International Journal on Advanced Science Engineering Information Technology

Vol.15 (2025) No. 3
ISSN: 2088-5334

Optimal Lot-Sizing Decisions in Production Systems Using the Wagner-Whitin Algorithm for Data-Driven Inventory Control

Bela Pitria Hakim [a,*], Muhammad Nashir Ardiansyah [a]

[a] *Faculty of Industrial Engineering, Telkom University, Jl. Telekomunikasi.1 Dayeuhkolot, Bandung, Indonesia*
Corresponding author: [*]belpitha@telkomuniversity.ac.id

***Abstract*—The intersection of automation, visualization, and lot sizing, particularly through the Wagner-Whitin algorithm, plays a crucial role in optimizing production processes and improving decision-making efficiency. Determining optimal lot sizes in multi-period production systems is complex due to fluctuating demand, setup costs, holding costs, and capacity constraints. Effective solutions must dynamically address these variables to ensure optimal resource utilization and minimize waste. This study aims to develop an automated calculator that streamlines lot-sizing computations by integrating advanced mathematical models, such as the Wagner-Whitin algorithm, and innovative data visualization techniques. To design and evaluate this calculator, the study compares its effectiveness with traditional methods, such as lot-for-lot, with a focus on enhanced usability and user satisfaction. The study uses historical production data, including demand forecasts, setup costs, holding costs, and capacity constraints, to validate the model. The tool integrates the Wagner-Whitin algorithm for optimal lot sizing and incorporates sensitivity analysis to assess various scenarios. A comparative analysis is performed, testing the automated calculator against conventional methods. Performance metrics, including accuracy, calculation speed, scalability, and error reduction, are evaluated in simulated multi-period production environments. The results demonstrate that the automated calculator significantly improves calculation accuracy, decision-making, and error reduction compared to traditional methods. This research highlights the transformative potential of automated solutions in enhancing manufacturing operations. Future studies could expand the tool to address complex constraints, such as supply chain disruptions and multi-echelon inventory systems, and incorporate machine learning for improved demand forecasting accuracy and adaptability.**

***Keywords*— Inventory; lot sizing; production planning; Wagner-Whitin algorithm; inventory management.**

Manuscript received 8 Jan. 2025; revised 2 Feb. 2025; accepted 4 May 2025. Date of publication 30 Jun. 2025.

I. INTRODUCTION

Lot sizing is the most challenging problem in production planning and optimization control [1]. Static approaches, such as the Economic Order Quantity (EOQ) model, were widely adopted due to their simplicity and straightforward application. These methods often fail to account for dynamic demand patterns and multi-period planning requirements, leading to suboptimal results in complex production environments. Complexity is further exacerbated by factors such as variable lead times, production disruptions, and machine-specific capacity constraints [2]. The determination of optimal lot sizes, particularly in multi-period, multi-product systems, requires sophisticated mathematical modeling that integrates dynamic demand patterns, setup costs, holding costs, and stringent production capacity constraints. Wagner-Whitin dynamic lot-sizing algorithm relies on complex recursive relations to minimize the total production and inventory costs over a production planning [3]. While highly effective, such methods often demand significant computational resources and specialized expertise, making them inaccessible for many small to medium-sized enterprises. To address these gaps, this study introduces a more user-friendly and adaptable approach that leverages advanced automated tools. This approach aims to streamline calculations, improve decision-making precision, and cater to a broader range of users, democratizing access to efficient lot-sizing solutions. Necessitating the use of more advanced automated tools that can streamline these calculations and provide precise solutions.

A. Mathematical Processes

Automating complex mathematical processes, production planning decisions by reducing manual effort, minimizing errors, and improving the efficiency of multi-period production systems [4]. An improved Wagner-Whitin algorithm is a tool to simplify the process of calculating optimal lot sizes in complex manufacturing environments. The Wagner-Whitin algorithm systematically evaluates the intricate trade-offs between setup and holding costs to derive cost-minimizing production strategies [5]. The development of this algorithm-based tool is to deliver substantial advantages in the industrial sector.

B. Industrial Sector

The industrial sector will benefit from optimized production processes, as the tool provides precise lot sizing recommendations that directly contribute to cost reduction and enhanced productivity. For example, pharmaceutical companies benefit from its ability to manage inventory levels effectively, minimizing waste of perishable goods while ensuring compliance with regulatory demands [6]. Additionally, manufacturers of consumer goods use the algorithm to synchronize their production schedules with market demand, thereby enhancing service levels and customer satisfaction [7].

C. The Integration

In the current environment, integrating automated spreadsheet calculators into workflows enhances operational efficiency, improves accuracy, and fosters collaboration across teams. Their versatility across various industries makes them a vital asset for organizations seeking to optimize processes and navigate the complexities of modern data management effectively. The principles of the Wagner-Whitin algorithm provide a framework that is applicable across various sectors with complex demand patterns [8]. The algorithm's ability to provide a structured, mathematical approach to inventory management supports these industries in achieving both efficiency and compliance. Through the implementation of an automated calculator, general manufacturers can achieve better control over inventory levels, cost management, and resource utilization, leading to more agile and effective operations [9], [10].

II. Materials and Method

Explores existing research related to lot-sizing optimization and the development of spreadsheet-based applications. It identifies gaps in current studies, highlighting the absence of accessible, practical, and cost-effective tools for solving lot-sizing problems. To enhance credibility, real-world data from the automotive industry are explicitly incorporated, demonstrating the tool's applicability beyond theoretical or numerical experiments. Additionally, the tool has been tested in practical scenarios, validating its effectiveness in real-world decision-making processes. The discussion concludes by highlighting the study's novelty and scientific contribution, emphasizing its significance in both academic and practical contexts.

