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Modernizing Dark Pool Infrastructure: Machine Consolidation via AKS

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Abstract: A cloud-native modernization of dark pool trading infrastructure based on Azure Kubernetes Service is presented with the emphasis on machine consolidation, scalability, and low-latency performance. The common problems associated with traditional dark pool systems include: expensive infrastructure, lack of scalability and poor utilization of resources. The suggested architecture will use microservices, containerization, and Kubernetes-based orchestration to facilitate dynamic scaling and efficient workload management. It contains the basic elements such as Order Management Service, dark pool matching engine, trade execution service, and the real-time event streaming platform to provide smooth and fast trading operations. Simulated high-frequency trading load experimental evaluation has shown that there are significant performance gains, such as a maximum of 70% decrease in latency, a four-fold throughput increase, and improved resource usage. Moreover, the AKS-based system is attaining a high level of machine consolidation and cost optimization, which decreases the overhead of operations. The results demonstrate the usefulness of cloud-native solutions in improving the efficiency, scalability, and reliability of contemporary dark pool trading systems.

Keywords—*Dark Pool Trading, Azure Kubernetes Service (AKS), Microservices Architecture, Horizontal Pod AutoScaling (HPA), Cloud-Native Infrastructure.*

I. INTRODUCTION

Dark pools are trading systems that are not declared as liquid and are based on the pricing of the light marketplaces. In the equities markets, dark pools are important. In 2017, dark pools accounted for 15% of trading in the US stock market[1]. In the beginning, dark pools were enormous transaction systems. However, the average volume of trading in dark pools is comparable to that of the illuminated market, suggesting that the phenomenon is informed commerce in the dark pools[2][3]. These systems are relied upon by the existing financial systems to secure institutional investors through their capability to stabilize disturbance in the market and investor secrecy [4]. Dark pools have turned out to be indispensable trading centers since they enable traders to conduct high-frequency trades using algorithmic trading that demands quick, secretive order execution. Trading volumes on these platforms have increased tremendously over the years, becoming a critical part of global equity market trading.

However, the conventional dark pool infrastructures have various limitations that limit their performance and scalability. The majority of legacy systems are monolithic and, therefore, lack flexibility and cannot be easily scaled [5]. Such systems usually incur high latency and performance bottlenecks, particularly during peak trading loads. Moreover, they use over-provisioned hardware to manage peak demand and thus, have poor resource utilization and high operational costs [6][7]. The fact that resources cannot be dynamically scaled to meet any changing workload is also a major contributor to inefficiencies and the maintenance and infrastructure costs are also very high. The increased need for low-latency and high-throughput trading systems requires the modernization of the current infrastructure. Financial markets need systems that can handle transactions in real time as well as being reliable, fault-tolerant, and can scale [8]. These changing needs no longer necessitate the use of traditional methods and require more flexible and efficient solutions.

Cloud-native solutions have emerged as a viable way to address these challenges [9][10]. Kubernetes is essential in setting up these containerized applications, allowing automated deployment, scaling and administration. These capabilities are further advanced in Azure Kubernetes Service (AKS), which offers a managed environment to deploy and run cloud-native applications[11]. Also, machine consolidation methods are used to optimize infrastructure by minimizing the number of physical or virtual machines needed thus enhancing efficiency and reducing costs.

Despite these advancements, in spite of these developments, the traditional systems are still not efficient when it comes to managing the modern trading workloads, which underscores the necessity of optimized infrastructure. The suggested solution provides a microservices architecture based on AKS and tailored to the demands of a latency-sensitive dark pool environment [12][13]. Basic trading services like order management, trade matching and execution are broken down into autonomous services which allow parallel processing and improved response time. A Horizontal Pod Autoscaler (HPA) can be integrated in order to dynamically increase

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Real-time workload measures (CPU usage and request rate) determine the computing resources[14]. The combination of all these solutions facilitates a very scalable, efficient and cost-optimized infrastructure that is adapted to the modern high-frequency trading requirements.

