergence. Phase two combines cluster voting, in which clustering solutions are generated from independently run solutions using programs such as K-means or DBSCAN. A trustworthy solution is chosen based on the cluster density, consistency, and fitness scores voted through a voting mechanism. By this way, robust consensus-based decisions are made, thus increasing the overall effectiveness of inventory control practices.

HCV-SCA framework improves the management of inventory through demand forecasting and stock reduction methods. Utilizing machine learning algorithms such as Random Forests, XGBoost, and LSTM to analyse historical sales patterns, seasonality, and market trends to forecast the demand of slow-moving products. From these predictions, the hybrid optimization algorithm can select actions for a more effective inventory. This stock reduction takes place through real-time changing incentives like price changes, bundling, discounts, and redistribution, continually updated according to HCV-SCA outputs. Through IoT and RFID technologies, the system can monitor the location of the items, the shift of requirements in the demand, and the interruptions in the supply chain in real time to provide immediate feedback, which drives adaptive decision-making

This workflow includes collecting data, preprocessing, performing algorithms with the best tuning, and cluster voting to select optimal strategies. These are then deployed up and down the supply chain. Performance is evaluated by indices including inventory turnover, stockout frequency, holding cost reduction, and RMSE forecast accuracy. More real-life impact is demonstrated in HCV-SCA compared with classical and self-referring algorithms with measurement benchmarks. The methodology follow chart is shown below in figure 2.