A. Review of Lot-Sizing Optimization

The problem of lot-sizing optimization has been extensively studied in the field of inventory management (see Fig. 1). Classical methods, such as the Economic Order Quantity (EOQ) model, offer simple solutions for static demand scenarios. For more dynamic environments, algorithms like the Wagner-Whitin method or dynamic programming. These algorithms calculate the optimal order quantities by balancing holding and setup costs while meeting fluctuating demand over time [11].

Mixed-integer linear programming (MILP) has been widely explored to optimize lot sizes in multi-period production systems, providing exact solutions for complex decision-making scenarios [12]. More sophisticated methods of hybrid genetic algorithms for dynamic lot-sizing in stochastic environments, as well as robust optimization frameworks for multi-product systems facing uncertainties in cost, demand, and lead times [13], [14]. Additionally, dynamic programming approaches have been utilized to solve joint replenishment problems, while advancements in reinforcement learning have been explored to make real-time lot-sizing decisions in dynamic and uncertain contexts [15]. These innovations highlight the range of methods developed to address various aspects of lot-sizing challenges.

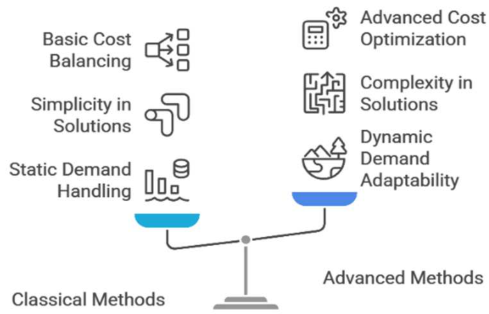

Fig. 1 Comparing Lot-Sizing Methods in Inventory Management

Practical implementation of these methods remains limited. Most tools that integrate these algorithms are embedded in commercial software, which is often expensive and complex to operate [16]. For instance, enterprise resource planning (ERP) systems or advanced optimization platforms require significant financial and technical investment. These constraints make them inaccessible for small- and medium-sized enterprises (SMEs) or individual users seeking practical solutions.

Cost trade-offs in single-item dynamic lot-sizing problems have been discussed extensively, but accessible tools to leverage these insights for real-world applications are rare. The limited availability of open-access tools capable of integrating these sophisticated algorithms into widely used platforms, such as spreadsheets, creates a significant barrier to adoption, particularly for small- and medium-sized enterprises or individual practitioners [17]. The lack of free or low-cost tools that implement advanced lot-sizing methods presents a critical gap. Most available resources either focus on theoretical derivations or provide basic heuristic approaches, leaving practitioners with limited options for optimizing their inventory systems efficiently [18].

B. Review of Spreadsheet-Based Applications

Spreadsheet applications, such as Microsoft Excel, have proven highly effective in decision-making across various domains. Their accessibility, flexibility, and ease of use make them a popular choice for small-scale problem-solving. In inventory management, spreadsheets are often employed for tasks such as demand forecasting, cost analysis, and simple EOQ calculations. The use of spreadsheet-based applications for lot-sizing optimization remains relatively underexplored.

Spreadsheet tools are often used for basic inventory models, such as the Economic Order Quantity (EOQ) or single-period problems. This suggests that most spreadsheet applications primarily focus on static, deterministic inventory models, rather than addressing the complexities of multi-period, dynamic lot-sizing scenarios [19].

Another limitation of existing spreadsheet-based applications is the lack of user-friendly interfaces for implementing custom optimization models. While spreadsheets can theoretically handle complex computations, translating advanced algorithms into functional spreadsheet models often requires substantial expertise. Many spreadsheet-based applications focus on general optimization tasks and are not tailored to the specific needs of inventory managers or practitioners [20]. This further limits the utility of existing applications for real-world inventory challenges.

The prevalence of commercial solutions and templates that are either proprietary or require paid licenses. While some open-access templates exist, they often lack the robustness and scalability needed to handle complex lot-sizing problems. This creates an unmet need for a free, open-access, and comprehensive spreadsheet-based application that can integrate advanced lot-sizing optimization models while remaining simple and intuitive for end-users.

This research addresses these gaps by developing a cost-effective, spreadsheet-based tool for dynamic lot-sizing optimization. By incorporating advanced algorithms, such as the Wagner-Whitin method, and designing an interface that strikes a balance between functionality and ease of use, the proposed application aims to bridge the gap between theoretical optimization models and practical decision-making tools. This contribution would empower users across various industries to optimize their lot-sizing decisions without incurring significant financial or technical barriers.

C. Statement of Novelty and Scientific Contribution

The novelty of this research lies in the development of a cost-effective and user-friendly spreadsheet-based application for optimizing lot-sizing decisions. The proposed spreadsheet tool addresses this gap by integrating dynamic programming algorithms, such as the enhanced Wagner-Whitin method, directly into a widely accessible platform. This approach allows users to achieve optimal lot-sizing solutions without relying on specialized software or technical expertise, making it a practical alternative for organizations with limited resources.

The scientific contribution of this research is twofold. First, it provides an open-access tool that translates advanced optimization techniques into a format that is easy to use and widely available. By enabling users to balance setup costs, holding costs, and demand across multiple periods, the application supports informed decision-making while minimizing total costs. Second, it advances the practical implementation of optimization techniques by offering features such as clear visualizations and output reports, making it a valuable decision-support tool. This solution bridges the gap between academic research and practical application, ensuring that theoretical advancements in lot-sizing optimization can be readily adopted in real-world settings without incurring additional financial or technical barriers. As such, it represents a novel contribution to both the academic community and industry by demonstrating how theoretical models can be operationalized into simple, accessible, and impactful tools.

III. Results and Discussion

The algorithm's decision-making process relies on two critical principles: cost decomposition, where total costs are broken down into period-specific components, and cost comparison, where all combinations of order timing and quantities are evaluated to identify the least-cost solution. The Wagner-Whitin algorithm is highly applicable to scenarios with fluctuating demand, seasonal trends, or production capacity constraints. Fig. 2 below shows the balancing cost strategies in algorithmic decision-making.