A. Motivation and Contributions of the Paper

The rise in the use of dark pool trading systems in the contemporary financial markets requires an infrastructure that can sustain high-frequency and low-latency trading with maximum efficiency. Conventional systems are based on monolithic architecture and over-provisioned equipment that results in high operating costs, low scalability, and underutilized resources. As the trading volumes increase and require real-time execution, there is a high demand for cloud-native solutions that are elastic, resilient, and performant. With containerization and orchestration tools like AKS, it is possible to achieve dynamic scaling and machine consolidation, which deal with important issues of performance, cost, and resource utilization. The following are the study's main contributions:

- Proposes AKS-based cloud-native dark pool trading architecture.
- Introduces a machine consolidation strategy to reduce infrastructure footprint.
- Implements microservices-based architecture of modular and scalable trading operations.
- Integrates Horizontal Pod AutoAlert (HPA) for dynamic workload-based scaling.
- Evaluates performance using latency, throughput, scalability, and cost metrics.
- Demonstrates significant improvements in latency reduction and throughput enhancement.
- Provides comparative analysis with traditional infrastructure systems.
- Highlights cost optimization through efficient resource utilization and container orchestration.

B. Justification and Novelty of the paper

The current literature is mainly general cloud computing or VM consolidation or Kubernetes-based deployments, without a specific emphasis on the demanding needs of latency-sensitive financial systems like dark pools. The new thing is that it combines AKS-based microservice architecture with machine consolidation with specific high-frequency trading environments. In contrast to the previous work, this design integrates real-time processing, dynamic scaling, and infrastructure optimization at low costs. The paper is the first to fill the gap between cloud-native and ultra-low latency trading systems, which offers real-world information about modernizing financial infrastructure.

C. Organization of the paper

The paper is structured as follows: Section II reviews existing literature and identifies research gaps. Section III presents the proposed AKS-based architecture and methodology. Section IV discusses performance evaluation and experimental results. Finally, Section V concludes the study and highlights future research directions.

II. Literature Review

The existing research examines microservices together with Kubernetes orchestration, VM consolidation and workload optimization methods. The research fails to investigate two specific areas, which are low-latency financial systems and AKS-based implementations.

D. L. Srinivasan and J. A. Nada (2021) present microservices as independent services that enterprises can deploy and manage as separate components because this approach enables organizations to achieve better system scalability while they protect their systems from multiple points of operational failure. The team uses Kubernetes to deploy their container-based microservices system which enables high availability through container and pod-based scaling and recovery capabilities. The researchers assess system performance by deliberately shutting down services to study system recovery and operational patterns during system breakdowns [15].

W. Ding et al. (2020) developed a proactive virtual machine consolidation framework that decreases energy consumption while eliminating service level agreement breaches caused by virtual machine migration costs. The system uses workload prediction through modified WMA and reinforcement learning for virtual machine placement on host systems through PPR and a greedy allocation system which balances performance with energy consumption. The Cloud Sim tests which used Planet Lab traces achieved an energy savings of 45.25% while preserving quality of service in diverse cloud environments [16].

S. Lee et al. (2020) suggest a workload profiling system that is cloud-native and has a multi-cluster setup controlled by Kubernetes. The following are the contributions made by this paper. The operating software uses monitoring across several cloud-native clusters to choose the best resources. Determine and create certain general service workloads for managing the various clusters. The general workloads were deployed in order to find the best resources, and resource utilization was regularly and thoroughly monitored. The resource variation is computed by comparing the average resource use following the deployment of the service workloads with the initial resource usage[17].

B. Panda et al. (2019) One of the most well-known technologies that offers flexibility in the distribution of network data resources is cloud computing. Users can pay according to consumption thanks to this technology.

Virtualization continues to be a crucial technology in cloud computing. Researchers are very interested in lowering the degree of load imbalance between virtual machines in virtualized environments. Virtual machine migration is still one of the most often used strategies to address load balancing issues. In this research, have developed a virtual machine migration-based load balancing method that not only reduces the degree of load imbalance but also efficiently uses energy[18].

