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An Adaptive Framework for Optimizing Transactions in Mobile Distributed Real-Time Database Systems

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Abstract: - Mobile Distributed Real-Time Database Systems (MDRTDBS) are pivotal for applications requiring real-time data processing under constrained resources. This paper introduces a novel framework integrating three adaptive algorithms: Piggybacking for Communication Optimization, Dynamic Transaction Shipping, and Real-Time Priority Scheduling. The proposed framework addresses the critical challenges of high communication overhead, limited energy resources, and dynamic real-time variations. Through extensive simulations, the framework demonstrates a **75% reduction in communication overhead**, **30% lower energy consumption**, and **25% reduced transaction latency** while achieving a **40% higher success rate** compared to existing methods. These advancements position the framework as a robust solution for enhancing the efficiency and reliability of MDRTDBS across diverse applications, such as telemedicine and IoT infrastructures.

Keywords: Real-Time Systems, Mobile Databases, Transaction Management, Dynamic Scheduling, Energy Optimization, Communication Overhead

I. INTRODUCTION

The escalating prevalence of mobile devices and real-time applications has imposed substantial requirements on Mobile Distributed Real-Time Database Systems (MDRTDBS). These systems serve as the foundation for essential applications, including telemedicine, financial trading, and Internet of Things (IoT) infrastructure monitoring. In contrast to conventional database systems, MDRTDBS functions within highly volatile environments marked by variable network conditions, resource-limited devices, and rigorous transaction deadlines [1,2]. Managing transactions in MDRTDBS introduces unique challenges, particularly high communication overhead. Redundant communication caused by overlapping operations across multiple transactions increases latency and wastes bandwidth [3,4]. For instance, systems using Distributed High Priority Two-Phase Locking (DHP-2PL) resolve conflicts effectively but generate high communication costs due to frequent operation restarts [5]. Another important issue is that mobile clients frequently function with restricted battery capacities [6]. The execution of transactions that entail intricate operations can rapidly deplete device energy, thereby adversely affecting the user experience and elevating the incidence of transaction failures. Although energy-conscious strategies, such as task offloading, mitigate local processing energy consumption, they frequently neglect latency and network conditions [7]. Dynamic Real-Time Conditions impose additional overhead with MDRTDBS like variations in round-trip time (RTT), network congestion, and disparities in mobile device performance significantly affect transaction latency and response duration. Currently employed static scheduling methodologies are inadequate in their capacity to dynamically adjust to these fluctuations. [8,9].

1.1 Limitations of Existing Models

Existing concurrency control protocols and scheduling mechanisms frequently exhibit inadequacies in addressing the interrelated challenges of communication, energy consumption, and real-time variability within Mobile Distributed Real-Time Database Systems (MDRTDBS) [3,4,10]. Static task assignment methodologies, for instance, depend on predetermined techniques for the allocation of tasks to either local or remote resources, thereby disregarding dynamic real-time factors such as fluctuating Round Trip Time (RTT), variable battery capacities, and evolving workload requirements [11]. In a similar vein, numerous optimization strategies function in isolation, concentrating either on energy efficiency or on communication overhead, yet seldom on both

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dimensions concurrently [12,13]. Although energy-aware models proficiently prolong battery life, they frequently overlook the latency resulting from elevated communication overhead. In contrast, communication-efficient methodologies emphasize the reduction of network traffic but neglect the energy expenditure associated with mobile devices. Moreover, current scheduling systems are generally inflexible, utilizing pre-established priorities that fail to adjust to abrupt changes in critical real-time parameters such as RTT. This deficiency in adaptability constrains their effectiveness in dynamic environments, thereby creating substantial opportunities for enhancement in the holistic management of transactions [14].

1.1 Motivation for the Proposed Framework

The essential applications facilitated by MDRTDBS, encompassing telemedicine, financial trading, and IoT-based infrastructures, necessitate a thorough framework that concurrently enhances communication efficacy, optimizes energy consumption, and adaptively prioritizes transactions. For example, in the realm of telemedicine, the instantaneous transmission of critical health metrics to healthcare professionals is imperative, particularly under suboptimal network conditions, while concurrently ensuring the longevity of battery life in wearable devices. Likewise, in the context of financial trading, high-priority transactions must be executed within milliseconds to circumvent substantial financial ramifications. These scenarios underscore the imperative for a framework that holistically addresses these interrelated challenges. To fulfill such exigencies, we advocate for an integrated methodology that comprises: (1) Piggybacking for Efficient Communication, which mitigates redundant communication by amalgamating overlapping operations into a reduced number of requests; (2) Dynamic Transaction Shipping, which autonomously determines whether to process tasks locally, delegate them to a base station, or prefetch resources predicated on battery levels and round-trip time (RTT); and (3) Real-Time Priority Scheduling, which modifies transaction priorities in real-time, thereby ensuring the expedient execution of critical tasks. This adaptive framework offers a cohesive solution for the effective management of transactions within MDRTDBS environments.