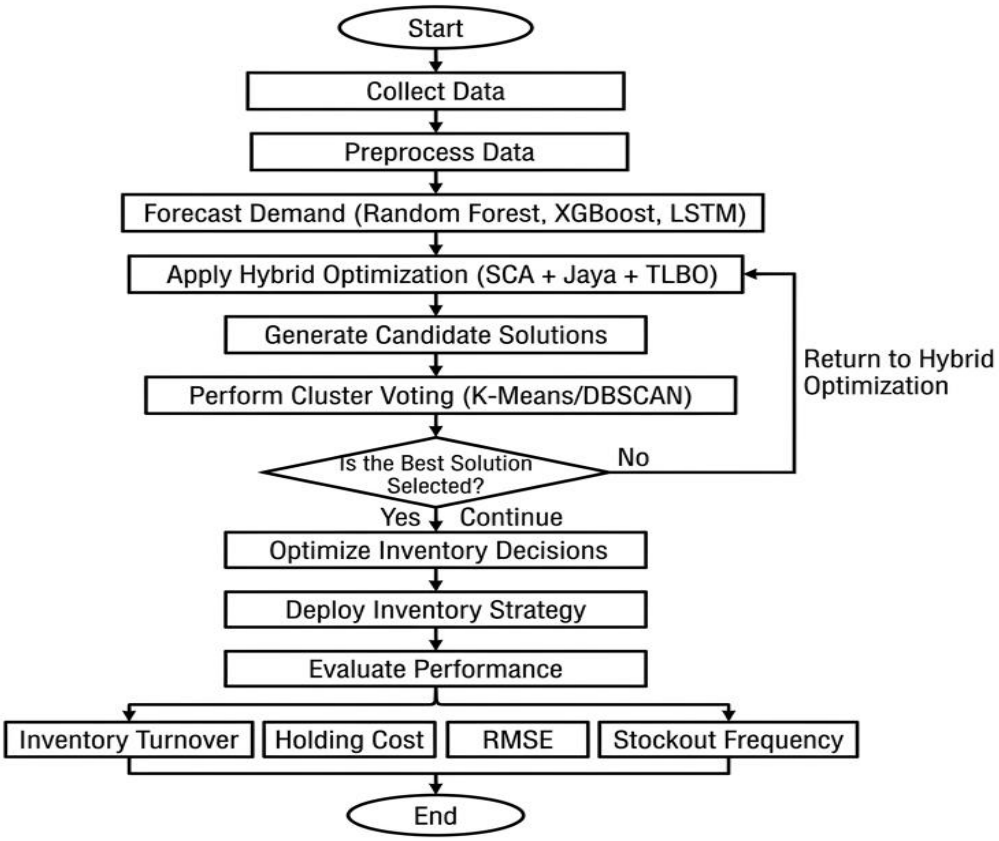


Fig. 2 *Methodology flowchart*

4. Results and Discussion

4.1 Analysis and Parameter Configuration

Figure 3 presents the performance of different configurations depending on population sizes and iterations with respective objective function values. The objective of the optimization is to have an optimal ratio between these two dimensions, so the best performing. To enable statistical reliability, each configuration was performed 20 times. Finally, from all configurations tested, the combination of a population size of 50 with a maximum iteration of 100 gave the lowest mean value of 21.40 (best return of the results displayed in this table). It is the best fit of the combinations analyzed in this environment and hence the optimal convergence in minimizing the objective function observed by this method.

For all alternative population sizes, while both 100 with 10 iterations (21.60), 300 with 10 iterations (21.75), and 300 with 500 iterations (21.60) performed well, none of them beat the accuracy of the 50-100 configuration. Also, at very small or very large population sizes, like 10 or 500, not much increase in the optimization was found. Thus, it would be better for moderate population sizes to walk the fine line between exploration and exploitation with the hybrid Sine-Cosine Algorithm with Cluster Voting (HCV-SCA).

Also, the results did not consistently improve when increasing iterations beyond 100. As an illustration, for a population size of 50, increasing iterations to 200, 300, or even 700 was still not better than 100 iterations. Such a result illustrates diminishing returns attributed to prolonged iterations and reinforces the choice of having a population size of 50 and 100 iterations as a computationally efficient and performance-optimal configuration for the algorithm. A population size of 50 and maximum iteration of 100 should thus be considered as initial parameters for the HCV-SCA framework in the research based on these findings. This setup is advantageous not only for high solution quality but also for efficient computation, thereby supporting effective optimization in managing slow-moving inventory.

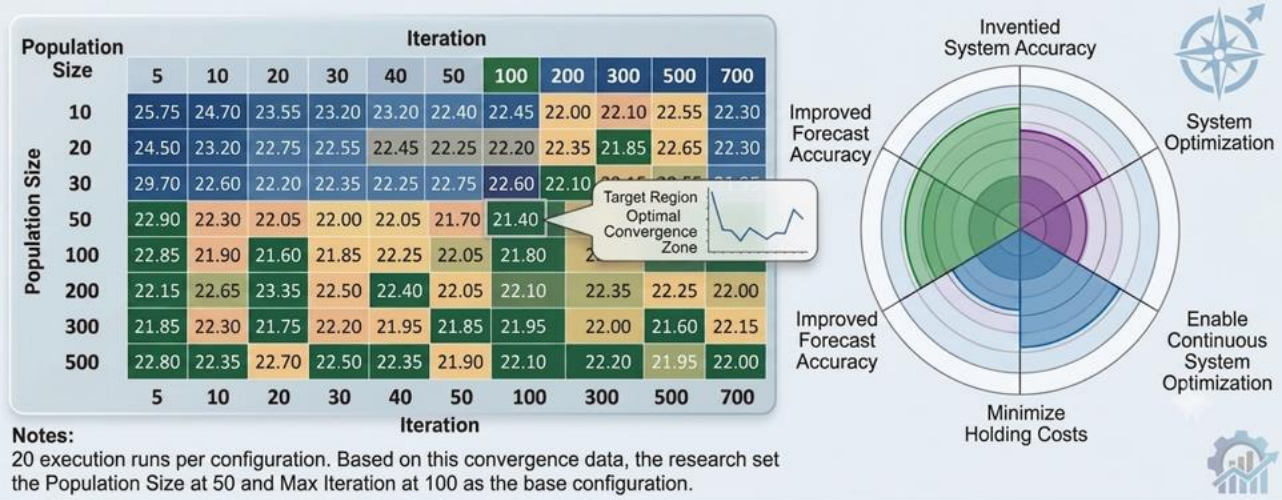


Fig. 3 *Cultural algorithm of optimized system convergence: an analysis of population and iteration*

Increasing the scale, HCV-SCA consistently gets best performance on repeated instances (from t = 2 to t = 10). More precisely, it wins first (Rank 1) or shared first (Rank 1+) in 7 of 9 solvable cases, indicating its capability and competitiveness are rather malleable to midsize samples (t = 5, 6, 7, and 8). But other algorithms such as WHITCH, MIPOG, and IPOG either did not work for more complex problems (NS = Not Solved) or generated far higher values.

