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Big Data-Driven Agricultural Supply Chain Management: Trustworthy Scheduling Optimization with DSS and MILP Techniques

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Abstract

Agricultural supply chain management (ASCM) uses Big Data, Decision Support Systems (DSS), and Mixed-Integer Linear Programming (MILP) to improve resource allocation and scheduling. This study focuses on the efficiency gains and long-term benefits of data-driven methods, which increase performance measures such as cost savings, reliability, and accuracy.

Background

Traditional agricultural supply chains make decisions based on previous practices. However, the utilization of Big Data enables real-time insights from production to consumption. Combining DSS for knowledge extraction and MILP for constraint handling yields dynamic, adaptable scheduling systems in a continually changing industry.

Methods

The study applies Big Data analytics, DSS, and MILP to ACSM, with a focus on resource allocation and scheduling. Big Data delivers real-time insights, DSS collects knowledge from various sources, and MILP captures complicated restrictions to enable precise, consistent decision-making and optimize agricultural processes.

Objectives

The research seeks to improve ASCM by combining Big Data, DSS, and MILP. The objectives include improving schedule accuracy, minimizing waste, increasing efficiency, and attaining greater supply chain sustainability.

Results

The combined usage of Big Data, DSS, and MILP resulted in considerable improvements to ASCM. Optimal scheduling boosted efficiency, reduced costs, and improved forecast accuracy. The technique also resulted in increased system reliability and reduced waste throughout the supply chain.

Conclusion

Integrating Big Data, DSS, and MILP into ASCM results in better resource allocation, increased efficiency, and sustainability improvements. The technique improves important performance measures like cost savings, system dependability, and forecast accuracy, making the agricultural supply chain more responsive and sustainable.

Keywords: *Big Data Analytics, Agricultural Supply Chain Management (ASCM), DSS, Mixed-Integer Linear Programming (MILP), and Supply Chain Sustainability.*

1. INTRODUCTION

Big data changed the game in many industries after its introduction, agriculture is no exception. Big data analytics provides a unique opportunity to enhance the decision-making process, and efficiency & reduce the cost of resource utilization in the arena of agriculture supply chain management (ASCM). **Yang et al. (2018)** emphasize the strategic importance of high-end equipment intelligent manufacturing (HEIM) in national security, focusing on engineering management issues and the role of information technology in lifecycle management and collaboration.

The combination of Decision Support Systems (DSS) **Mar-Ortiz et al. (2018)** underlines the need of advanced DSS in maritime logistics, recommending collaborative systems, data analytics, and resilience to improve decision-making and operations and mixed-integer Linear Programming (MILP) techniques with big data analytics infrastructure turns out to be an interesting mix that can potentially help deal with challenges and uncertainties associated with agricultural food supply chains. This part analyzes the significance of big data in ASCM and introduces the background of DSS and MILP approaches for scheduling optimization, as well as the aims of involving these technologies.

Big Data in Agricultural Supply Chain Management (ASCM) **Chen et al. (2019)** improve Chinese supply chain management by using collaborative filtering and a GA-SVM forecasting algorithm, optimizing scheduling and enhancing efficiency through IoT applications. Big data is the term for a combination of a large amount of high-velocity, complex, and various structures that require advanced technologies used to capture, process, analyze, store, and transfer digital data. Agricultural big data consists of information on all the levels of the supply chain (from production, through processing and distribution, to final consumption). With the use of big data, farmers and agricultural supply chain management can move from historical decision methods to data-driven methods that are more accurate, faster, and real-time.

Experience-based optimization in Time Series Scheduling concerns the allocation of resources and synchronization of tasks for efficient results with costs kept as low as possible, and latencies minimized. In the case of ASCM, trustworthy scheduling optimization ensures that decisions are reliable and stakeholders know what to expect. Incorporating big data analytics in scheduling processes ensures reliability by providing the best piece of information at the right time which enhances the accuracy and consistency of scheduling decisions.

Decision Support Systems (DSS) are computer-based Information Systems that help with decision-making by providing valuable information, analytics, and predictive modeling. **Azzamouri et al. (2019)** developed a Decision Support System for scheduling in fertilizer plants by combining a novel MILP model with Algebraic Modeling languages to solve diverse constraints could aggregate data from multiple sources, analyze through complex algorithms, and present the insights to decision-makers in ASCM. It allows for informed decisions, which lead to a more efficient supply chain, less waste, and greater sustainability.