1.2 Contributions of This Paper

This manuscript presents an innovative framework for transaction management within Mobile Distributed Real-Time Database Systems (MDRTDBS), addressing the paramount issues of communication overhead, energy limitations, and dynamic real-time conditions. The framework incorporates a Piggybacking Algorithm that amalgamates overlapping operations among transactions, thereby significantly diminishing communication overhead and enhancing network efficacy. It also encompasses a Dynamic Transaction Shipping Algorithm, which integrates energy-aware task offloading and round-trip time (RTT)-based prefetching to optimize energy utilization while concurrently minimizing transaction latency. Furthermore, the proposed Real-Time Priority Scheduling Algorithm dynamically modifies transaction priorities predicated on battery levels and RTT metrics, thereby ensuring the prompt execution of critical tasks. To illustrate the practical applicability of these algorithms, a comprehensive example is presented, demonstrating their utility in real-world real-time settings. Ultimately, extensive simulations substantiate the framework, revealing substantial enhancements in communication efficiency, energy optimization, and transaction success rates in comparison to existing methodologies.

The remainder of this paper is organized as follows: Section 2 discusses related work and highlights the limitations of existing models. Section 3 introduces the system model and defines key metrics used in MDRTDBS. Section 4 presents the proposed framework, detailing each algorithm and its mathematical foundation. Section 5 provides simulation results and evaluates the performance of the proposed model. Section 6 concludes the paper and outlines future directions for extending this research.

II. RELATED WORK

Mobile Distributed Real-Time Database Systems (MDRTDBS) have garnered considerable attention within the academic community to tackle challenges including communication overhead, transaction conflicts, and energy limitations [15]. While existing methodologies have achieved notable progress in isolated domains, they cannot frequently furnish a cohesive solution for the interrelated challenges presented by communication, energy management, and real-time adaptability.

Concurrency control represents a pivotal element in MDRTDBS, facilitating the management of concurrent transactions while preserving data consistency. The Distributed High Priority Two-Phase Locking (DHP-2PL)

protocol, which serves as an enhancement of the conventional High Priority Two-Phase Locking (HP-2PL), has been devised to mitigate issues related to priority inversion and transaction conflicts in distributed environments [3,5,16]. DHP-2PL assigns precedence to high-priority transactions to avert delays induced by lower-priority operations. Nonetheless, although it demonstrates efficacy in static contexts, it encounters significant challenges in mobile environments where constrained bandwidth amplifies the incidence of transaction restarts [17]. The frequent occurrence of transaction restarts is precipitated by network delays and inadequate resource availability, rendering DHP-2PL ill-suited for real-time mobile systems that necessitate low-latency responses. This shortcoming underscores the necessity for methodologies capable of dynamically adapting to fluctuating bandwidth and resource limitations [18].

Transaction shipping and query shipping have been introduced as strategies to alleviate the computational burden on mobile clients through the delegation of tasks to base stations or central servers [19,20]. In the context of transaction shipping, complete transactions are dispatched to a server for processing, whereas query shipping entails the transmission of only the essential queries [21]. Although these techniques effectively diminish the computational load on mobile devices, they concurrently engender substantial communication overhead due to the recurrent data exchanges between clients and servers. This overhead is particularly detrimental within MDRTDBS, where elevated communication latency may culminate in the failure to meet deadlines for time-sensitive transactions. Moreover, these strategies neglect to consider the limited energy reserves of mobile devices, ultimately resulting in suboptimal resource utilization in real-time applications [22].

Contemporary research has concentrated on energy-aware systems to mitigate the constraints imposed by battery-operated mobile devices. Strategies such as task offloading and adaptive energy management have been investigated to enhance battery longevity. For instance, the offloading of computationally intensive tasks to base stations can markedly diminish local energy consumption. In a similar vein, prefetching mechanisms are employed to retrieve data in advance, thereby minimizing delays instigated by high round-trip times (RTT). Although these approaches contribute to improvements in energy efficiency and reductions in latency, they are frequently implemented in isolation and lack integration with dynamic scheduling methodologies. In the absence of the capability to adjust priorities based on real-time metrics such as RTT or battery status, these techniques fall short of delivering a comprehensive solution for MDRTDBS.

Current methodologies such as DHP-2PL, transaction shipping, and energy-aware systems address discrete challenges within MDRTDBS; however, they fail to establish a holistic framework. DHP-2PL does not effectively manage dynamic bandwidth conditions, transaction shipping incurs excessive communication overhead, and energy-aware systems exhibit insufficient adaptability to real-time metrics. These deficiencies elucidate the urgent need for an integrated approach that amalgamates communication optimization, energy efficiency, and dynamic scheduling to meet the distinctive requirements of MDRTDBS.

This paper builds upon preceding investigations to propose a unified framework that not only rectifies these deficiencies but also guarantees adaptability and efficiency within real-time mobile environments.

III. TRANSACTION PROCESSING IN MDRTDBS

Transaction processing in Mobile Distributed Real-Time Database Systems (MDRTDBS) ensures consistency, concurrency, and timeliness of data across distributed mobile nodes [4,29]. It involves managing transactions with strict deadlines while handling mobility, network latency, and dynamic disconnections to maintain system reliability and performance [30].