Y. Laili et al. (2018) present a novel iterative budget method that concurrently finds appropriate migration items and targets using a budget heuristic and a multi-stage selection technique. Experiments demonstrate that the proposed approach substantially outperforms existing common heuristics and metaheuristic algorithms in terms of lowering decision time, energy consumption, the quantity of virtual machines that are migrated, and total communication overhead[19].

J. Kon et al. (2017) examine the performance of Docker, a well-liked container-based virtualizing technology, particularly in highly consolidated environments. First, compare the performance with and without container-based virtualization. Next, demonstrate that while container-based virtualization can achieve comparable performance in networking and CPU processing, it is unable to achieve comparable performance in I/O processing with the default configuration. Second, investigate the connection between the quantity of containers and the performance obtained[20].

The Table I compares methodologies, findings, advantages, and limitations of existing studies, which reveal gaps in container-based consolidation and real-time performance testing and AKS integration for latency-sensitive dark pool systems

TABLE I. COMPARATIVE STUDY OF EXISTING APPROACHES TOWARD MACHINE CONSOLIDATION AND THEIR RESEARCH GAPS FOR AKS-BASED DARK POOL MODERNIZATION

Reference	Methodology	Findings	Advantages	Limitations	Future Work
D. L. Srinivasan and J. A. Nada (2021)	Microservices architecture deployed using Kubernetes with container orchestration; failure simulation by stopping services	Demonstrated improved scalability, resilience, and fault isolation in microservices environments	High availability, independent deployment and effective fault isolation	Focus limited to general cloud applications; lacks financial system (dark pool) context and latency-sensitive workloads	Need to explore microservices with ultra-low latency systems like dark pools and integrate AKS-specific optimizations for trading infrastructure
W. Ding et al., (2020)	Proactive VM consolidation using workload prediction (WMA), reinforcement learning (PPR), and greedy allocation; simulated in CloudSim	Achieved up to 45.25% energy savings while maintaining QoS	Efficient energy utilization, intelligent VM placement, SLA-aware	Simulation-based validation; lacks real-world containerized or Kubernetes environments	Extend consolidation techniques to container-based environments (AKS) and evaluate performance in real-time financial workloads
S. Lee et al., (2020)	Cloud-native workload profiling using Kubernetes multi-cluster orchestration; resource monitoring and analysis	Identified optimal resource allocation through workload profiling across clusters	Supports multi-cluster management, improved resource utilization	Limited focus on workload diversity and dynamic scaling under high-frequency workloads	Apply workload profiling to high-frequency trading systems and integrate predictive scaling in AKS environments
B. Panda et al., (2019)	VM migration-based load balancing to reduce imbalance and improve energy efficiency	Reduced load imbalance and improved energy usage in virtualized environments	Effective load distribution, energy-efficient VM migration	Relies on VM-based systems; lacks containerization and microservices support	Transition from VM-based load balancing to container orchestration (AKS) for modern trading infrastructures

Y. Laili et al., (2018)	An iterative budget algorithm with heuristic and multi-stage selection for VM migration	Reduced energy consumption, migration count, communication overhead, and decision time	Optimized migration decisions, efficient resource utilization	Focus on VM migration; lacks real-time orchestration and container-based deployment	Adapt migration strategies for containerized microservices and evaluate in latency-critical systems like dark pools
J. Kon et al., (2017)	Performance evaluation of Docker containers under high consolidation; comparison with non-virtualized systems	Similar CPU/network performance, but degraded I/O performance with increased containers	Validates container efficiency, highlights scalability limits	I/O bottleneck under high consolidation; lacks orchestration layer like Kubernetes/AKS	Improve I/O performance in highly consolidated container environments and optimize AKS for high-throughput financial systems