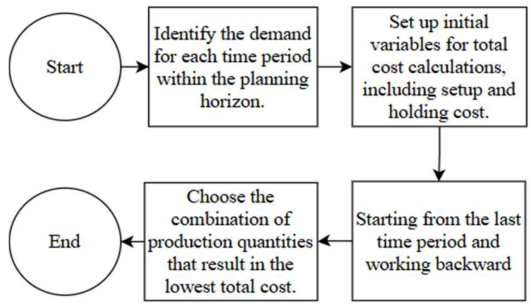

Fig. 2 Balancing Cost Strategies in Algorithmic Decision-Making

Wagner-Whitin algorithm efficiently manages inventory by employing a dynamic programming approach to minimize total production and holding costs through careful calculation and planning [21]. Future developments, integration of cloud-based solutions. The integration with larger systems, such as Enterprise Resource Planning (ERP) platforms. Designed as an exact optimization algorithm with fast computation times, it ensures scalability and efficiency, even when dealing with large datasets and complex analyses.

Hybrid algorithms are beneficial in certain contexts, but they are suboptimal for real-time operations due to their inability to provide optimal results within the required time constraints consistently. MILP [22], on the other hand, delivers optimal solutions but demands significantly more computational resources and processing time, making it less feasible for real-time applications. These limitations were considered when designing the current system, which is specifically tailored to meet the needs of SMEs seeking an affordable and efficient Material Requirements Planning (MRP) optimization tool (See Fig. 3).

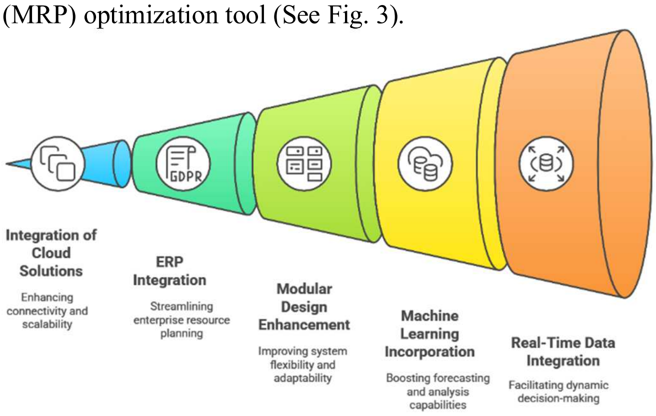

Fig. 3 Optimizing SME's MRP System

Future iterations of this system will build upon the modular structure, enhancing integration with databases for more efficient data accumulation and analysis. This will enable the incorporation of machine learning and other advanced analytical tools, improving forecasting accuracy and optimization reliability. Moreover, real-time data integration will allow businesses to respond to fluctuations in demand, cost, and other variables more dynamically, enhancing their decision-making capabilities [23]. By exploring these integration possibilities, this research aims to meet the growing demands of the evolving manufacturing and supply chain sectors, enhancing decision-making efficiency and optimization in both small-scale and enterprise-level organizations.

A. *Development of the Model*

The Wagner-Whitin algorithm is a deterministic dynamic programming approach to determine the optimal lot-sizing strategy over a finite planning horizon, minimizing total costs, which include ordering and holding costs. The algorithm proceeds in three main steps: Step 1 involves calculating the total cost (*Oen*) for every potential ordering strategy based on ordering costs and cumulative holding costs. Step 2 determines the optimal cost (*fn*) up to each period by evaluating all possible order combinations iteratively and selecting the minimum cost. Step 3 translates the selected strategy into specific lot sizes (*qt*), ensuring demand is met for each planning period while adhering to the optimized total cost. The calculations for each step can be performed manually using formulas and validated in spreadsheet software, such as Excel, for accuracy and comparison.

Step 1 Calculate Total Costs (O_{en}) Wagner-Whitin algorithm focuses on minimizing the total cost, which includes setup and holding costs [24]. The main formula used to determine total costs can be expressed as follows:

$$Total\ Cost\ (O_{en}) = A + h\sum_{t=1}^{N}(q_{en} + q_{et}) \qquad (1)$$

The total cost for ordering in a given period (O_{en}) is calculated by adding the fixed ordering cost (A) to the holding costs (h), which are based on the cumulative demand from the period of the order up to the end of the planning horizon. In Excel, create cumulative demand using the SUM function =SUM(C2:Ct) *(Drag to calculate cumulative demand for all periods)* Calculate O_{en} in the next column =\$B\$1 + \$B\$2 * SUM(D2:Dt). The step 1 total cost is shown in Fig. 4.

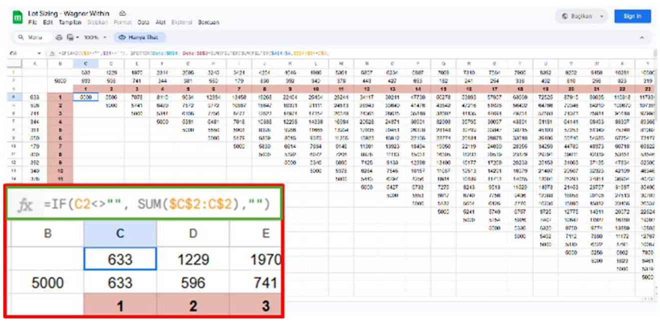

Fig. 4 Step 1 Total Cost

Step 1 involves precise calculations of cumulative demand and total costs using Excel formulas. The SUM function computes cumulative demand across periods, while cost components are integrated using dynamic cell references. These formulas enable systematic evaluation of ordering scenarios, ensuring accurate determination of the optimal lot sizes.