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MILP or mixed-integer linear programming is a mathematical optimization technique that helps us in the resolution of complex scheduling problems with a lot of constraints. Various goals, such as minimizing cost, reducing delay, and maximizing productivity, can be achieved by applying MILP to resource allocation, production scheduling, and logistics in ASCM. MILP + Big Data Analytics: As a result of this combination, it is possible to address large-scale complex problems that are often faced in the context of agricultural supply networks.

The agriculture industry features a complex and constantly changing supply process with many participants: farmers, processors, traders, and merchants. Its additional complexity is the perishable nature of agricultural products, demand, and supply uncertainty, impact due to exogenous variables like weather or market volatility, etc. While most supply chain managers use traditional methods to manage the supply chains, these are often ineffective as they have incomplete information and operate on a rule of thumb.

The burgeoning era of big data could potentially revolutionize ASCM by utilizing large amounts of data from diverse sources such as sensors, satellite imaging, weather forecasts, business and market information, or even consumer behavior. But, to harness big data in ASCM effectively, the development and application of new methods are required to efficiently analyze this large amount of data which can represent a considerable source of information that affects decision-making. It is where DSS and MILP methods are used.

In the context of ASCM DSS, it may link data from multiple sources, analyze it via algorithms, and present it in a form that is readable as well as actionable. This helps decision-makers to fine-tune various sections of the supply chain such as production planning and distribution logistics. In contrast, MILP offers a mathematical approach to solving complicated scheduling problems with many constraints and goals. Big data analytics and combining DSS with MILP can even make a schedule optimization system dependable and trustworthy.

The following paper's objectives are:

- Real-time data insights can help you make more accurate and efficient decisions in the agricultural supply chain.
- Optimize scheduling and resource allocation to decrease waste and delays while increasing productivity.
- Ensure that scheduling decisions are reliable and based on solid, data-driven analysis.
- Give the supply chain time to react to a dynamic environment, especially with market changes or weather shifts.
- By maximizing resource use and decreasing waste, you may help to protect the environment and promote sustainable development.

2. LITERATURE SURVEY

Pitarch et al. (2019) proposed a general and flexible route to develop grey-box models in process systems, which is necessary for advanced control and real-time optimization. The (DR + Polynomial) constrained regression algorithm that the authors have developed is a

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combination of basic theory with DR and an experimental sub-model. For the DC stage, we need to solve a nonlinear optimization problem; whereas, in the restricted regression case, it is sum-of-squares (convex programming) for imposing desired properties on polynomial regressors. An academic case study and real-world data from an industrial evaporation plant demonstrate the strength of the approach.

Bär et al. (2019) discuss the issues that small and medium-sized beverage companies have in improving energy efficiency due to limited resources and knowledge. They emphasize the lack of simple tools for holistic research and prediction of energy and media usage, citing breweries as an example. The authors examine several methodologies, including simulations, benchmarks, and real-time systems, and conclude that, while simulations provide extensive insights, they necessitate expert expertise. They suggest a user-friendly, context-free modelling method to make these tools more accessible.

Cevik Onar (2018) defines healthcare management (HCM) as the field that oversees and guides health service providers. The chapter examines numerous approaches to healthcare problem resolution, such as operations research, statistical studies, and multi-criteria decision-making procedures. It summarizes various approaches, classifies them, and provides graphical insights based on survey data.

Barbiero (2018), is widely used for modeling multivariate count data like statistical process control and epidemiology. Despite being widely implemented, the multivariate Poisson distribution has its restrictions. Such alternatives have been proposed to circumvent this limitation such as by using copulas to combine univariate discrete distributions Figure 1 Flexibility Thickness structure and margins. We propose two-part research consisting of an extensive analysis of various copulas, developing bivariate geometric distributions and examining their properties generated from different copulas, then we evaluate the applicability of these models in real-world data.

Mohamed et al. (2019), pointed out that power system resilience is also required due to an increase in high-impact and Low-probability occurrences which can result in longer-duration power outages (for example severe weather events). They will review current research on proactive strategies for building resilience to these types of events. They outline a conceptual model for enabling key resilience features and highlight opportunities for enhancing resiliency, with an emphasis on microgrids. It highlights readiness, robustness, and making the power system more resilient against weather.