III. METHODOLOGY

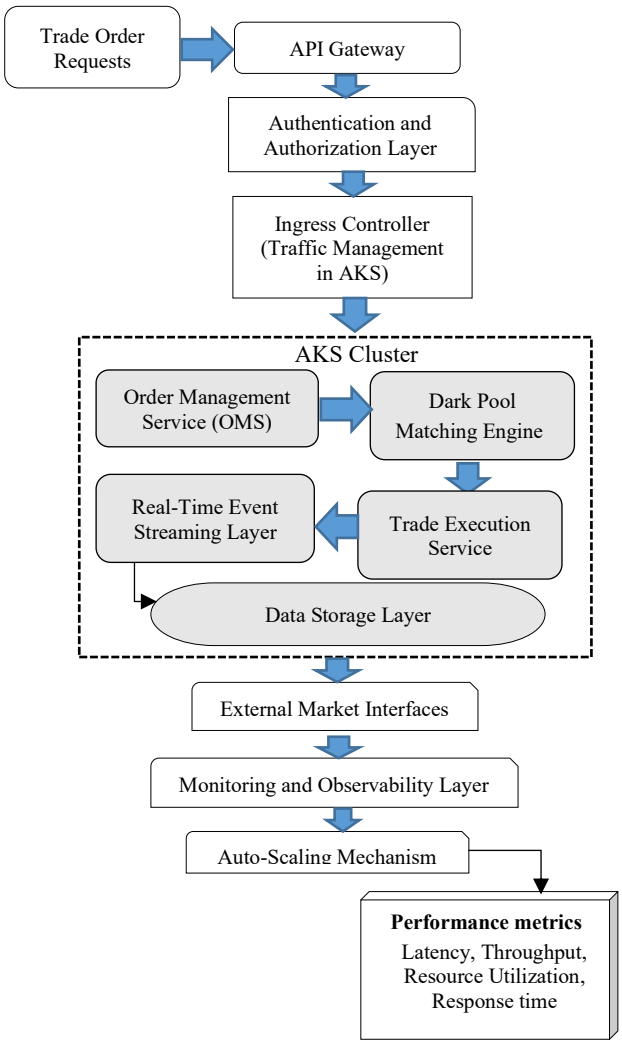

Fig. 1. Proposed AKS-Based Dark Pool Trading System Architecture

The proposed architecture illustrates a modernized dark pool trading infrastructure deployed on an Azure Kubernetes Service (AKS) cluster, emphasizing machine consolidation and cloud-native scalability (as shown in Fig. 1). Trade order requests are made using API Gateway, and thereafter an authentication and authorization layer is used to implement safe access control. An ingress controller is an efficient solution that directs incoming traffic into the AKS cluster, where core microservices are deployed. These are the Order Management Service (OMS) to manage order validation and lifecycle management, the dark pool matching engine to conduct anonymous trades on price-time priority, and the trade execution service to confirm and record the transactions. The event streaming layer is set up in real time, allowing the services to communicate with each other smoothly and with low latency. The data storage layer ensures reliability and compliance with the real-time and historical data. The integration is facilitated through the use of external market interfaces and the performance of the system is monitored and observed. Auto-scaling makes sure that resources are efficiently used according to the demand of the workload.

A. Trade Order Ingestion Layer

The layer that receives retail trade orders is responsible for receiving structured financial information containing the order type (buy/sell), the quantity, the price, the request time and the asset identifier. These are orders based on trading applications and broker-dealer systems. This layer is mainly meant to act as the interface for market information into the system, ensuring that all incoming orders are recorded with high throughput and accurate order timelines.

B. API Gateway

Data preprocessing plays a critical role in data analysis and machine learning projects. In this study, We carried out data transformation involving handling missing or damaged data and converting data into a suitable format for machine learning algorithms. Missing values were carefully imputed to avoid bias and maintain prediction accuracy, while categorical variables were label-encoded to convert them into numerical values. Additionally, continuous numerical features (Total Charges, Monthly Charges, Tenure Months)were normalized using Min-Max Scaler to fit within

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The API Gateway handles the incoming messages with order and manages the request validation, routing and the standardization of the protocols. It processes organized trading requests and makes them adhere to system-defined formats before sending them to inner services. This element is employed to manage and control the external data traffic, block malformed requests, and only legitimate trading instructions are transferred down the pipeline.

C. Authentication and Authorization Layer

This layer handles identity-related information including user credentials, API tokens, and institutional certificates. It confirms the authority of the trading entity that has received the incoming trading information to either post or update orders. It applies secure access control policies, so that only known parties in the market are able to access the trading system, and regulatory compliance is maintained, as well as unauthorized trading activity.