B. *Determine Optimal Cost (f_n)*

Step 2 identifies the optimal cost (f_n) for fulfilling demand up to each period by analyzing all possible order combinations. It aims to find the most cost-effective strategy to minimize the total cost by comparing various order scenarios.

$$f_n = \min\{O_s + f_{s-1}\} \qquad (2)$$

The optimal cost is determined by comparing the total cost (O_s) of ordering in a specific period with the cumulative cost (f_{s-1}) up to the previous period. The ordering strategy with the lowest combined cost is selected as optimal. In Excel formula Use the MIN function in Excel to find the lowest cost for each period =MIN(E2 + F1) E2 represents the total cost for the ordering strategy, and F1 is the optimal cost for the previous period. Drag this formula to calculate optimal costs for all periods. The step 2 optimal cost is presented in Fig. 5.

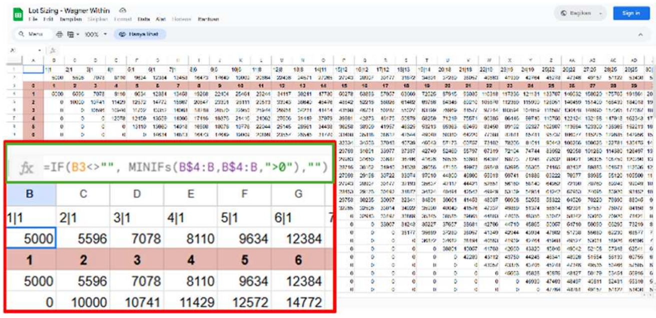

Fig. 5 Step 2 Optimal Cost

The application of the formula ensures an optimal balance between ordering and holding costs. By utilizing the MINIFS function in Excel, the lowest combined cost for each period is determined systematically. This approach supports efficient production planning and inventory management over multiple periods.

C. *Determine Lot Sizes (q_t)*

Step 3, the optimal ordering strategy is translated into lot sizes. This step ensures that the demand for each period is fulfilled efficiently based on the chosen order timing and quantity.

$$q_t = \sum_{t=8}^{N} D_t \qquad (3)$$

Lot sizes are determined by summing up the demand for periods covered by a single order. This ensures that the ordering strategy satisfies the demand without incurring unnecessary holding costs. Use the SUM function in Excel to calculate the lot size for each period =SUM(C2:Cn) Here, C2:Cn represents the demand values for periods covered by the current order. Each step in this process builds upon the previous one, culminating in an optimized ordering strategy that minimizes total costs while meeting demand requirements. Excel can be used to replicate manual calculations, ensuring the accuracy of the results and enabling scalability for larger datasets. The Step 3 Lot Sizes is shown in Fig. 6 below.

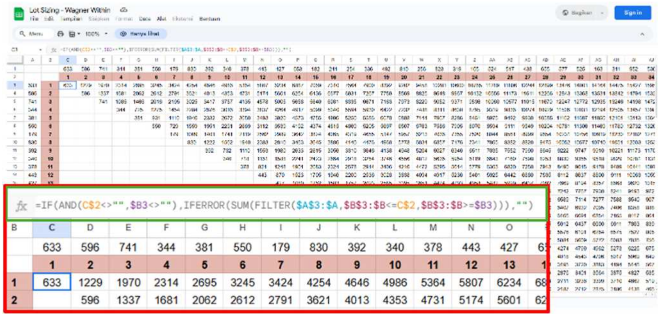

Fig. 6 Step 3 Lot Sizes

The application of Excel formulas in Step 3 ensures that the lot sizes are calculated accurately to fulfill demand efficiently while minimizing total costs. The use of the SUM and FILTER functions replicates the manual process of summing demands for each order period, aligning with the equation. This approach confirms the validity of the formula implementation and supports scalability for complex datasets. Lot sizing problem introduced by Wagner and Whitin (1958). In this numerical experiment, the setup cost (S) is fixed at 5000 for the automotive industry, and the holding cost (ht) is set at 1 for each period. The planning horizon spans 100 periods, with lead time (Lt) fixed at 1 period. The objective is to compare the performance of the Mathematical Model and the Wagner-Whitin Algorithm in terms of minimizing the total cost, which includes both setup and holding costs, over the specified period. The Mathematical Model uses the demand (dt) for each period, while the Wagner-Whitin Algorithm works by determining the optimal lot size for each period. A binary variable (Yt) indicates whether production occurs in period t, where Yt equals 1 if production takes place, and 0 otherwise. The quantity produced in each period (Xt) and the inventory level at the end of each period (It) are also considered. The total cost, including setup and holding costs, is calculated for both models, and the elapsed time required to solve each model is compared. Both models are subjected to non-negativity constraints to ensure that inventory and production levels remain non-negative. The results of the experiment are summarized by comparing the total cost and elapsed time between the two approaches, demonstrating the efficiency of each method in optimizing inventory management for automotive production over 100 periods.

The algorithm begins by initializing the necessary input data, including demand for each period, holding costs, and ordering costs. These inputs are essential for calculating the total cost of inventory management. The next step involves calculating the cumulative cost for each possible demand combination across the periods from 1 to T. Once the cumulative costs are computed, the algorithm determines the optimal solution for each period by evaluating various lot-sizing scenarios that minimize total costs. Following this, the optimal ordering schedule is identified based on the minimum cost table, which facilitates the selection of the best ordering strategy. The algorithm then iterates through each period to ensure that the optimal solution is consistent across all periods, refining the scheduling decisions. Finally, the algorithm stores the minimum cost result for each period, creating a comprehensive table that shows the optimal lot sizes and associated costs for each period. Once the entire process is complete, the optimal ordering schedule is generated, providing an efficient solution that minimizes costs while meeting demand throughout the planning horizon. The cumulative cost for each possible demand calculated is presenten in Fig. 7.