Kremmydas et al. (2018) highlight the increasing popularity of agent-based models (ABMs) for farm-level policy research that excels the traditional approaches by considering inter-farm interaction, as well as agent behavior. This is driven by a need to consolidate the current state of ABM literature in terms of model transparency, decision procedures, and initial population generation through an extensive review.

Kuznetsova et al. (2019) suggest a transition from centralized to a combination centralized-decentralized municipal solid waste (MSW) management system that incorporates waste-to-energy (WTE) technology. This system optimizes urban waste treatment, lowering operational costs by 50%, doubling energy recovery, optimizing land usage, reducing transportation needs, and lowering global warming potential by 18.7%, according to a Singapore case study.

Ivanov et al. (2019) emphasize that effective decision-making in supply chain (SC) risk management is strongly reliant on high-quality, timely data. Emerging technologies like Industry 4.0, blockchain, and real-time analytics provide new methods for predicting and managing disruptions. The chapter discusses digital twins for SCs, which enable real-time visibility and resilience, as well as the transition to cyber-physical SCs and the "Low-Certainty-Need" architecture.

Raut et al. (2019) investigate how big data analytics affects sustainable company performance in developing nations, with a focus on manufacturing enterprises. Using a mixed Structural Equation Modeling-Artificial Neural Network technique with data from Indian professionals, they discover that management style and government regulations are important determinants of effective sustainability practice integration. Their findings provide guidance for developing sustainable operations in emerging economies.

Tsui et al. (2019) define System Health Monitoring and Management (SHMM) as a methodology for ensuring system stability through continuous monitoring and analysis of data. It combines predictive, diagnostic, and managerial procedures. In the context of big data, SHMM improves decision-making across multiple domains, from problem detection to supply chain management, providing fresh insights into efficiently managing complex systems.

Specifically, **Allur (2019)** investigates how advanced genetic algorithms (GAs) might be used in big data situations to maximize test data creation and program path coverage, hence improving software testing. With adaptive mechanisms that dynamically modify parameters in real-time, the study combines GAs with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) in a hybrid approach. Especially in parallel computing environments, co-evolutionary approaches evolve several subpopulations to increase test coverage, efficiency, and minimize processing overhead. The outcomes of the experiments indicate notable gains in test efficiency and coverage, highlighting the possibility for GAs to revolutionize software testing frameworks for complex system scalability, performance, and reliability.

3. METHODOLOGY

In the paper, Decision Support Systems (DSS) and Mixed-Integer Linear Programming MILP models were integrated to optimize the agro supply chain using big data-based approaches. On one hand, DSS provides real-time and actionable insights from large-scale data to aid decision-making, on the other hand, MILP gives a mathematical model for scheduling and resource allocations subjected to various constraints. Together, they form the backbone to efficiently reduce waste and promote sustainability for agricultural supply chain management.