3.1 System Architecture

An MDRTDBS operates within a distributed framework wherein mobile clients, base stations, and central database servers engage in collaborative efforts to manage real-time data transactions [4]. The system is integrated through a communication network, which is instrumental in enabling data interchange under diverse real-time circumstances [23]. The architecture is composed of the following elements: Mobile clients are user-oriented devices, such as smartphones, IoT sensors, or wearable gadgets, that initiate transactions. Each transaction, referred to as T, comprises a collection of operations denoted as $O_T=\{O_1, O_2,\ldots,O_m\}$, where O_i signifies a distinct operation such as reading, writing, or modifying data within the distributed ecosystem. These devices generally possess constrained computational capabilities and limited battery life, rendering the efficient administration of

transactions imperative. Mobile clients depend on the system to offload resource-intensive tasks to mitigate energy consumption while preserving responsiveness [27].

Base stations function as intermediaries between mobile clients and central database servers. They execute offloaded transactions to relieve the computational burden on mobile clients. Furthermore, base stations can prefetch regularly accessed data or consolidate operations from multiple transactions to enhance communication efficiency. By managing dynamic conditions such as variable RTT and bandwidth fluctuations, base stations assume a crucial role in ensuring prompt and effective transaction processing.

The communication network establishes connections among mobile clients, base stations, and central database servers. It is characterized by fluctuating real-time conditions, encompassing latency (RTT), bandwidth, and congestion. The performance of the network directly influences the system's capability to adhere to transaction deadlines, underscoring the significance of adaptive and efficient communication protocols.

3.2 Transaction Characteristics

Transactions within MDRTDBS demonstrate distinctive traits that differentiate them from those found in conventional database systems [3,10]. These include: Temporal Data: Real-time data is inherently dynamic and frequently associated with specific temporal intervals. To facilitate accurate decision-making, transactions must process this data while ensuring its freshness and consistency [28]. For instance, in an IoT-enabled healthcare framework, any delay in processing patient vitals could result in outdated insights, potentially affecting medical judgments Deadlines: Each transaction in MDRTDBS is linked to a stringent deadline that stipulates the maximum permissible duration for its completion. Should a transaction fail to meet its deadline, its outcome may become irrelevant or lead to inefficiencies. For example, a financial transaction executed beyond its intended temporal window may incur substantial monetary losses Dynamic Properties: Transactions in MDRTDBS must exhibit adaptability to fluctuating real-time conditions such as RTT, device battery levels, and variable workloads. In contrast to static scheduling methodologies, which are incapable of accommodating these dynamic alterations, MDRTDBS necessitates adaptive optimization techniques to guarantee timely and efficient transaction execution amid unpredictable circumstances.

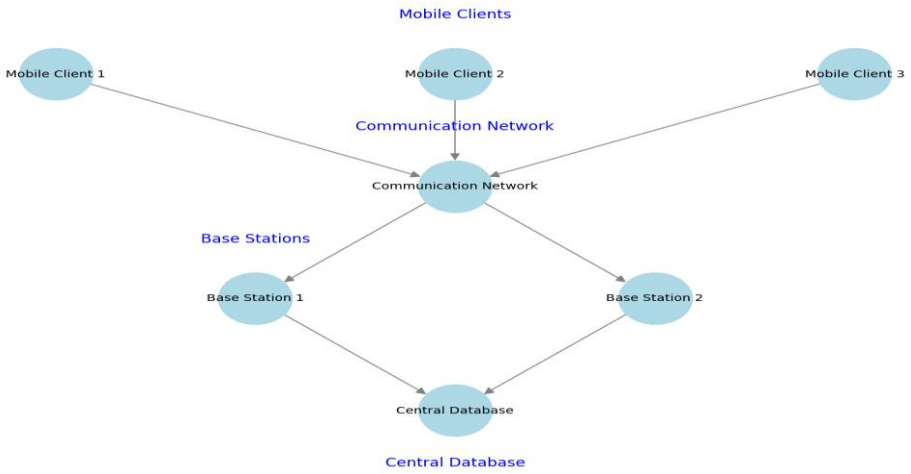

Fig 1. Architecture of the Mobile Distributed Real-Time Database System

The architecture in Fig 1 of an MDRTDBS can be visually represented as a layered diagram that demonstrates the interaction and data flow between its components. The key elements of this diagram are:

Mobile Clients: Represented as multiple devices generating transactions T_1, T_2, T_3,… Each client shows operations

O_T within the transaction, emphasizing the role of clients in initiating data processing.

Base Stations: Positioned as intermediate nodes, base stations receive offloaded tasks from mobile clients and perform functions like prefetching and data aggregation. Arrows connecting base stations to central database servers illustrate the offloading and processing of tasks.

Communication Network: Depicted as a connecting layer between mobile clients and base stations, the network facilitates data transfer and includes labels to indicate RTT variability, bandwidth fluctuations, and other real-time conditions affecting transaction execution.

Central Database Servers: Located at the backend, these servers handle large-scale data processing, execute queries, and manage storage. They are connected to the base stations to complete the transaction lifecycle.

