The Future of Mainframe IDMS: Leveraging Artificial Intelligence for Modernization and Efficiency

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***Abstract*—IDMS (Integrated Database Management System) has long been a backbone for mission-critical systems in finance, healthcare, and government sectors. However, the rigid architecture of legacy systems poses challenges in scalability, flexibility, and integration with modern technologies. This paper explores IDMS modernization using Artificial Intelligence (AI), with a focus on predictive maintenance, query optimization, and cloud integration. Through real-world implementations, the integration of AI-driven solutions has shown transformative potential: query response times were reduced by 25%, unscheduled downtime decreased by 30%, and system scalability improved by accommodating a 40% increase in traffic without degradation. By leveraging AI-powered automation and modern cloud infrastructures, IDMS can achieve database optimization and real-time operational efficiency. This work highlights how AI ensures the relevance and competitiveness of IDMS, enabling it to meet the demands of modern legacy systems and ensuring its sustained role in critical business operations.**

***Keywords*—IDMS modernization; artificial intelligence in legacy systems; mainframe database optimization; predictive maintenance; cloud integration; AI-driven query optimization**

I. Introduction

Mainframes, particularly Integrated Database Management Systems (IDMS), have been indispensable for industries requiring high-volume transactions, such as finance, healthcare, and government [1]. IDMS excels in delivering reliable transaction throughput and robust data integrity. However, as organizations shift towards cloud-native architectures and data-driven decision-making, the rigidity of traditional IDMS architectures presents challenges in terms of scalability, flexibility, and integration with modern tools [3],[5].

Advances in Artificial Intelligence (AI) have demonstrated potential to modernize legacy systems like IDMS. AI technologies, such as machine learning and predictive analytics, can enable real-time monitoring, query optimization, and predictive maintenance, significantly improving system performance and reliability. Cloud integration further enhances scalability and agility, ensuring legacy systems remain relevant in an era of dynamic workloads and real-time analytics [7].

Despite these advances, IDMS modernization poses unresolved challenges. Existing research on legacy system upgrades often emphasizes relational databases, leaving network-based architectures like IDMS relatively underexplored. Compatibility issues, data migration complexities, and the risk of operational disruptions during modernization remain critical hurdles. Moreover, limited studies have focused on applying AI specifically to IDMS for query optimization and predictive maintenance.

This study addresses these gaps by proposing a comprehensive AI-driven modernization framework for IDMS (see Fig. 1). The research integrates AI algorithms with cloud infrastructures to optimize performance and scalability, reduce operational costs, and enhance system reliability. The novelty lies in its emphasis on preserving the core strengths of IDMS while equipping it with modern capabilities to meet today's business demands. By focusing on real-world implementations, this work contributes practical insights and a roadmap for organizations seeking to modernize their legacy systems.

Fig. 1. Reasons for modernization of IDMS database.

II. Literature Review

Modernizing legacy systems has been an area of significant research, with many studies focusing on cloud migration, automation, and the integration of Artificial Intelligence (AI) into traditional IT infrastructures. Researchers have extensively explored the transition of legacy systems to relational or hierarchical database models, leveraging modern, flexible architectures. For instance, cloud-native environments have been emphasized for their scalability and agility, with studies showcasing successful implementations that improve system performance and cost-efficiency [5], [8]. Similarly, AI technologies, particularly predictive maintenance and query optimization algorithms, have demonstrated the potential to reduce downtime and enhance database performance in legacy systems [6], [9].

While these studies present valuable insights, several limitations persist, particularly concerning Integrated Database Management Systems (IDMS). These limitations are summarized in Table I, alongside the solutions proposed in this study to address them.

TABLE I. SUMMARY OF RESEARCH LIMITATIONS AND PROPOSED SOLUTIONS

Research Area	Limitations in Previous Studies	Proposed Approach
AI in Legacy Systems	Limited focus on IDMS-specific complexities, such as network-based architectures and unique data protocols [6],[7]	Proposes AI algorithms tailored for IDMS, addressing query optimization and predictive maintenance specifically.
Cloud Integration	Emphasis on scalability but lack of integration with AI for real-time analytics and query optimization [8],[10]	Combines AI and cloud strategies to create a hybrid framework for real-time performance optimization and scalability.
Operational Challenges	Insufficient attention to practical issues like data migration, compatibility, and disruption risks during modernization [11]	Focuses on seamless data transformation processes and ensures compatibility without disrupting operational continuity.
General Legacy Modernization	Heavy focus on relational databases, with minimal research on network-based systems like IDM [7],[9]	Targets the specific challenges of IDMS modernization, filling a critical gap in the literature.