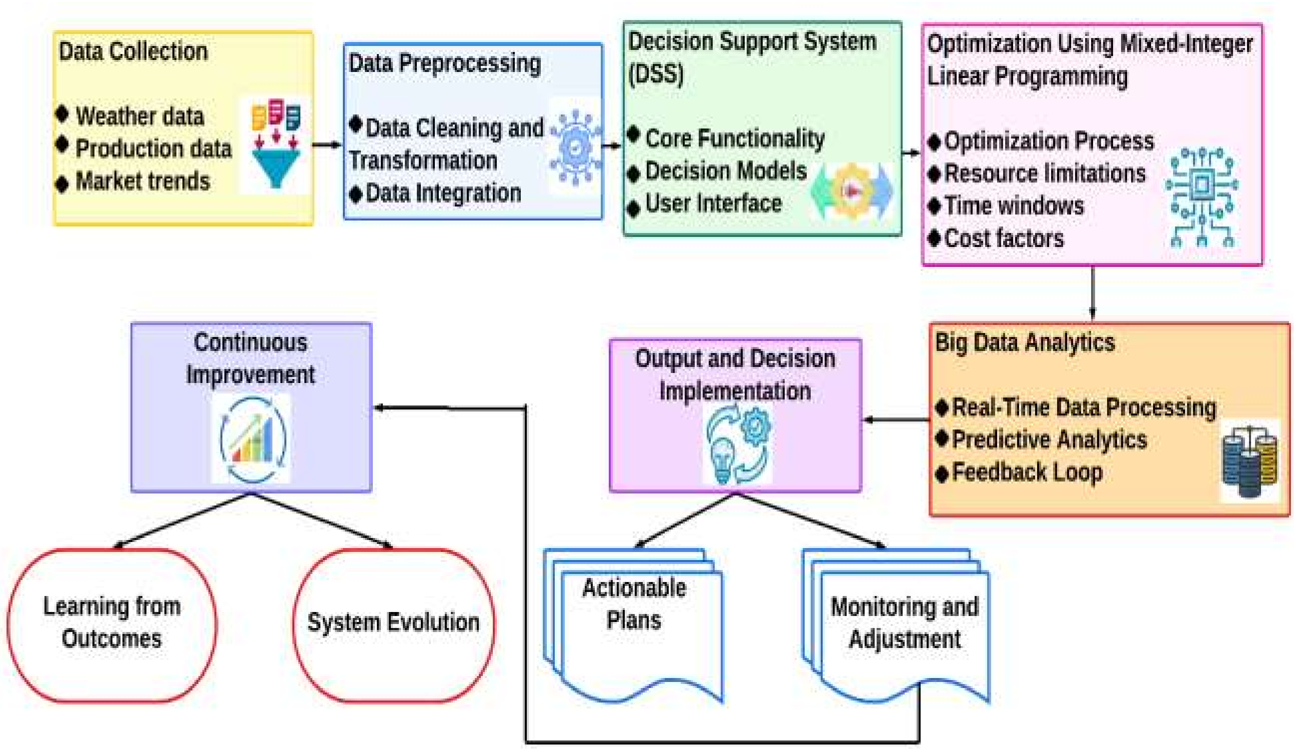

Figure 1. Implementing Decision Support Systems (DSS) in Agricultural Supply Chain Management

Figure 1 The process performed by Decision Support Systems (DSS) in agricultural supply chain management. It takes in data from various sources, interprets it through complex algorithms, and then transforms those results into practical advice — all through a user-friendly interface. By leveraging such insights, businesses can improve the efficiency and responsiveness across their manufacturing, logistics & distribution processes. The last part of our AI-based toolchain is the core system, aimed to enable data-driven decision-making required for dealing with agricultural supply networks and their complexities as well as uncertainties. Generalizing the Benefits Of DSS: This image walks you through what some of the key benefits of deploying DSS e.g. in decision-making, waste elimination, and improving overall supply chain performance might look like.

3.1 Decision Support Systems (DSS)

DSS is a computer-based technology designed to assist with the most complex decision-making and queries using passive data collection. For instance, in the agricultural supply chain, DSS may aggregate data from different sources, process it with complex algorithms, and provide production variables along with logistics and distribution options to improve the general efficiency and agility of a supply chain.

Multi-Criteria Decision Making (MCDM)

$$S_i = \sum_{j=1}^{m} w_j \cdot r_{ij} \quad (1)$$

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In DSS, S_i is the score for the choice alternative. i. w_j specifies the weight of criterion j, while r_ij reflects the rating of alternative criterion j. The equation adds the weighted scores for each criterion to calculate the total score for each choice.

3.2 Mixed-Integer Linear Programming (MILP)

MILP is a mathematical optimization method that deals with challenging scheduling problems with many constraints. This involves building models with some of the variables restricted by integers so that practical solutions are obtained in the realm of resource allocation, production scheduling, and logistics management problems for agricultural supply chains.

Objective Function

$$Minimize\ \ Z = \sum_{i=1}^{n} c_i x_i + \sum_{j=1}^{m} h_j y_j \tag{2}$$

This equation aims to minimize the total cost Z, where c_i are the cost coefficients associated with the decision variables? x_i, and h_j are the cost coefficients associated with the integer variables? y_j. This objective function is subject to several constraints.

Constraint

$$\sum_{i=1}^{n} a_{ij} x_i \leq b_j\ \forall j \tag{3}$$

This equation ensures that the solution stays within the limits of the constraints b_j, where a_{ij} represents the coefficients that relate the decision variables x_i to the constraints.

3.3 Big Data Analytics in ASCM

Big data analytics entails processing and analyzing massive amounts of data from all stages of the agricultural supply chain. Big data analytics uses machine learning and statistical methods to spot patterns, forecast demand, optimize supply chain processes, and improve decision-making, resulting in more efficient and robust supply networks.