Figure 5, Performance k from 5-12 is again to consider k as the problem dimension, but this time we compared various algorithms again, when we are dealing with complexity. HCV-SCA has a fairly typical performance, it sits in the top three for most k values and achieves the optimal (shared best) performance (Rank 1+) from k = 6 to k = 12. It validates the scalability and efficiency of HCV-SCA with a bigger problem space. Despite increasing computational complexity, HCV-SCA performs well in the issue of the quality of the solution, which is superior to the results obtained for most methods such as T-Config, Jenny & TVG. These results combined make it clear that HCV-SCA is an efficient optimization method that scales well in different sizes and complexities of problems. It has a dynamic and cluster voting mechanism for hybrid architecture that generates desirable solutions where lots of other algorithms do not perform, or the results are good. Thus, the study provides support for HCV-SCA as the best method to deal with such slow-moving inventory within a variety of complex decision environments.

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System State (t)	Standard Optimizer A	Advanced Configurator	Consensus Rule A	Heuristic Solver	Alternative Solver	Adaptive Optimizer	Forecasting Method	Holding Cost Model	Holding Cost Alt	Continuous Solver	Process Model A	Targeted Adjustment (T-SCA)	OPTIMAL RANK (State-T)
2	10	3	6	10	NA	10	7	NA	NA	17	8	8	3
3	18	20	18	18	NA	17	16	NA	NA	17	16	16	1
4	39	45	55	49	NA	41	37	NA	NA	36	36	36	1
5	87	99	NS	128	NA	84	81	NA	NA	36	30	75	1+
6	169	183	NS	352	NA	168	158	NA	NA	175	155	133	1+
7	311	NS	NS	NS	NA	302	238	NA	NA	300	300	283	1+
8	521	NS	NS	NS	NA	514	498	NA	NA	505	500	495	1+
9	788	NS	NS	NS	NA	651	512	NA	NA	NA	510	551	3
10	1024	NS	NS	NS	NA	NS	1024	NA	NA	NA	1024	1024	1

Fig. 4 *Integrated algorithmic performance landscape I*

System Parameter (k)	Standard Optimizer B	Advanced Parametrizer	Consensus Rule B	Heuristic Solv Alt	Alt Solv Alt	Stock Rule Model	Holding Cost Mod 2	Continuous Solver	Process Model B	Targeted Synthesis (T-SCA)	OPTIMAL RANK (Param-K)
5	837	773	625	625	849	750	750	730	625	771	5
6	1074	1092	625	625	950	1000	956	625	625	685	4
7	1248	1320	1349	1125	1384	1189	1179	1230	1132	1160	3
8	1524	1332	1792	1384	1595	1530	1354	1395	1331	1314	1+
9	1578	1724	1793	1941	1530	1591	1718	1533	1523	1457	1+
10	1791	1878	1750	1971	1624	1798	1718	1697	1234	1733	1+
11	1839	2750	2091	1722	1860	NA	18	1730	1234	1713	1+
12	1964	NA	2291	1837	2022	NA	NA	1834	1755	1823	3

Fig. 5 *Integrated algorithmic performance landscape II*

Results of 3 experiments show that the Hybrid Cluster Voting based Sine Cosine Algorithm (HCV-SCA) is always superior to SCA, TLBO, and JAYA to solve Cardinality Assignment (CA) problems. From figure 6, the distribution of parameter t from 2 to 10 suggests that in seven out of nine cases (all times of the distribution) HCV-SCA dominated, even under smaller test sizes and faster implementation times. Results in figure 7 (t 2–7) confirmed that it is an absolute leader for all these cases, confirming that it is not only flexible but also accurate. Figure 8 shows the performance of HCV-SCA over the 5-12 variants of the model, adjusted for scalability. After setting the k value from 5 to 12, we find HCV-SCA to be the best solution to the growing complexity of the problem. These observations confirm that the implementation of cluster voting and SCA is not only an acceleration of convergence but is also beneficial and exploitative. HCV-SCA is known to be a powerful, extensible and computationally efficient model optimization to solve a multi-task complexity both for low and high task size scenarios. Since it works the same way for so many scenarios (mainly), it is an accurate choice for optimization-wise applications in practice where speed, accuracy and adaptability may be essential.