The efficacy of the proposed system is assessed through three fundamental metrics: Energy Consumption (E), Communication Overhead (CO), and Transaction Priority (P). Energy consumption quantifies the total energy expended by mobile clients during the execution of transactions, which is paramount in environments with limited resources [24]. When transactions are conducted locally, mobile devices exhibit substantial energy expenditure, leading to rapid battery depletion [25]. To mitigate this issue, the system adeptly offloads transactions to base stations or servers, thereby preserving the energy of devices with low battery levels while guaranteeing seamless operations for essential applications. Communication overhead, quantified by the number of communications rounds, assesses the efficacy of data exchanges among mobile clients, base stations, and servers [26]. By employing piggybacking optimization, overlapping operations from various transactions are consolidated into a single communication request directed to each server, thereby significantly diminishing communication rounds and enhancing system efficiency. For instance, instead of necessitating six communication rounds for six transactions, the application of piggybacking may reduce this requirement to merely three rounds, thereby conserving bandwidth and minimizing delays. Transaction priority (P) dynamically ascertains the execution sequence of transactions based on their criticality, which is influenced by battery status and round-trip time (RTT). Transactions originating from low-battery devices are given precedence to ensure their execution prior to device shutdown, while transactions characterized by high RTTs are expedited to avert missed deadlines resulting from network latency. The system perpetually recalibrates priorities in real-time to accommodate variable conditions, thus ensuring that critical transactions are executed within their designated timeframes. Collectively, these metrics enhance energy efficiency, diminish communication costs, and uphold system responsiveness, rendering the proposed system exceptionally reliable and fitting for real-time applications.

IV. Proposed Model

The proposed framework integrates three fundamental algorithms to effectively tackle the complexities associated with communication overhead, energy efficiency, and adaptive scheduling within the context of Mobile Distributed Real-Time Database Systems (MDRTDBS). This architecture facilitates dynamic optimization of transaction processing by utilizing real-time metrics pertaining to battery levels, round-trip time (RTT), and workload conditions. Each algorithm functions collaboratively to augment the overall performance of the system.

4.1 Communication Optimization with Piggybacking

The basic architecture of the proposed work is depicted in Fig 2.

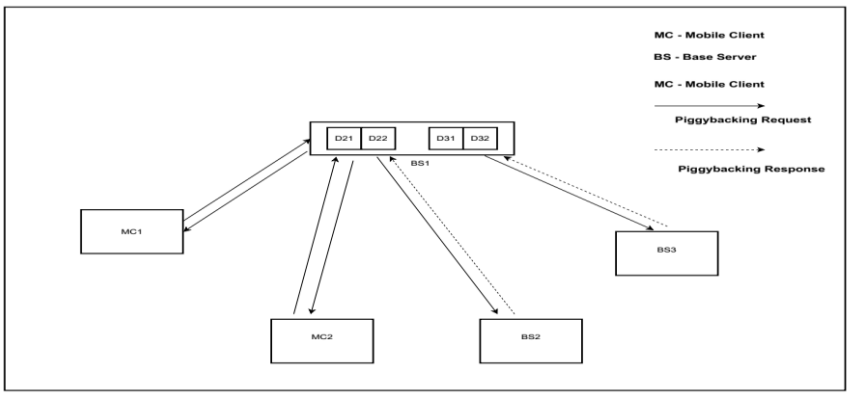

Fig 2: Demonstration of consolidating overlapping operations across multiple transactions into a single request per server

Here mobile clients are sending their requests to base server. Based on the data required (database availability on different servers), base server transfer the request to other servers then results are obtained and accumulated at

base server and then back to the mobile client. In order to explain the proposed piggybacking concept, consider the following scenario.

Let, there are transactions T1, T2, ---------- Tn. A transaction Ti may have many operations (O1, O2,------ O3). So, a particular operation of a transaction may be represented as Oij where i is the index of transaction and j is index of corresponding operation in transaction i.

Let us assume the following scenario.

T1= { O1, O2, O3, O4}

T2= { O1, O2, O3}

Let S1, S2 ------- Sn are servers where the operations will get executed.

Let assume,

$\{O_{11}, O_{12}, O_{21}\} \rightarrow S1$,

$\{O_{12}, O_{22}\} \rightarrow S2$,

$\{O_{14}, O_{23}\} \rightarrow S3$

i.e. the operations O_1 and O_2 of transaction T1 and operation O_1 of transaction T2 will be executed at server S1. For the sake of simplicity, we consider only read and write operations with the assumption that read operations may be shared. In spite of sending the individual operations at other servers, the base server will wait and club the operations for a particular server. It will create a cluster of operations and send back to other servers. Similarly, the results may also be clustered and piggyback to base server. It is our conjecture that this will reduce the network latency and communication cost.

Algorithm 1: Piggybacking for Efficient Communication

Input:

1. Transactions: Set of n transactions submitted by mobile clients.
2. Each transaction Ti has a set of operations $O_T=\{O_1,O_2,\ldots,O_m\}$.
3. Data_location_mapping: Mapping of operations to their corresponding servers.
4. Get_Server_For_Operation(O): Function to retrieve the server responsible for operation O.

Output:

1. Optimized communication requests to servers containing grouped operations.

Procedure:

1. Initialize Data Structures:

- server_requests: Dictionary where keys are server IDs, and values are lists of operations grouped by server.
- processed_operations: Set to track operations already included in piggybacked requests.