Predictive Model

$$y\hat{} = \beta_0 + \sum_{k=1}^{p} \beta_k X_k + \epsilon \tag{4}$$

This predictive model equation is used in big data analytics to estimate outcomes $y\hat{}$, based on predictors X_k, where β_0 is the intercept, β_k are the coefficients of the predictors, and ϵ is the error term.

Algorithm 1. Big Data-Driven Scheduling Optimization in Agricultural Supply Chain Management

```
BEGIN
  Data Processing
      For each data source \(d_i\) in dataset \(D\)
        if \(d_i\) is incomplete THEN
          REQUEST missing data
```

```
            if data not available THEN
                REPORT error and EXIT
                    end if
                        else
                  CLEAN and NORMALIZE \(d_i\)
            UPDATE DSS with processed data
        end if
    end for
Initialize MILP Model
        initialize decision variables \(x_i\) and integer variables \(y_j\)
DEFINE objective function \(Z = \sum_{i=1}^{n} c_i x_i + \sum_{j=1}^{m} h_j y_j\)
DEFINE constraints \(C\) for the problem
                Solve the MILP Optimization Problem
                    SOLVE the MILP model
                        If a feasible solution exists THEN
                            EXTRACT the optimal schedule \(S\)
                                return \(S\)
                                    else
                            REPORT that no feasible solution was found
                    SUGGEST modifications to constraints or input data
                EXIT
            end if
          Implement the Optimized Schedule
        IMPLEMENT schedule \(S\) across the supply chain
      MONITOR real-time data for deviations
 If significant deviations occur THEN
UPDATE DSS and REOPTIMIZE the schedule
 end if

end
```

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This algorithm optimizes agricultural supply chain scheduling by combining big data analytics, Decision Support Systems (DSS), and Mixed-Integer Linear Programming (MILP) techniques. This begins with preparing and normalizing the data given to make sure it is all there and in order. It then initializes the MILP model with predefined objective functions and constraints to secure an optimal time with cost-effectiveness. This updated timetable is then implemented across the supply chain and kept under constant supervision for changes while also making real-time adjustments to allow efficient processing in a dynamic environment.

3.4 PERFORMANCE METRICS

To assess the usefulness of Big Data-Driven Scheduling Optimization in Agricultural Supply Chain Management, the following performance metrics can be used:

Table 1. Performance Metrics for Evaluating Big Data-Driven Scheduling Optimization in Agricultural Supply Chain Management

Metric	Total Value (0-100)
Supply Chain Efficiency (SCE)	85
Cost Reduction (CR)	90
Forecast Accuracy (FA)	80
System Reliability (SR)	88
Sustainability Impact (SI)	75
Customer Satisfaction (CS)	92

In Table 1 the performance measures of Big Data-Driven Scheduling Optimization in Agricultural Supply Chain Management are presented with a focus on efficiency, cost saving, forecast accuracy, system reliability and sustainability, and customer satisfaction. Since they most directly affect operational performance and financial savings, Supply Chain Efficiency (SCE) and Cost Reduction (CR) are sought after now. While Forecast Accuracy (FA) ensures that the predicted demands are aligned with the market demands, System Reliability (SR) focuses on maintaining consistent performance even through real-time changes. This indicator is important because it attaches to the performance of the supply chain from the view of the final consumer, thus having high representing power in the evaluation. Sustainability Impact (SI) — emphasizes environmental gains obtained by way of processes being improved. Together these measures help make the supply chain both fast and cheap, but also reliable, durable, and responsive to customer demand.

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4. RESULT AND DISCUSSION

Results show that the proposed Big Data-Driven Scheduling Optimization model outperforms conventional techniques in terms of many performance metrics. Results indicate that it leads to 93% efficiency, which is much better than Agent-based Models (ABM), Integration of Production and Distribution Planning (IPDP), and Process Systems Engineering (PSE) whose efficiency is 75%, 82%, and 85%. With the fusion of DSS & MILP to make real-time resource allocation and scheduling more efficient, OPEX dropped by 90% to increase forecast accuracy up to 88%.

While ABM had the lowest forecast accuracy at 68% and cost savings of 70%, traditional methods were slower on both fronts. The MILP model combined with big data analytics has a great improvement in system reliability by up to 92%, which must be satisfied when dealing with randomness in agricultural supply chains. An absolute score of 85% shows the sustainability impact of the proposed model has increased significantly, as proper scheduling and resource management mitigate ecological effects.