D. Ingress Controller (AKS Traffic Management)

The Ingress Controller handles internal routing metadata in the cluster of the Azure Kubernetes Service. It spreads validated trading requests on microservices in accordance with load-balancing policies and service provision. It is employed to optimize internal traffic flow ensuring effective utilization of compute resources with minimal latency communication between services.

E. Azure Kubernetes Service (AKS) Based Dark Pool Trading Cluster

The following section provides an overview of basic microservices on the Azure Kubernetes Service (AKS) cluster that allow processing orders, anonymous matching, trade execution, and real-time data processing in a scalable cloud-based setup.

- **Order Management Service (OMS):** Organizes order data order states (new, partially filled, executed), validation rules, and routing metadata. It takes care of the entire order lifecycle, so as to ensure accurate tracking, validation and consistency prior to being sent to the matching engine, thus averting any duplication and execution errors.
- **Dark Pool Matching Engine:** Handles anonymized order book data such as price levels, timestamps, and quantity matching logic. It performs confidential trade matching using price-time priority without revealing participant identity, ensuring minimal market impact and efficient execution in high-frequency trading environments.

- **Trade Execution Service Matched processes:** Trade records with execution price, execution quantity, anonymized counterparty ID and settlement status were matched. It finalizes the trading execution, creates confirmation records and makes sure that all the executed trades are captured appropriately to be settled and audited.
- **Real-Time Event Streaming Platform:** Processes all ongoing events of trading, such as order updates, execution confirmations and system alerts. It facilitates real-time data propagation of the system components to support analytics, monitoring and decoupled communication in a microservices architecture.
- **Data Storage Layer:** maintains both real-time cached data (e.g. order status and open trades) as well as maintains historical information (e.g. trade history, audit trail and execution logs). It guarantees the data longevity, auditability, and speedy access, and assists in efficient working and compliance.

F. External Trading Interfaces

This component processes structured trade output information sent to external systems such as exchanges, clearing banks and regulatory reporting agencies. It is applied to align executed trades with the external financial market infrastructure, bringing transparency and adherence to financial regulations.

G. Monitoring and Observability Layer

This layer collects and centralizes system telemetry, including latency, throughput, error rates, CPU and memory utilization, network performance, and order execution efficiency of all microservices. Trading activities can be continuously monitored because it provides real-time system health and performance data. It is also useful in anomaly detection, performance diagnosis, and SLA compliance monitoring, which are used in determining the bottlenecks, abnormal system behavior.

H. Auto-Scaling Mechanism using Horizontal Pod Autoscaler

In the Azure Kubernetes Service cluster, the Horizontal Pod Autoscaler (HPA) takes advantage of dynamic performance indicators such as CPU consumption, request latency, memory usage, and system load. It provides system elasticity by scaling pods automatically depending on the workload demand. This ensures low-latency trade execution when it is under peak load, resource utilization is optimized and over-provisioning during low-traffic times is minimized leading to improving overall system efficiency and stability.

I. Performance Evaluation Metrics

The effectiveness of the suggested AKS-based dark pool trading system is measured with the help of quantitative indicators and respective analytical equations [21]. The Latency of trade execution (L_e) and the order matching time (L_m) is calculated as the difference between request and completion times as indicated in Equation (1):

$$L = T_{response} - T_{request} \quad (1)$$

System throughput (T_p) is measured as the number of successfully processed trades per unit time, calculated in the Equation. (2):

$$T_p = \frac{N_{trades}}{T_{total}} \quad (2)$$

Resource utilization (U) evaluates CPU or memory usage efficiency [22]. The Equation. (3) shows the resource utilization formula:

$$U = \frac{Resources\ Used}{Total\ Available\ Resource} \times 100 \quad (3)$$

Scaling efficiency (S_e) under HPA is measured as the ratio of workload to allocated pods, shown in Equation. (4):

$$S_e = \frac{Workload}{Number\ of\ Pods} \quad (4)$$

Cost efficiency (C_e) is computed as performance per unit cost. The Equation. (5) calculates the Cost efficiency below:

$$C_e = \frac{Throghput}{Total\ Cost} \quad (5)$$

This set of metrics evaluates the performance of the system across a high-frequency trading environment in terms of latency, throughput, scalability, resource utilization, and cost efficiency, and provides a complete measure of the system performance.