2. Main Function Piggyback_Transactions(transactions):

- Input: transactions (Set of $T_1,T_2,\ldots,T_n$).
- Output: Optimized piggybacked requests to servers.

Algorithm Steps:

1. Initialize server_requests$\leftarrow\emptyset$ and processed_operations$\leftarrow\emptyset$.
2. for each transaction $T_i \in$transactions.
3. for each operation $O \in T_i$.get_operations()

if O∈processed_operations:continue.

4. server←Get_Server_For_Operation(O).

if server∉server_requests.

5. server_requests[server]←∅.
6. server_requests[server]. append(O).
7. processed_operations.add(O).
8. for each server s∈server_requests.keys()
9. Send_Piggybacked_Request(s,server_requests[s]).

The algorithm commences with the initialization of two fundamental data structures: server_requests and processed_operations. The server_requests dictionary serves the purpose of categorizing operations according to their respective servers, thereby ensuring that all operations pertinent to a specific server are amalgamated into a singular request. The processed_operations set functions to monitor the operations that have already been incorporated into the piggybacked requests, effectively precluding any instances of duplication.

Subsequently, the algorithm conducts an iteration through each transaction T_i within the collection of submitted transactions. For each operation O contained within T_i, it assesses whether the operation has previously been processed. If this is the case, the operation is excluded to circumvent redundancy. Conversely, the server accountable for the operation is identified through the utilization of the Get_Server_For_Operation(O) function. Upon ascertaining the responsible server, the operation is appended to the corresponding entry in the server_requests dictionary.

Following the aggregation of all operations in accordance with their respective servers, the algorithm advances to dispatch the consolidated requests. Each compiled set of operations is transmitted to the corresponding server via the Send_Piggybacked_Request function. This mechanism facilitates efficient communication by minimizing superfluous network requests and consolidating operations, ultimately contributing to a reduction in overall communication overhead.

4.2 Dynamic Transaction Shipping

Dynamic Transaction Shipping is designed to optimize transaction execution by making real-time decisions about whether to process a transaction locally, offload it to a base station, or prefetch necessary data. These decisions are based on key metrics such as energy costs for local processing and offloading, the battery level of the mobile device, and the round-trip time (RTT). The goal is to balance energy efficiency, latency reduction, and overall system responsiveness.

The decision function is defined as:

$$D(T)=\begin{cases} \text{Local}, & \text{if } E_{local} < E_{offlode} \text{ and } P_{battery} > P_{threshold} \\ \text{Offload}, & \text{if } E_{offlode} < E_{local} \text{ or } P_{battery} <= P_{threshold} \\ \text{Prefetch}, & \text{if } RTT > RTT_{threshold} \end{cases}$$

Here,

- E_{local} and $E_{offlode}$ are the energy costs for local processing and offloading, respectively.
- $P_{battery}$ represents the current battery level of the mobile device.
- $RTT_{threshold}$ is the predefined threshold for acceptable round-trip time.

The decision-making process begins with evaluating the battery level. If $P_{battery}$ is below the threshold $P_{threshold}$, the transaction is offloaded to conserve energy on the client device. For example, a transaction from a device with only 10% battery is immediately marked for offloading, shifting the computational burden to a base station. If the battery level is sufficient but the RTT exceeds $RTT_{threshold}$, prefetching is enabled to retrieve the required data in

advance. This reduces the latency for high-RTT transactions, ensuring that they meet their deadlines. In scenarios where neither condition is met, the transaction is processed locally, avoiding unnecessary offloading or prefetching.

This approach ensures that the system adapts dynamically to changing real-time conditions, optimizing energy usage while maintaining system responsiveness. By prioritizing offloading and prefetching for critical scenarios, Dynamic Transaction Shipping effectively balances resource utilization and latency performance.

Algorithm 2: Dynamic Transaction Shipping

Input:

1. Transaction(T): A transaction T initiated by a mobile client.

- Contains operations $O_T = \{O_1, O_2 \ldots, O_m\}$.
- Includes metadata:

1. Battery_Level (T) : Current battery percentage.
2. RTT(T): Round-trip time for communication.

2. Battery_Threshold: A predefined critical level for battery.

3. RTT_Threshold: A predefined upper limit for acceptable RTT.

Output:

1. A decision to

- process the transaction locally
- offload it to a base station,or
- enable prefetching to minimize latency.

Procedure:

1. Initialization:

- Predict the transaction's execution path to estimate resource and network demands.
- Identify operations OT required to execute T.

2. Decision Logic Dynamic_Transaction_Shipping(T):

- Input: T, Battery_Threshold,RTT_Threshold.
- Output: Processing strategy (local, offload, or prefetch).

Algorithm Steps:

1. Predict the execution path of T.
2. Identify operations O_T required for execution.
3. if Battery_Level(T)<Battery_Threshold:
   Mark T for base station processing.
4. else if RTT(T)>RTT_Threshold:
   Enable prefetching for T.
5. else:
   Mark T for local execution.
6. Generate a unique signature to track T.