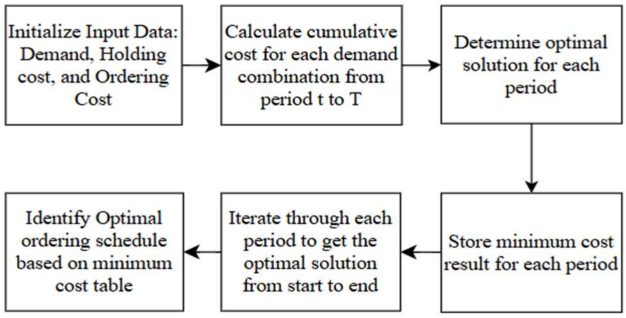

Fig. 7 Calculating the cumulative cost for each possible demand

A. Numerical Experiment

Demand fluctuation significantly influences inventory planning and production scheduling, impacting cost efficiency and resource allocation [25]. The observed product demand pattern demonstrates significant fluctuations over 52 periods, characterized by frequent peaks and troughs. This variability poses challenges for inventory management and production planning, requiring adaptive lot-sizing strategies to minimize total costs while ensuring demand fulfillment. The data, sourced from an automotive manufacturer, serves as a crucial benchmark for evaluating the robustness of inventory models under dynamic demand conditions. The demand fluctuation 1 is shown below.

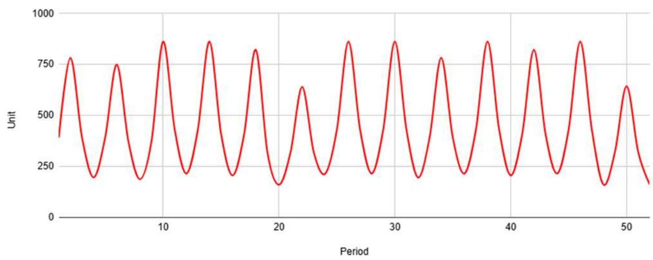

Fig. 8 Demand fluctuation 1

These fluctuations necessitate adaptive lot-sizing strategies, as inconsistencies in demand may lead to periods of overstocking or stockouts. Incorporating demand variability into numerical experiments ensures a robust evaluation of inventory models, particularly when comparing the effectiveness of the Wagner-Whitin Algorithm and traditional mathematical models in optimizing total cost and computational efficiency. The demand fluctuation 2 is provided below.

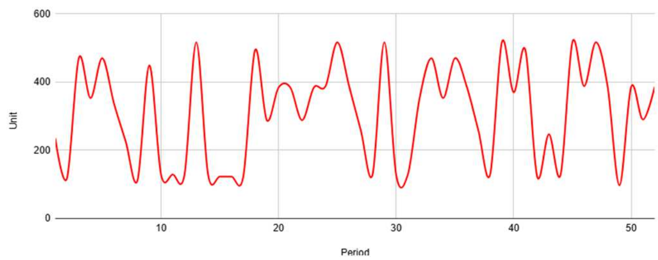

Fig. 9 Demand fluctuation 2

The second product demand pattern exhibits a high degree of fluctuation, with frequent peaks and troughs across the 52 periods. This variability suggests an unpredictable demand structure that poses challenges for inventory management and production planning. The presence of sharp increases and decreases in demand highlights the need for dynamic lot-sizing techniques that can efficiently adjust to changing requirements. In numerical experiments, this fluctuating pattern is essential for evaluating the adaptability and robustness of inventory models, particularly in minimizing total costs while ensuring demand fulfillment.

The formula used in Excel for implementing the Wagner-Whitin algorithm includes calculating holding costs by multiplying the per-unit holding cost by the demand in each period and the number of periods for which inventory is held. Ordering costs are treated as a fixed value, applied each time an order is placed. The total cost for each combination is then derived by summing the ordering cost with the holding costs over the selected intervals [26]. This approach enables the algorithm to identify the lowest cost across combinations by utilizing the MIN function to select the least costly combination, resulting in the optimal lot size that minimizes overall inventory costs.

In implementing the Wagner-Whitin Algorithm in Excel, several key formulas are used to calculate the optimal lot size and total costs [27]. The formulas used are explained in Table 1 below:

TABLE I
FORMULA FOR THE OPTIMAL LOT SIZE AND TOTAL COSTS

Explanation	Excel Formula
Formula for Calculating Holding Costs per Period	=Inventory * Holding_Cost
Formula for Calculating Ordering Costs	=Setup_Cost
Formula for Calculating Total Costs for Period Combinations	=Setup_Cost + (Holding_Cost * (Inventory_At_End_Period))
Formula for Total Cost Across All Periods	=SUM(Total_Inventory_Cost + Total_Setup_Cost)

The Wagner-Whitin Algorithm works by analyzing all possible order combinations and selecting the one that yields the lowest total cost, balancing holding and ordering costs [28]. This approach enables cost optimization for demand that varies across periods. Using Excel, calculations are performed automatically with formulas structured as needed. This study compares the Wagner-Whitin Algorithm with a traditional mathematical model in terms of total cost and computational efficiency. Excel formulas facilitate automatic calculation of lot combinations, saving time compared to manual methods, and allow for dynamic recalculation when parameters like holding or ordering costs change. The use of graphs in Excel helps visualize results, making it easier to interpret cost data and optimize decision-making.

The table as shown in Fig. 10 compares the performance of the Mathematical Model and the Wagner-Whitin Algorithm, focusing on total cost and elapsed time across various problem sets. Both models yield nearly identical total costs, demonstrating that the Wagner-Whitin Algorithm is as effective as the Mathematical Model in optimizing costs associated with inventory holding and setup.