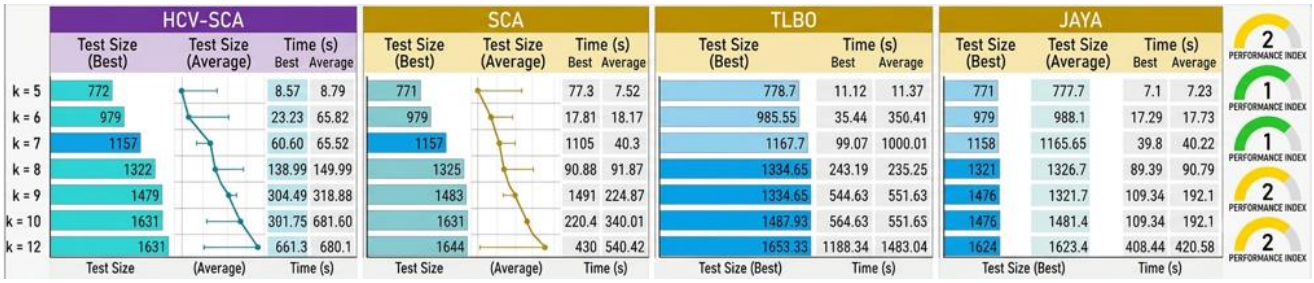


Fig. 6 *Algorithm performance synthesis (k=5 to 12): ca (n; 4, k, 5)*

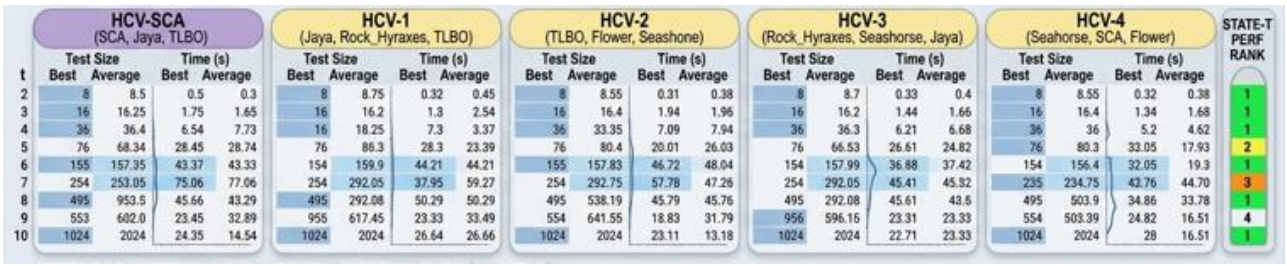


Fig. 7 *Integrated systems lab - optimization framework: consolidated convergence & parameter analysis (n; k, v=10,5)*