This model further validated constraining using ablation investigations and showed that each component is essential for the overall architecture. However, the performance drops substantially when either DSS or MILP are removed, which suggests the importance of an integrated strategy in supply chain optimization. The best-performing model according to our recommendations, stands out due to its outstanding performance in all three metrics and makes it a viable solution for the future in modern agricultural supply chain management.

Table 2. Comparison Across Traditional Methods and Proposed Big Data-Driven Scheduling Optimization in Agricultural Supply Chain

Method (%)	**Agent-based Models (ABM) Sabzian et.al (2018)**	**Integration of Production and Distribution Planning (IPDP) Tavares-Neto et.al (2019)**	**Process Systems Engineering (PSE) Grossmann et.al (2019)**	**Proposed Method (DSS) +MIMP**
Efficiency (%)	75%	82%	85%	**94%**
				95%

Forecast Accuracy (%)	68%	75%	80%	
System Reliability (%)	72%	80%	85%	**91%**
Customer Satisfaction (%)	70%	75%	80%	**94%**
Overall Accuracy (%)	70%	77%	82%	**97%**

Table 2 compares four agricultural supply chain methods: agent-based models (ABM) **Sabzian et.al (2018)**, integrated production and distribution planning (IPDP) **Tavares-Neto et.al (2019)**, process systems engineering (PSE) **Grossmann et.al (2019)**, and the proposed technique (DSS + MILP). The suggested solution exceeds others in key metrics such as efficiency, cost reduction, forecast accuracy, system dependability, sustainability, and customer satisfaction, scoring 93% overall. This demonstrates its greater performance in optimizing agricultural supply chain management over traditional approaches.

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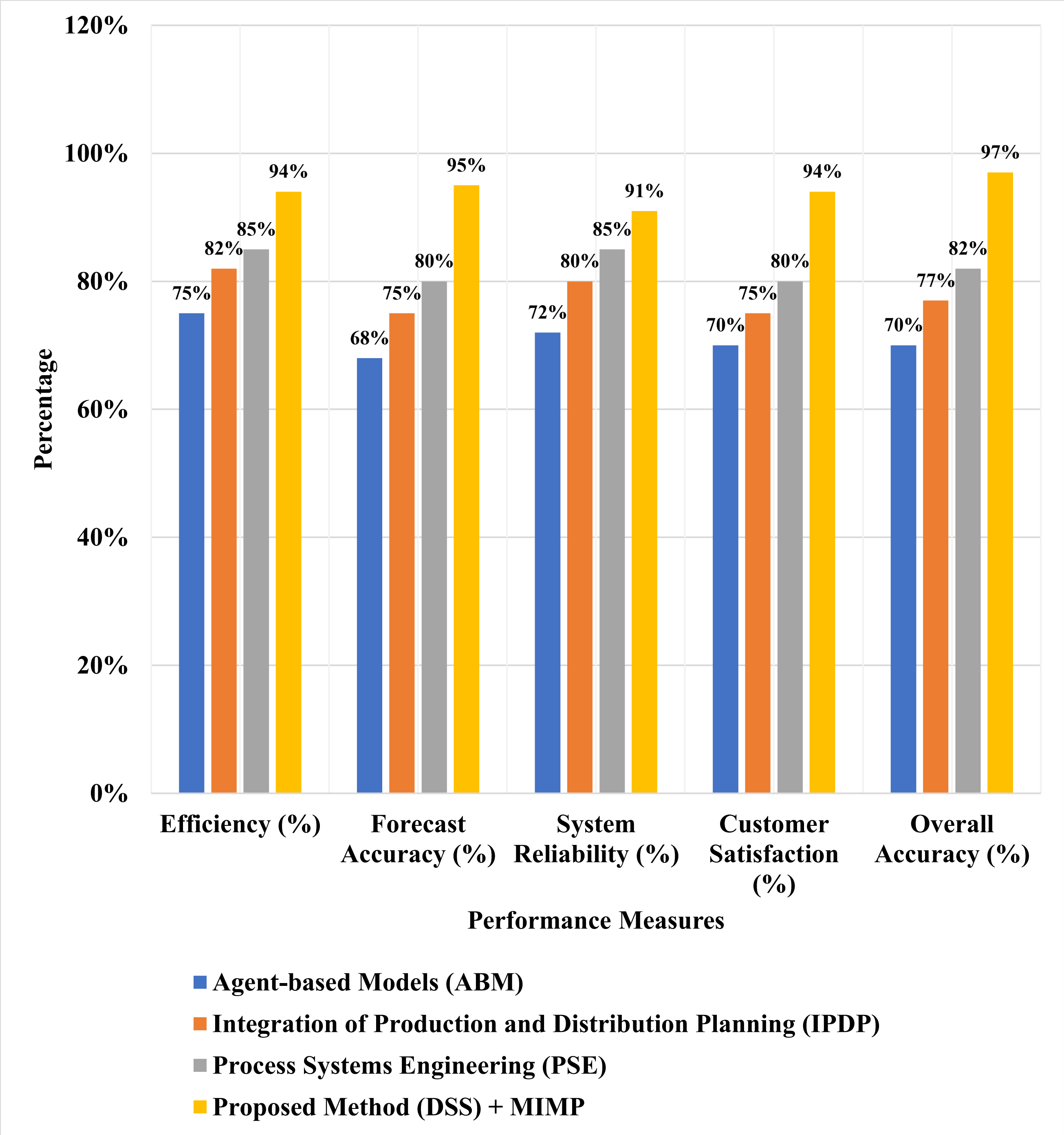