Problem Set	Holding Cost	Set-Up Cost	Mathematical Model		Wagner Within	
			Total Cost	Elapsed Time	Total Cost	Elapsed Time
1	1	5000	190,796	0.97	190,796	1.50
2	1	5000	195,482	0.33	195,482	1.50
3	1	5000	186,869	0.61	186,869	1.50
4	1	5000	189,789	0.33	189,789	1.50
5	1	5000	187,489	0.37	187,489	1.50
6	1	5000	190,072	0.27	190,072	1.50
7	1	5000	195,970	0.71	195,970	1.50
8	1	5000	203,032	0.37	203,032	1.50
9	1	5000	192,250	1.02	192,250	1.50

Fig. 10 Result of Numerical Experiment

However, the elapsed time for the Wagner-Whitin Algorithm remains consistently at 1.50 seconds, indicating higher computational demand compared to the Mathematical Model, which exhibits more variability in elapsed times, ranging from 0.27 to 1.02 seconds. Despite the longer computational time, the Wagner-Whitin Algorithm offers stable performance, making it a reliable choice for optimizing lot-sizing decisions, especially when consistency is prioritized. Ultimately, the choice between the two models depends on whether computational speed or cost optimization is more critical for the specific production environment.

B. *Advantages of Using the Wagner-Whitin Algorithm*

Wagner-Whitin achieved cost savings of up to 232.14% compared to the One Time Purchase method and 102.38% compared to the Lot for Lot method. This algorithm helps prevent unnecessary inventory buildup, which often results in high holding costs. It ensures sufficient inventory to meet demand in each specific period. Wagner-Whitin effectively balances order frequency with holding costs, resulting in an efficient ordering schedule. This algorithm is ideal for variable demand, enabling companies to optimize costs based on changing demand patterns.

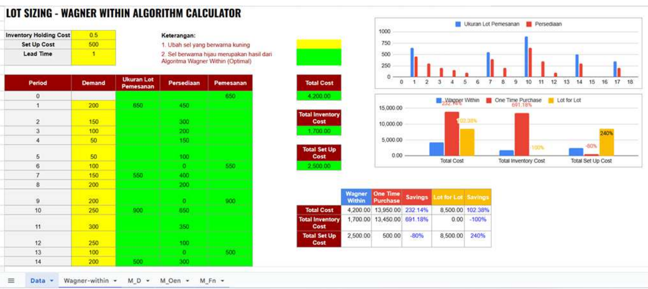

Fig. 11 The Excel dashboard user interface can be accessed publicly

The Excel dashboard was created to illustrate the optimal lot-sizing approach for inventory management using the Wagner-Whitin Algorithm (See Fig. 11). Key components of the dashboard include columns for demand, order lot size, inventory levels, and ordering actions, as well as a cost breakdown to show the impact of each order decision (See Table 2).

TABLE II
KEY COMPONENT

Inventory Holding Cost	0.5
Set Up Cost	500
Lead Time	1

The inventory holding cost is set at 0.5 units of currency per unit per period. This parameter is critical as it influences the decision to delay or expedite orders based on holding cost trade-offs. This parameter represents the cost incurred each time an order is placed, regardless of order size. The setup cost is set at 500 units of currency. Higher setup costs generally incentivize fewer orders with larger quantities, while lower setup costs might result in more frequent, smaller orders. The lead time refers to the time elapsed between placing an order and receiving it, and is set to 1 period in this study. This parameter affects the timing of orders, as it determines how early an order must be placed to meet demand in the subsequent period (See Fig. 12).

Period	Demand	Lot Size Order	Supply	Order
0				
1	633	3424	2791	3424
2	596		2195	
3	741		1454	
4	344		1110	
5	381		729	
6	550		179	
7	179		0	

Fig. 12 The result is after setting the demand in a subsequent period.

The "Demand" column displays the demand levels for each period, which vary over time. The "Order Lot Size" column reflects the algorithm's calculated order quantities, strategically sized to meet demand in the most cost-efficient way. For instance, in period 1, an order size of 650 units is set to meet both current and future demands, minimizing setup costs. Inventory levels in each period are shown in the "Inventory" column. This is the quantity left in stock after fulfilling demand, and it declines as demand is met until a new order is placed. For instance, in period 5, inventory drops to 100 units before a replenishment order of 550 units is placed in period 6. The "Ordering" column indicates the specific periods in which the algorithm advises placing orders. Only selected periods involve new orders, reducing the frequency of setups and thus lowering setup costs. For example, orders are placed in periods 1, 5, 8, 10, and 12, based on optimal cost-balancing calculations

C. Optimal Solution

Using the Wagner-Whitin Algorithm, the total cost is divided into Total Inventory Cost (the cost of holding inventory over periods) and Total Setup Cost (the cost of placing orders). For this scenario, the Total Cost calculated is 4,200 units. This includes a Total Inventory Cost of 1,700 and a Total Setup Cost of 2,500 (See Fig. 13).

	Wagner Within	One Time Purchase	Savings	Lot for Lot	Savings
Total Cost	4,200.00	13,950.00	232.14%	8,500.00	102.38%
Total Inventory Cost	1,700.00	13,450.00	691.18%	0.00	-100%
Total Set Up Cost	2,500.00	500.00	-80%	8,500.00	240%

Fig. 13 Optimal lot size

The algorithm determines the optimal order sizes for each relevant period based on the cost parameters and demand patterns. For example, in period 1, a bulk order of 650 units is placed to satisfy demand over multiple periods, thereby reducing the number of setups and lowering overall costs. The dashboard also compares the Wagner-Whitin solution to other common inventory strategies, such as One Time Purchase and Lot for Lot. The Wagner-Whitin method achieves significant cost savings: compared to the One Time Purchase, it saves 232.14% in total costs, and compared to Lot for Lot, it saves 102.38%. These comparisons demonstrate the superiority of the Wagner-Whitin method in balancing setup and holding costs effectively.

D. Cost Analysis

The dashboard's cost analysis shows specific savings percentages for each cost component. For example, the inventory holding cost is reduced by 691.18% compared to the One Time Purchase approach, highlighting the effectiveness of placing orders only when necessary. Additionally, setup costs are reduced by 80% compared to the Lot for Lot method, demonstrating how larger, infrequent orders can be beneficial (See Fig. 14)..