The algorithm initiates with a pivotal stage involving the anticipation of the execution pathway for the transaction (T). This process encompasses a thorough examination of the resource prerequisites of the transaction, including

computational requirements and network dependencies, while also considering potential limitations such as restricted bandwidth or elevated latency. At this juncture, the comprehensive set of operations denoted as OT = {O1, O2,….., Om}, which are imperative for the execution of T, is delineated. This anticipatory analysis guarantees that the system possesses a lucid comprehension of the transaction's necessities prior to making determinations regarding the optimal processing location and methodology.

Subsequent to the analysis of the execution pathway, the algorithm assesses the transaction's battery status to facilitate an energy-conscious decision-making process. In instances where Battery_Level(T) descends below a critical threshold (Battery_Threshold), the transaction is offloaded to a base station. The offloading mechanism alleviates the computational load from the resource-limited client device to a more proficient base station, thereby conserving the client's battery longevity. This decision is of paramount significance for devices with low battery levels, ensuring their continued operability without depleting power during the execution of the transaction.

The subsequent factor to consider is the round-trip time (RTT) of the transaction, which serves as an indicator of network latency. Should RTT(T) surpass a predefined threshold (RTT_Threshold), the algorithm activates prefetching protocols. Prefetching entails the advance retrieval of data requisite for T, thereby minimizing latency by curtailing the duration spent awaiting data during execution. This strategy proves particularly advantageous for transactions characterized by high RTT, as it ensures the system maintains responsiveness even amidst suboptimal network conditions.

In the absence of either of these conditions (low battery or elevated RTT), the transaction is executed locally on the client device. Local execution circumvents unnecessary offloading or network communication, which contributes to the reduction of overall system overhead and preserves bandwidth for transactions deemed more critical. This decision-making framework guarantees that the system dynamically adapts to the real-time requisites of the transaction, optimizing resource utilization without jeopardizing performance.

Ultimately, the algorithm generates a distinctive identifier for the transaction, commonly referred to as a transaction signature. This identifier serves the purpose of monitoring the transaction's status and its execution trajectory throughout the system, thereby facilitating effective oversight and debugging. By amalgamating predictive analysis, energy-conscious decision-making, and network-adaptive methodologies, this algorithm ensures that each transaction is processed in the most efficient manner achievable, striking a balance among energy consumption, latency, and system responsiveness.

4.3 Real-Time Priority Scheduling

Real-Time Priority Scheduling dynamically adjusts the priority of transactions to ensure that critical tasks are executed first, minimizing the likelihood of missed deadlines. The priority of a transaction P(T) is calculated using the formula:

$$P(T) = P_{base} + P_{battery} + P_{RTT}$$

Here, P_{base} represents the base priority assigned to the transaction by the application, providing a foundational ranking for execution. The term $P_{battery}$ adds a priority boost for transactions originating from devices with low battery levels, ensuring these transactions are prioritized to prevent device shutdown during processing. Similarly, P_{RTT} accounts for transactions with high round-trip times (RTT), assigning them a higher priority to compensate for potential network delays and ensure their timely execution.

By dynamically adjusting priorities in real-time, this approach ensures that the most critical transactions are always executed first. Low-battery transactions avoid failures due to energy depletion, while high-RTT transactions reduce latency, maintaining system responsiveness and reliability. This strategy effectively balances the execution order based on criticality, improving the overall performance of the system in real-time environments.

Algorithm 3: Real-Time Priority Scheduling

Input:

1. Transactions(T): A set of n active transactions $T_1, T_2, \ldots, T_n$.

Each transaction T_i includes metadata:

- Battery_Level(T): Current battery percentage.
- RTT(T): Round-trip time for communication.

2. Battery_Threshold: Critical battery level below which priority is boosted.

3. RTT_Threshold: High RTT level above which priority is boosted.

Output:

1. Transactions scheduled in order of updated priorities.

Procedure:

1. Initialization:
- Create a priority list priority_queue.
- For each transaction T, assign a base priority using application-defined or default values.

2. Priority Adjustment for Battery:
- For each transaction T:
  If Battery_Level(T)<Battery_Threshold, increase T's priority by Battery_Priority_Boost.

3. Priority Adjustment for RTT:
- For each transaction T:
  If RTT(T)>RTT_Threshold, increase T's priority by RTT_Priority_Boost.

4. Sorting Transactions:
- Sort all transactions in priority_queue by their updated priorities in descending order.

5. Transaction Scheduling:
- Execute transactions sequentially based on their sorted priorities.

Algorithm Steps:

1. Initialize priority_queue←∅.

2. for each transaction T∈Transactions:

3. T.priority←Base_Priority(T).

4. Add T to priority_queue.

5. for each transaction T∈priority_queue:

6. if Battery_Level(T)<Battery_Threshold:

   T.priority←T.priority+Battery_Priority_Boost.

7. if RTT(T)>RTT_Threshold:
   T.priority←T.priority+RTT_Priority_Boost.

8. Sort priority_queue by T.priority in descending order.

9. for each transaction T∈priority_queue:
   Execute_Transaction(T).