IV. Result Analysis and Discussion

The experiment was carried out on Azure Kubernetes Service on compute-optimized nodes and Azure CNI networking. Synthetic trading workloads were tested on latency, throughput, scalability, resource usage, and cost efficiency with different loads. Table II gives a performance comparison of traditional and AKS-based systems with less trade execution latency and order-matching time, much higher system throughput, and better response time, showing an improved efficiency and a much faster trading performance.

TABLE II. Performance Metrics

Metric	Traditional System	AKS-Based System	Improvement
Trade Execution Latency	20–50 ms	5–15 ms	↓ ~70%

Order Matching Time	10–20 ms	2–8 ms	↓ ~60%
System Throughput	5,000 trades/sec	20,000+ trades/sec	↑ ~4×
Response Time	High	Low	Improved

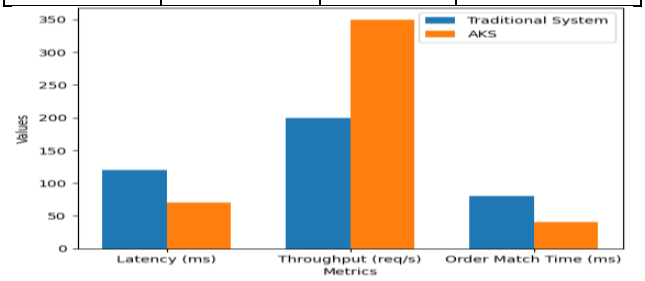

Fig. 2. System Performance Comparison between Traditional System and AKS

Fig. 2. compares latency, throughput and order match time to illustrate that AKS provides a considerable boost to system performance due to a decrease in latency, improvement in throughput and faster execution of trades, consequently leading to better efficiency and responsiveness in dark pool trading infrastructure.

Table III illustrates the scalability performance of the system under varying load conditions, demonstrating that HPA dynamically increases or decreases the number of pods in relation to CPU utilization, consuming fewer resources during low-load on the system and scaling effectively in high-demand scenarios.

TABLE III. SCALABILITY AND AUTO-SCALING PERFORMANCE

Load Condition	CPU Usage	Pods (Traditional)	Pods (HPA Enabled)
Low Load	20%	5	3
Medium Load	60%	5	8
High Load	90%	5	15–20

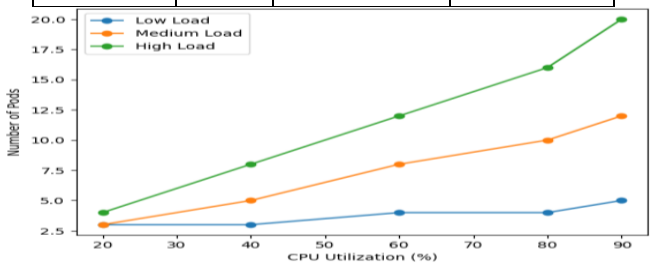

Fig. 3. Auto-Scaling Behavior using Horizontal Pod Autoscaler (HPA)

Fig. 3 presents AKS auto-scaling behavior in relation to different levels of CPU utilization, dynamic pod scaling to low, medium, and high workloads, which ensures efficient resource usage, system stability, and responsiveness in high-frequency dark pool trading scenarios.

Table IV illustrates the effect of machine consolidation, whereby the number of machines was reduced significantly, the resources were better utilized, and the deployment time was reduced in the AKS-based system relative to the traditional infrastructure.