Fig. 14 The result of Wagner-Whitin

These results suggest that the Wagner-Whitin model offers a highly effective solution for inventory management, particularly in scenarios with variable demand patterns. By aligning order timing with demand, companies can reduce unnecessary costs and improve efficiency. The flexibility of the Wagner-Whitin Algorithm allows it to respond to varying demand, making it a suitable approach for businesses dealing with seasonal or fluctuating demand cycles. The dashboard provides inventory managers with a comprehensive view of ordering patterns and cost impacts, supporting data-driven decisions. The charts in the dashboard allow users to see the relationship between order quantities, inventory levels, and total costs over time, enhancing the interpretability of the results.

The visual result as shown in Fig. 15 illustrates a comparative analysis of total cost, total inventory cost, and total setup cost among three different inventory management strategies: Wagner-Whitin, One-Time Purchase, and Lot-for-Lot. The data highlights the percentage differences in cost components for each approach, providing insights into their efficiency and cost-effectiveness.

Fig. 15 Visual result for comparative analysis of total cost

The Wagner-Whitin algorithm demonstrates the lowest total cost, as indicated by its minimal inventory and setup costs. This optimization approach effectively balances holding and ordering costs, making it the most economical choice among the three methods. In contrast, the One-Time Purchase strategy shows a significantly higher total cost, driven by an excessive inventory cost increase of 691.18%. This highlights the inefficiency of purchasing large quantities at once without considering holding cost implications. The Lot-for-Lot strategy, while avoiding excessive inventory costs, incurs a 240% higher setup cost due to frequent ordering, which negatively impacts its overall cost-efficiency.

E. Managerial Insight

Implementing efficient and affordable production processes can significantly enhance the competitiveness of Micro, Small, and Medium Enterprises (MSMEs) by reducing costs, improving productivity, and enabling scalability. Cost-effective tools allow MSMEs to minimize expenses, increase profit margins, and offer competitively priced products, while user-friendly systems streamline workflows, enhance product quality, and reduce the need for extensive training. These improvements empower MSMEs to expand market access, differentiate their brands, and reinvest savings into growth opportunities, such as new product lines or market expansions. Additionally, adopting accessible production methods fosters job creation, boosts local economies, and contributes to the overall sustainability of the MSME sector, ensuring these businesses can adapt to market changes and maintain resilience in a competitive landscape.

IV. CONCLUSION

By calculating the optimal order sizes based on demand, holding, and setup costs, this approach minimizes total costs and achieves efficient inventory turnover. The dashboard illustrates the superiority of this model over traditional approaches such as One Time Purchase and Lot for Lot, with substantial savings in both inventory holding and setup costs.

Implementing the Wagner-Whitin method offers several advantages, including reduced inventory costs, fewer setups, and flexibility in adapting to demand fluctuations. These benefits are particularly valuable in complex supply chains where cost control and responsiveness to demand are essential. In summary, this study demonstrates that the Wagner-Whitin Algorithm is a practical, data-driven approach that enhances inventory management efficiency, ensuring optimal resource use and cost minimization.

The current system is optimized for SMEs, its scalable, modular design and integration potential position it for broader application in larger enterprises. Future research will focus on expanding this system's capabilities by integrating it with ERP solutions and utilizing cutting-edge technologies, ensuring that the tool remains relevant and effective in an increasingly data-driven, cloud-based business landscape.

ACKNOWLEDMENT

We express our sincere gratitude to all those who have supported and contributed to the completion of this research paper. The Excel dashboard user interface can be accessed publicly
https://docs.google.com/spreadsheets/d/1OzjjDpJDrM75PHtbOfoduAEKFe0Vy2dN7ITesFB-7Y8/edit?usp=sharing

REFERENCES

[1] Y. Li, F. Saldanha-da-Gama, M. Liu, and Z. Yang, "A risk-averse two-stage stochastic programming model for a joint multi-item capacitated line balancing and lot-sizing problem," *Eur. J. Oper. Res.*, vol. 304, no. 1, pp. 353-365, Jan. 2023, doi: 10.1016/j.ejor.2021.09.043.

[2] L. Mönch and L. Shen, "Parallel machine scheduling with the total weighted delivery time performance measure in distributed manufacturing," *Comput. Oper. Res.*, vol. 127, p. 105126, Mar. 2021, doi: 10.1016/j.cor.2020.105126.

[3] R. Bin Hasan, H. Osman, A. Azab, and F. Baki, "Improvement to an existing multi-level capacitated lot sizing problem considering setup carryover, backlogging, and emission control," *Manuf. Lett.*, vol. 35, pp. 28-39, Aug. 2023, doi: 10.1016/j.mfglet.2023.07.012.

[4] C. Li, P. Zheng, Y. Yin, B. Wang, and L. Wang, "Deep reinforcement learning in smart manufacturing: A review and prospects," *CIRP J. Manuf. Sci. Technol.*, vol. 40, pp. 75-101, Feb. 2023, doi:10.1016/j.cirpj.2022.11.003.

[5] M. H. Jabeur et al., "Optimizing integrated lot sizing and production scheduling in flexible flow line systems with energy scheme: A two level approach based on reinforcement learning," *Comput. Ind. Eng.*, vol. 190, p. 110095, Apr. 2024, doi: 10.1016/j.cie.2024.110095.

[6] V. Suhandi and P.-S. Chen, "Closed-loop supply chain inventory model in the pharmaceutical industry toward a circular economy," *J. Clean. Prod.*, vol. 383, p. 135474, Jan. 2023, doi:10.1016/j.jclepro.2022.135474.

[7] M. M. Pereira and E. M. Frazzon, "A data-driven approach to adaptive synchronization of demand and supply in omni-channel retail supply chains," *Int. J. Inf. Manage.*, vol. 57, p. 102165, Apr. 2021, doi:10.1016/j.ijinfomgt.2020.102165.