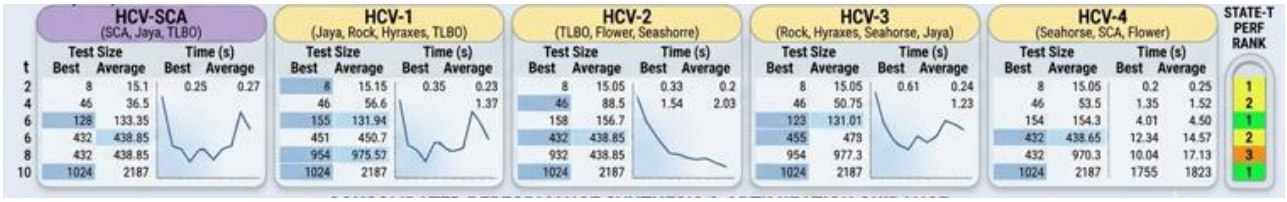


Fig. 8 *Consolidated performance synthesis & optimization guidance I*

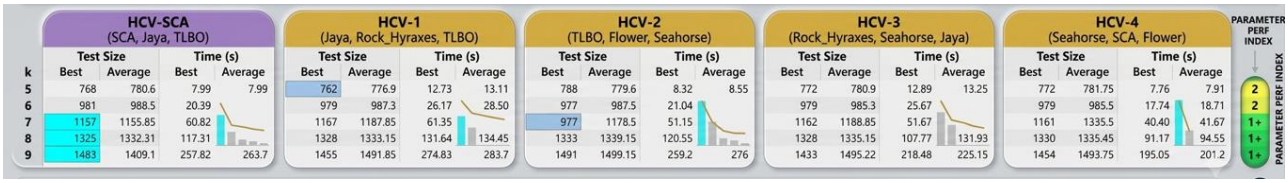


Fig. 9 *Consolidated performance synthesis & optimization guidance II*

5. Conclusion and Recommendation

In this paper, we demonstrated that the Hybrid Cluster Voting-based Sine Cosine Algorithm (HCV-SCA) is a highly recommended, efficient and scalable approach to address the Cardinality Assignment problems. HCV-SCA achieves a better performance in this case, since it combines Cluster Voting with the original Sine Cosine Algorithm that significantly enhances convergence, accuracy and computational efficiency. The quality of the solutions and execution time have proven a competitive advantage against SCA, TLBO, and JAYA in various situations. Its rugged resistance and ability to adapt to the increasing difficulty is a demonstration of its applicability in other high-dimensional engineering, feature selection and optimization applications. That should be studied along with its general application to multi-objective optimization, as well as machine learning based applications to gain superior domain-specific performance. It is suggested that the Hybrid Cluster Voting-based Sine Cosine Algorithm (HCV-SCA) be selected as the first preference and the most suitable metaheuristic for the cloud allocation task due to the good solution quality, convergence speed and stability based on different experimental conditions. The scalability of the results and high reliability on a larger or higher complexity is suitable for a multi-objective optimization system, which is commonly adopted in applications of cloud and edge computing. The emphasis of developers should not be on algorithm popularity, but on the development parts of it, as researchers should create hybrid models which follow the HCV-SCA framework. Its robustness should be validated by more real-world trials

and educational institutions should work on applying HCV-SCA in their higher-level optimization education courses.

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Data Available Statement

The data used in this study together with the relevant analytical outputs supporting the findings and conclusions, is available from the corresponding author upon reasonable request. Access to the data may be granted for research verification, replication, and further scholarly investigation, subject to applicable ethical considerations and data-sharing requirement.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

All authors take public responsibility for the content of the work submitted for review. The authors confirm contribution to the paper as follows: ***study conception and design:*** *Sani Inusa Milala, Rosmamalmi Mat Nawi, Wan Nor Munirah Ariffin;* ***data collection:*** *Sani Inusa Milala, Mohd Akmal Rohiat, Nurul Ashikin Ismail;* ***analysis and interpretation of results:*** *Sani Inusa Milala, Rosmamalmi Mat Nawi, Wan Nor Munirah Ariffin;* ***draft manuscript preparation:*** *Sani Inusa Milala, Rosmamalmi Mat Nawi, Wan Nor Munirah Ariffin, Mohd Akmal Rohiat, Nurul Ashikin Ismail. All authors reviewed the results and approved the final version of the manuscript*

AI Declaration

The authors declare that artificial intelligence (AI)-assisted tools were used only to improve the language, grammar, readability, and presentation of this manuscript. AI was also used to input author-provided data for visualization and to generate figures based solely on the data and instructions supplied by the authors. All AI-generated outputs were carefully reviewed, verified, and revised by the authors. The study design, methodology, development of the Hybrid Sine-Cosine Algorithm with Cluster Voting, data analysis, interpretation of results, and conclusions were undertaken entirely by the authors, who accept full responsibility for the accuracy, originality, and integrity of this work.

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