TABLE IV. MACHINE CONSOLIDATION AND RESOURCE UTILIZATION

Parameter	Traditional System	AKS-Based System	Improvement
Number of Machines	50+	12–15 Nodes	↓ ~70%
Resource Utilization	40–50%	75–90%	↑ ~2×
Deployment Time	Hours	Minutes	↓ ~90%

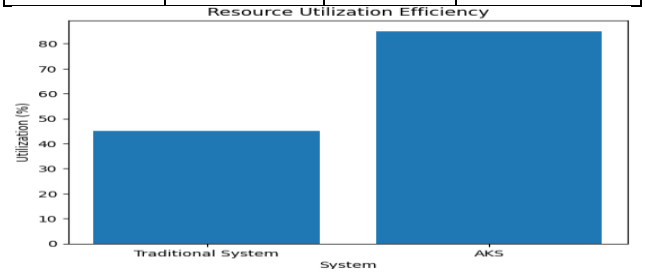

Fig. 4. Resource Utilization Efficiency Comparison

Fig. 4. illustrates improved resource utilization efficiency achieved by AKS over traditional systems, highlighting better workload distribution, minimized idle resources, and enhanced compute optimization through Kubernetes orchestration in modernized dark pool infrastructure environments.

Table V presents the cost optimization achieved using the AKS-based architecture, indicating reduced infrastructure and maintenance costs along with improved scaling efficiency, resulting in overall better cost management compared to traditional systems.

TABLE V. COST OPTIMIZATION

Component	Traditional system Cost	AKS Cost	Reduction
Infrastructure	High	Moderate	↓ ~50%
Maintenance	High	Low	↓ Significant
Scaling Cost	Inefficient	Optimized	Improved

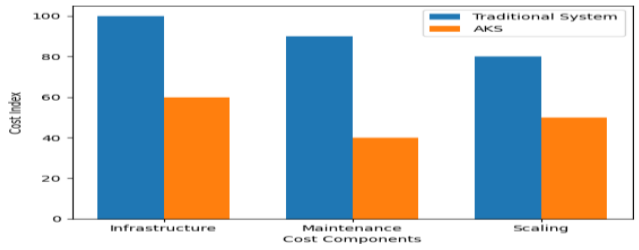

Fig. 5. Cost Optimization Analysis of Traditional Infrastructure vs AKS

Fig. 5. provides a comparison of cost indices between infrastructure, maintenance, and scaling items and shows that AKS saves a considerable amount in operational costs due to the consolidation of containers, automated processes, and effective use of resources in comparison to traditional dark pool infrastructure.

A. Discussion

The findings prove that the implementation of AKS can substantially improve the performance and efficiency of dark pool trading systems. The latency and order equivalence to time is an indication of how well containerized microservices can support high-frequency workloads. HPA enables dynamic scaling, which is characterized by the optimal distribution of resources based on the conditions of the load, which is why over-provisioning is avoided and the system is responsive to the load. Machine consolidation also simplifies the infrastructure and lowers operation expenses as well as enhances utilization efficiency. Nonetheless, network overhead, complexity of container orchestration, and dependency management issues should be tackled. In sum, the results confirm that cloud-native architectures deliver a scalable, economical, and high-performance solution to trading environment in the modern world.

V. Conclusion and Future Scope

The current financial trading systems demand the use of highly scaled, low-latency, and cost-effective infrastructure to sustain growing volumes of transactions and real-time processing requirements. The suggested AKS-based architecture effectively deals with those issues through the use of microservices, containerization, and Kubernetes orchestration. These findings indicate that there were significant improvements in performance measures, such as lowering latency, improving throughput, improving scalability, and improving resource utilization. Machine consolidation reduces the infrastructure demand by a large margin without compromising system reliability and responsiveness. Also, automated scaling features will provide efficient management of dynamic loads, and the system will be flexible to high-frequency trading. Although these developments have been made, there are more issues that can be improved. Future research may be aimed at minimizing network latency in containerized systems and enhancing efficiency of inter-service communication. System performance can also be improved by the combination of sophisticated scheduling algorithms and predictive scaling with AI. Also, the use of real-time monitoring and intelligent anomaly detection can enhance reliability and fault tolerance of the system. Resilience can also be increased and geographical latency minimized by exploring hybrid cloud or multi-region deployments. These advancements will be used to create stronger, effective and smarter cloud-native systems to support next-generation dark pool trading systems.

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