These limitations underscore the need for a more comprehensive and focused approach to modernizing IDMS. Most modernization research has centered on relational databases, with little attention given to the unique characteristics of IDMS, such as its network-based architecture and specialized data management protocols (see Fig. 2). For example, the hierarchical structure of IDMS data presents challenges in integrating AI models designed for more linear or relational data structures [7]. Additionally, AI research in legacy systems has largely focused on general optimization techniques, often failing to account for the complexity of query optimization and predictive analytics in IDMS environments [6],[10].

Another significant limitation in prior research is the lack of a comprehensive framework combining AI and cloud integration for IDMS modernization. Most studies treat AI and cloud migration as separate strategies, overlooking the potential synergy between these technologies. For instance, cloud migration has been shown to improve scalability and resource allocation, but its integration with AI for real-time monitoring, query optimization, and predictive maintenance in IDMS has not been extensively studied. Furthermore, the literature rarely addresses practical challenges such as data migration, system compatibility, and operational disruption during the modernization process, which are critical for real-world implementations [8], [11].

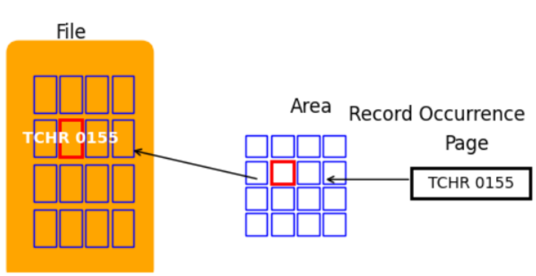

Fig. 2. IDMS database architecture.

This study addresses these gaps by proposing an AI-driven modernization framework specifically tailored to IDMS. Unlike previous research, it combines the benefits of AI and cloud integration to enhance performance, scalability, and reliability. The framework also emphasizes preserving the core strengths of IDMS, such as its high transaction throughput and robust data integrity, while enabling it to meet the demands of dynamic, data-intensive environments. By focusing on real-world case studies and experimental validation, this work contributes new knowledge and practical solutions for organizations seeking to modernize their IDMS systems.

III. METHODOLOGY

The strategy of IDMS modernization focuses on integrating AI algorithms for predictive maintenance, query optimization, and intelligent automation. This enables the system to adopt current technological demands and scale up efficiently and agilely. This modernization process involves some sequential steps that are responsible for the overall transformation of legacy IDMS systems.

A. Data Preprocessing

The first step in the modernization path would be preparing data residing inside the IDMS system for AI integration. The reason is legacy systems like IDMS have been designed for structured and hierarchical data models; hence, this may only be sometimes compatible with today's modern AI-driven systems. Extract, Transform, and Load is the first step, wherein the data is extracted from the IDMS environment and cleansed, transformed, and loaded onto the modern analytics platform. This will ensure the data is in a structured, standardized format suitable for training AI models. Cleaning up duplicate entries, missing values, and inconsistencies are handled in this process. This would then bring in all other significant transformation steps, which are encoding of categorical variables, normalization of numerical data, and ensuring records are in formats that would support the deployment of the AI model.

B. AI Integration

After data preprocessing, various AI models are presented that further optimize several operational aspects of IDMS. Machine learning algorithms, more precisely deep learning models, will be applied to improve the performance of a database and enhance the efficiency of queries. Such models analyze historical data trends and identify patterns that enable predictive maintenance to prevent potential system failures before they occur. Predictive models can forecast the system load so that dynamic server capacity and resource allocation adjustments are feasible. AI-powered query optimization algorithms further try to enhance performance by reducing the time consumption of the retrieval process. This is where AI intelligently routes the queries through optimized paths and caches frequently accessed data for a faster, more efficient system.

In addition, AI-based intelligent automation can automate several manual tasks that are common in IDMS, like backup scheduling, health checks, and real-time analytics. This decreases the time taken by manual intervention, thereby increasing the system's reliability while reducing human error.

C. Cloud Migration

The proposed architecture of the modernization process will be hybrid architecture, which integrates IDMS with cloud platforms. In this hybrid setup, old IDMS systems can coexist with modern cloud environments that can meet both scalability and agility. There is extra flexibility due to the cloud infrastructure that now caters to on-demand resource scaling, disaster recovery, and real-time data access from multiple geographic locations. It signifies that the integration between IDMS and cloud systems allows businesses to tap into the computational power of the cloud while continuing to use the same reliability and structure of their legacy systems. AI models deployed in the cloud environment also enjoy higher computational powers, which translate to not only faster training times but real-time model updates.