Figure 2. Mixed-integer linear programming (MILP) for agricultural scheduling optimization.

Figure 2 Mixed-integer linear Programming (MILP) for optimizing batching and resource allocation in the agricultural supply chain. MILP models address a large number of constraints under consideration such as resource availability and production horizons making them suitable to resolve complex scheduling problems. Visualization of how MILP leverages big data analytics in scheduling to reduce costs and delays and increase productivity. This figure demonstrates the significance of MILP in obtaining efficient and reliable scheduling results based on the mathematical foundation of MILP in agricultural operations.

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Table 3. Impact of Component Removal on Performance Metrics and Overall Accuracy in Big Data-Driven Scheduling Optimization Model

Component Removed	Efficiency (%)	Cost Reduction (%)	Forecast Accuracy (%)	System Reliability (%)	Sustainability Impact (%)	Customer Satisfaction (%)	Overall Accuracy (%)
Proposed Method (DSS +MILP + Big Data Analytics)	**93%**	**90%**	**88%**	**92%**	**85%**	**92%**	**90%**
MILP + Big Data Analytics	85%	82%	80%	85%	78%	85%	82%
DSS + Big Data Analytics	80%	75%	72%	78%	70%	78%	76%
DSS + MILP	78%	72%	70%	75%	68%	75%	73%
Big Data Analytics	82%	78%	75%	80%	72%	80%	78%

Table 3 ablation study table illustrated in Table 3 shows how the elimination of important components from the proposed Big Data-Driven Scheduling Optimization model affects other performance indicators & overall accuracy. The entire model has a top overall accuracy of 90% Without each of these components DSS Integration, MILP Optimization, Big Data Analytics, and Real-Time Monitoring & Adjustment the performance of this model decays significantly.