[8] S. Beraudy, N. Absi, and S. Dauzère-Pérès, "Timed route approaches for large multi-product multi-step capacitated production planning problems," *Eur. J. Oper. Res.*, vol. 300, no. 2, pp. 602-614, Jul. 2022, doi: 10.1016/j.ejor.2021.08.011.

[9] J. Chen, B. Panigrahi, and M. Khojasteh, "Spreadsheet model for activity-on-node project using Excel evolutionary solving method," *J. Acad. Bus. Econ.*, vol. 23, no. 1, pp. 41-52, Mar. 2023, doi:10.18374/jabe-23-1.3.

[10] N. Kumar, B. J. Singh, and P. Khope, "Unleashing an ML-based selection criteria for economic lot sizing in a smart batch-type production system," *TQM J.*, vol. 36, no. 1, pp. 90-107, Jan. 2024, doi:10.1108/tqm-05-2022-0166.

[11] M. Lujak, A. Fernández, and E. Onaindia, "Spillover algorithm: A decentralised coordination approach for multi-robot production planning in open shared factories," *Robot. Comput.-Integr. Manuf.*, vol. 70, p. 102110, Aug. 2021, doi: 10.1016/j.rcim.2020.102110.

[12] B. Beykal, S. Avraamidou, and E. N. Pistikopoulos, "Data-driven optimization of mixed-integer bi-level multi-follower integrated planning and scheduling problems under demand uncertainty," *Comput. Chem. Eng.*, vol. 156, p. 107551, Jan. 2022, doi:10.1016/j.compchemeng.2021.107551.

[13] T. Hamadneh et al., "Application of stork optimization algorithm for solving sustainable lot size optimization," *Comput., Mater. Contin.*, vol. 80, no. 2, pp. 2005-2030, 2024, doi: 10.32604/cmc.2024.052401.

[14] I. Slama et al., "Stochastic program for disassembly lot-sizing under uncertain component refurbishing lead times," *Eur. J. Oper. Res.*, vol. 303, no. 3, pp. 1183-1198, Dec. 2022, doi: 10.1016/j.ejor.2022.03.025.

[15] P. K. Mutyala and A. Kaur, "Inventory optimization of multi-echelon supply chain under market uncertainties," in *Proc. 1st Int. Conf. Pioneering Develop. Comput. Sci. Digit. Technol. (IC2SDT)*, Aug. 2024, pp. 257-262, doi: 10.1109/IC2SDT62152.2024.10696052.

[16] M. Bertolini et al., "Machine learning for industrial applications: A comprehensive literature review," *Expert Syst. Appl.*, vol. 175, p. 114820, Aug. 2021, doi: 10.1016/j.eswa.2021.114820.

[17] A. Kallmuenzer et al., "Adoption and performance outcome of digitalization in small and medium-sized enterprises," *Rev. Manag. Sci.*, pp. 1-28, 2024, doi: 10.1007/s11846-024-00744-2.

[18] P. Suryawanshi and P. Dutta, "Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions," *Transp. Res. E, Logist. Transp. Rev.*, vol. 157, p. 102553, Jan. 2022, doi: 10.1016/j.tre.2021.102553.

[19] L. L. Lorente-Leyva, M. M. E. Alemany, and D. H. Peluffo-Ordóñez, "A conceptual framework for the operations planning of the textile supply chains: Insights for sustainable and smart planning in uncertain and dynamic contexts," *Comput. Ind. Eng.*, vol. 187, p. 109824, 2024, doi: 10.1016/j.cie.2023.109824.

[20] S. Ramingwong et al., "Factory logistics improvement: A case study analysis of companies in Northern Thailand, 2022-2024," *Logistics*, vol. 8, no. 3, p. 88, Sep. 2024, doi: 10.3390/logistics8030088.

[21] R. Kumar and S. Pande, "Medical inventory cost reduction: A survey based study," *AIP Conf. Proc.*, p. 020022, 2023, doi:10.1063/5.0162741.

[22] M. F. Zia et al., "Energy management system for a hybrid PV-wind-tidal-battery-based islanded DC microgrid: Modeling and experimental validation," *Renewable Sustain. Energy Rev.*, vol. 159, p. 112093, May 2022, doi: 10.1016/j.rser.2022.112093.

[23] M. Koot, M. R. K. Mes, and M. E. Iacob, "A systematic literature review of supply chain decision making supported by the Internet of Things and Big Data Analytics," *Comput. Ind. Eng.*, vol. 154, p. 107076, Apr. 2021, doi: 10.1016/j.cie.2020.107076.

[24] M. Arampatzis, M. Pempetzoglou, and A. Tsadiras, "Two lot-sizing algorithms for minimizing inventory cost and their software implementation," *Information*, vol. 15, no. 3, p. 167, Mar. 2024, doi:10.3390/info15030167.

[25] Y. Tadayonrad and A. B. Ndiaye, "A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality," *Supply Chain Anal.*, vol. 3, p. 100026, Sep. 2023, doi: 10.1016/j.sca.2023.100026.

[26] O. Abbaas and J. A. Ventura, "A flexible combinatorial auction bidding language for supplier selection and order allocation in a supply chain with price sensitive demand," *Comput. Ind. Eng.*, vol. 194, p. 110373, Aug. 2024, doi: 10.1016/j.cie.2024.110373.

[27] E. M. D. O. Sánchez, L. L. Hernández, and A. L. Hernández, "Supply of raw materials in an automotive manufacturing company," *Int. J. Manag. Decis. Making*, vol. 20, no. 4, p. 323, 2021, doi:10.1504/ijmdm.2021.118541.

[28] K. Tamssaouet, E. Engebrethsen, and S. Dauzère-Pérès, "Multi-item dynamic lot sizing with multiple transportation modes and item fragmentation," *Int. J. Prod. Econ.*, vol. 265, p. 109001, Nov. 2023, doi: 10.1016/j.ijpe.2023.109001.