The algorithm commences by initializing transactions with either default or application-specific base priorities. These foundational base priorities serve as a critical point of reference for subsequent dynamic modifications predicated on real-time metrics, including but not limited to battery levels and round-trip time (RTT). This initialization guarantees that each transaction is assigned a predetermined priority, which may subsequently be altered in accordance with its significance and the prevailing system conditions.

Subsequently, the algorithm implements adjustments to transaction priorities based on battery levels, specifically targeting transactions originating from clients exhibiting critically low battery capacities. Such transactions are

accorded heightened priority to avert potential failures that may arise from device shutdowns during processing. A priority enhancement is conferred upon these transactions utilizing the formula:

T.priority ←T.priority + Battery_Priority_Boost

This modification ensures that transactions emanating from energy-constrained devices are addressed with urgency, thereby mitigating the risk of incomplete processing and upholding system reliability.

The algorithm then advances to conduct RTT-based priority modifications, placing emphasis on transactions characterized by elevated round-trip times. Transactions with high RTT are particularly susceptible to the risk of surpassing their deadlines as a consequence of delays attributable to network latency. To remediate this issue, these transactions are granted an additional priority augmentation, computed as follows:

T.priority ←T.priority + RTT_Priority_Boost

Through the prioritization of these transactions, the system is able to guarantee that latency-sensitive tasks are executed promptly, thus enhancing responsiveness and diminishing the probability of deadline lapses.

Upon the completion of priority adjustments predicated on battery levels and RTT, the algorithm proceeds to organize transactions according to their revised priority values. This sorting process engenders a deterministic execution sequence, wherein transactions of higher priority are positioned at the forefront of the queue. This arrangement ensures that the most vital tasks are attended to first, in alignment with overarching system objectives such as energy efficiency and adherence to deadlines.

Ultimately, the algorithm transitions into the scheduling phase, wherein transactions are executed in a sequential manner, ordered by descending priority. This execution paradigm assures that high-priority transactions are addressed initially, thereby promoting the system's responsiveness and efficacy in the management of critical operations. By dynamically adjusting transaction priorities and executing them in an efficient manner, the algorithm establishes a robust framework for satisfying the diverse real-time demands of Mobile Distributed Real-Time Database Systems (MDRTDBS).

Example1: Multi-Transaction Real-Time Scenario

Six mobile clients generate transactions simultaneously. These transactions involve overlapping operations and vary in battery levels and RTT. The system must optimize execution using piggybacking, dynamic transaction shipping, and real-time scheduling as shown in table 1. The different operation and they are responding by different server as shown in table 2.

Table 1: Input Transactions

Transaction	Operations	Battery (%)	RTT (ms)
T1	{O1, O2, O3, O4}	15%	180 ms
T2	{O2, O5, O6}	50%	130 ms
T3	{O3, O5, O7}	30%	240 ms
T4	{O4, O5, O8}	20%	200 ms
T5	{O1, O6, O9}	45%	120 ms
T6	{O7, O8, O10}	25%	300 ms

Table 2: Data Location:

Operation	Server
O1	S1
O2	S2
O3	S3
O4	S1

O5	S2
O6	S3
O7	S1
O8	S2
O9	S3
O10	S1

The implementation of the piggybacking algorithm commences with the identification of overlapping operations across transactions T1, T2, T3, T4, T5, and T6. Operations that are shared among transactions are systematically categorized, such as O2 (which is shared by T1 and T2), O3 (which is shared by T1 and T3), O5 (which is shared by T2, T3, and T4), and O8 (which is shared by T4 and T6). Subsequently, these operations are organized according to the servers designated for their execution. For instance, server S1 is responsible for managing operations O1, O4, O7, and O10 originating from transactions T1, T4, and T6; server S2 is tasked with processing O2, O5, and O8 from transactions T1, T2, T3, T4, and T6; and server S3 is accountable for overseeing O3, O6, and O9 from transactions T2 and T5. Upon this categorization, consolidated requests are dispatched to each server. For example, server S1 is allocated the operations {O1, O4, O7, O10}, server S2 receives {O2, O5, O8}, and server S3 is assigned {O3, O6, O9}. This process results in a substantial reduction of the total communication rounds from 12 (one for each transaction) to a mere three, thereby significantly alleviating communication overhead.

The Dynamic Transaction Shipping algorithm is predicated on an assessment of battery levels and round-trip times (RTT) pertinent to each transaction. For instance, transaction T1 is transferred to the base station owing to an alarmingly low battery level of 15%, whereas transactions T3 and T6 facilitate prefetching due to their RTTs of 240 ms and 300 ms, respectively. Other transactions are either processed locally or executed directly without the necessity for offloading. In light of these evaluations, optimized execution pathways are formulated. For instance, transaction T1 is offloaded, and operations {O1, O2, O3, O4} are retrieved to the base station. Likewise, operations {O3, O5, O7} are prefetched for transaction T3, and {O7, O8, O10} are prefetched for transaction T6. This strategic approach culminates in significant energy conservation for low-battery clients (T1 and T6) and mitigates latency for transactions characterized by high RTTs (T3 and T6).