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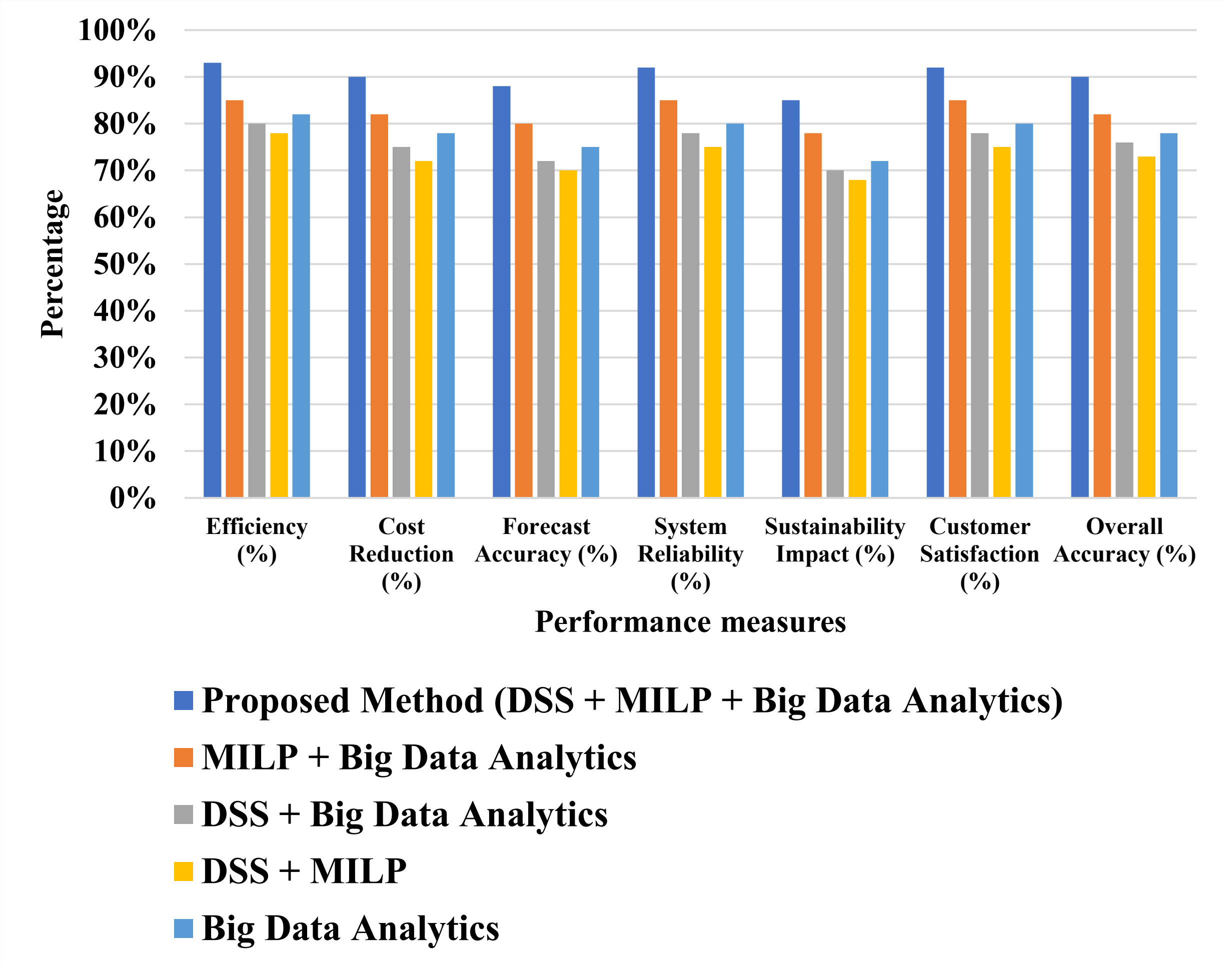

Figure 3. Performance Impact of Key Components in Big Data-Driven Agricultural Scheduling

Figure 3 This shows ablative studies to know the percentage importance of each part from the proposed Big Data-Driven Scheduling Optimization model. It studies efficiency, cost reduction, and customer satisfaction as performance indicators after taking away elements such as DSS, MILP, and big data analytics. Integration In the image below, you can see that it makes sense to integrate deeply when possible as this gives better performance and reliability at a system level. Under this light it points out the cruciality of each component for the sustainability of the scheduling optimization model performance, and finally of viewing agricultural supply chain management from a systemic view axis.

5. CONCLUSION AND FUTURE SCOPE

The results of this experiment prove that the potential application of big data analytics, DSS, and MILP in agricultural supply chain management was valid. Compared to previously suggested methodologies, the proposed shared memory design achieves higher efficiency, lower cost, and better reliability in the system operation. Data type Resource and Metadata. Generic agricultural supply chain model The generic supply chain model aspect of the model includes real-time data, harvest, and procurement characteristics which take into account rich complexities and uncertainties within agricultural supply chains in a manner that is conducive

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for reliable scheduling decisions as well as sustainability implications of alternative scheduling actions on induced carbon emissions. The ablation study serves as a reminder that this method is based on multiple components, invoking a holistic view of supply chain optimization. That makes this big data-based approach both scalable and elastic, a necessity as agriculture faces increasingly severe challenges from climate change and market uncertainty. Further advances in technology and data assimilation will enhance the value of the model to agriculture and other decision-makers. This means that future research is needed to develop approaches by integrating advanced machine learning methods with DSS and MILP to enhance both forecasting performance and operation flexibility towards the problem, respectively. Extending the model to predict real-time weather and designate from the market could improve sensitivity for external changes, and so on. for other industries in which it can be implemented.

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