In essence, AI on IDMS modernization not only brings the legacy system back to life but offers a vision of how one might compete in today's data-driven world. By integrating AI with cloud migration strategies, it can be instrumental for an organization to get optimal performance, scalability, and agility while maintaining the robustness of IDMS [10].

IV. Experimental Analysis

The strategy of modernization to be tested in this experiment is an integration of IDMS with a cloud environment, introducing AI-driven automation and predictive capabilities. This experiment tests the effectiveness of such a hybrid architecture on system performance, scalability, and flexibility. Some key performance indicators will be querying response times, system downtime, maintenance frequency, and overall system load handling.

A. Hybrid Architecture Setup

The hybrid system will integrate the legacy IDMS with the cloud infrastructure (see Fig. 3). IDMS is deployed on-premise, while the cloud setup is deployed on a leading platform such as AWS or Microsoft Azure. Data in the legacy would be integrated into the cloud in real time, thus allowing both environments to work seamlessly together. Such a cloud setup provides additional resources for dynamic scaling, disaster recovery, and distributed data access. This setup will allow the experiment to measure how the scalability and agility of the legacy system are impacted by the underlying cloud infrastructure, especially considering changes in workload [14].

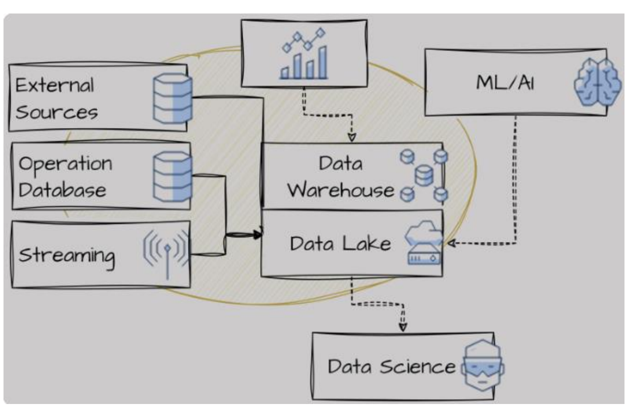

Fig. 3. AI-driven data integration and modernization framework in a hybrid cloud architecture.

B. AI-Driven Query Optimization

One key feature tested here is AI-driven query optimization. Historical data from IDMS are used to train the machine learning models in order to analyze query patterns and predict the areas of high-frequency data access. [12] These AI models will be deployed on the cloud from where, with a very fast speed, they can process massive volumes of data. Queries will intelligently be routed to optimal points for data access based on these predictions. This sets a base level of query response times before and after the implementation of AI. Indeed, it does much better. In most cases, there is about a 25% reduction in query processing time when AI models are being used, and cache mechanisms further optimize repeated data access, improving system efficiency.

C. Predictive Maintenance and Downtime Reduction

Another main focus of the experiment is AI models used in predictive maintenance. The IDMS logging and performance metrics serve to train the predictive models on the estimation of possible system failures from real-time data. Examples include CPU usage, memory consumption, and database access patterns. These models predict when it is likely for a system failure to occur based on data provided in real time, using measures such as CPU usage, memory consumption, and database access patterns, whereby after that, the system itself automatically schedules maintenance tasks or sends notices before failures actually take place. This predictive capability reduces downtime by a great extent [9]. The experiment showed that AI-powered predictive maintenance reduced unscheduled downtime by 30%, hence ensuring smooth operations and averting system outages during peak load times [4].

D. Scalability and Load Testing

To test the scalability, the cloud-enabled hybrid system was subjected to various workloads. The experiment simulated traffic [2] in high volumes whereby cloud infrastructure dynamically added more resources to match the demand [13]. Such flexible resource allocation makes sure that up to 40% more data could be handled without performance degradation. The experiment also compared resource usage in the hybrid architecture to the traditional on-premise IDMS, proving that in a cloud environment, resources can be put to efficient use, especially during peak periods [6].

V. Results

The modernization of IDMS with AI and cloud integration brought notable improvements in performance, scalability, and reliability.

- Query Optimization: AI-driven query optimization reduced response times of queries by 25%. Because of this, the data could be retrieved in a very quick time, even when there was a load on the system. Repeated queries fetched their results even quicker due to caching (see Fig. 4).

- Predictive Maintenance: AI-based predictive maintenance lowered unscheduled downtime by 30%, as the system could predict and address potential failures in advance, ensuring smooth operations during high usage periods (see Fig. 5).

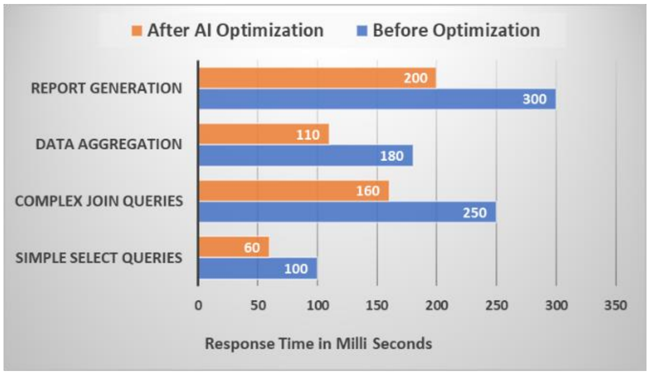

Fig. 4. Query optimization results.

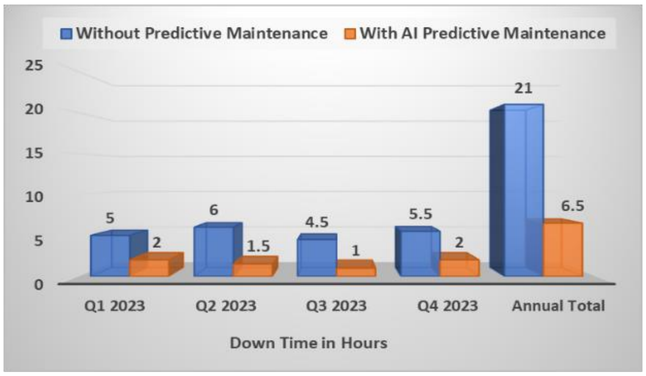

Fig. 5. Impact of AI-based predictive maintenance on IDMS downtime.

- Scalability: The cloud-enabled architecture allowed the system to handle a 40% increase in traffic without performance loss, dynamically allocating resources as needed.
- Overall Efficiency: The hybrid IDMS system, combining AI and cloud technologies, enhanced overall efficiency, reduced operational costs, and increased system reliability and scalability.

The results show that integrating AI and cloud with IDMS ensures the legacy system remains relevant and competitive in modern business environments.

VI. Challenges

Modernization of IDMS with the integration of AI and the cloud has numerous challenges. Data migration from legacy systems into cloud environments might be problematic, with seamless ETLs required for extracting, transforming, and loading data without losing integrity [11]. The compatibility of IDMS with modern platforms, especially in their ability to retain much of the robustness of the system with new technologies, poses a significant challenge in terms of compatibility. Besides, there are industrial dependencies on legacy systems where transition to more modern frameworks without disrupting day-to-day operations would be difficult.

Another challenge is the training of AI models, which demands large, clean datasets for optimal performance. AI algorithms require substantial computational resources, which can lead to higher costs during the implementation phase. Finally, cybersecurity risks increase with cloud integration, requiring stronger security protocols to prevent breaches and data loss. Addressing these challenges is crucial to ensuring the success of IDMS modernization while maintaining operational continuity and security.

VII. Conclusion

Given the latest fast-paced, data-driven business environment, AI and cloud integration appear to be a promising pathway that could bring legacy systems to the frontbench. Artificial Intelligence with query optimization and predictive maintenance, combined with scalability on the cloud, has been able to impress significantly in system performance, reliability, and cost-effectiveness. Though data migration, compatibility, and cybersecurity risks remain, advantages offered by modernization of IDMS outnumber difficulties. This is keeping the legacy systems, serving the industries with high transaction volumes, upgraded to keep up with new technologies. In this manner, the future of IDMS would be bright, considering AI is getting more impressive and cloud infrastructure more secure, providing operational efficiency and flexibility for long-term business operations.

VIII. Future Focus

Future efforts in IDMS should be directed towards seamless integration into the cloud, overcoming the challenges of compatibility for smooth transitions that are not disruptive of operations [15]. Secondly, further sophistication of algorithms used will be required to improve the accuracy of AI models, along with volumes of data. Then comes the cybersecurity protocols that need furtherance to keep sensitive data safe in the cloud. Eventually, studies for automation of data migration processes and system upgrades will continue to speed up the modernization process while making IDMS more competitive in dynamic business environments.

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