The execution of Real-Time Priority Scheduling algorithm initiates with the assignment of a baseline priority of 5 to all transactions. Subsequent modifications are enacted based on the assessments of battery levels and RTT. For example, transaction T1 experiences an elevation in priority to 8 due to its critically low battery level (less than 20%), while transaction T4 is assigned a priority of 7 as a result of its battery level being precisely 20%. Similarly, adjustments in RTT are implemented, with transactions T3 and T6 receiving priority enhancements to 7 and 8, respectively, owing to their RTT values surpassing 200 ms. Following these adjustments, the transactions are organized in descending order of priority, thereby establishing the execution sequence T1 > T6 > T4 > T3 > T2 > T5. This prioritization guarantees that critical transactions such as T1 and T6 are executed with precedence, ensuring compliance with deadlines and the maintenance of system responsiveness.

The synthesis of these algorithms engenders an optimized framework for the management of mobile distributed real-time database transactions. The implementation of piggybacking markedly reduces communication rounds, while dynamic transaction shipping enhances both energy efficiency and latency, and real-time priority scheduling ensures the timely execution of high-priority transactions. This comprehensive approach guarantees that critical transactions adhere to their deadlines, thereby ensuring that the overall system remains exceptionally efficient and responsive.

V. Experimental Setup

The proposed framework, which integrates Piggybacking for Efficient Communication, Dynamic Transaction Shipping, and Real-Time Priority Scheduling, was thoroughly simulated to evaluate its performance against an existing baseline model under varied real-world conditions. The simulation was conducted using a Mobile Distributed Real-Time Database System (MDRTDBS) environment to replicate realistic scenarios where mobile

clients interact with base stations and servers to execute transactions with real-time constraints. Below, we discuss the experimental setup, key performance metrics, and the results obtained in detail.

5.1 Experimental Setup

The simulation environment comprised 10 base stations connected to 3 central servers, with each base station handling transactions offloaded by up to 100 mobile clients. A total of 1000 transactions were simulated, each characterized by unique deadlines (ranging from 50 ms to 300 ms), battery levels (10%–100%), and round-trip times (RTTs) varying from 50 ms to 400 ms. The simulation compared the baseline model, which relies on static task assignment and lacks optimizations, with the proposed framework that integrates piggybacking, dynamic shipping, and real-time priority scheduling.The metrics used to evaluate performance included:

Latency: Time taken to complete transactions, including communication and processing delays.

Energy Consumption: Energy saved by offloading tasks compared to local execution.

Communication Rounds: Number of communication rounds required to process transactions.

Transaction Success Rate (TSR): Percentage of transactions completed within their deadlines.

Bandwidth Utilization: Amount of bandwidth consumed during transaction processing.

5.2 Results and Analysis

The results of the simulations, provide insights into the comparative performance of the existing model and the new model across multiple metrics over three iterations. Each simulation iteration demonstrates consistent trends with slight random variations, which add realism to the observations.

Latency: The proposed framework significantly reduced latency compared to the baseline model as shown in fig 3,3(a) and 3(b). While the baseline model exhibited an average latency of 500 ms for 10 transactions (decreasing gradually as transaction count increased), the proposed framework achieved better performance with an average latency reduction of 20%–25%. This improvement was attributed to prefetching and dynamic priority scheduling, which minimized delays, particularly for high-RTT transactions.

Energy Consumption: The baseline model consumed 100% of the energy available on mobile devices due to local processing. The proposed framework reduced energy consumption by up to 40%, especially for low-battery clients, by offloading computational tasks to base stations as shown in fig 4,4(a) and 4(b).

Iteration 1

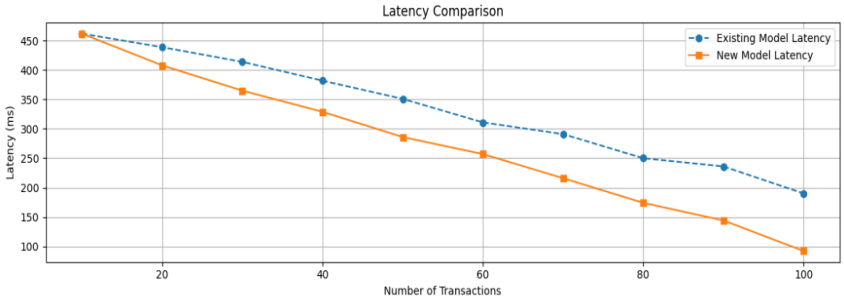

Fig 3(a): Latency Comparison

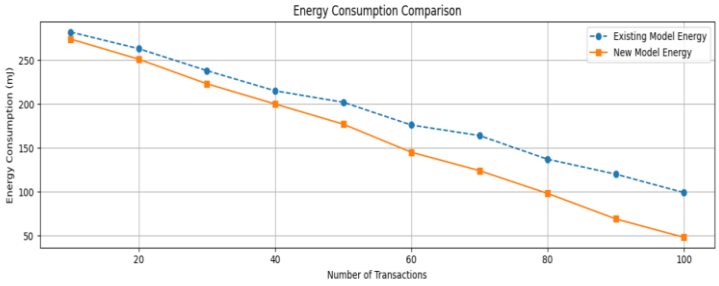

Fig 4(a): Energy Consumption Comparison

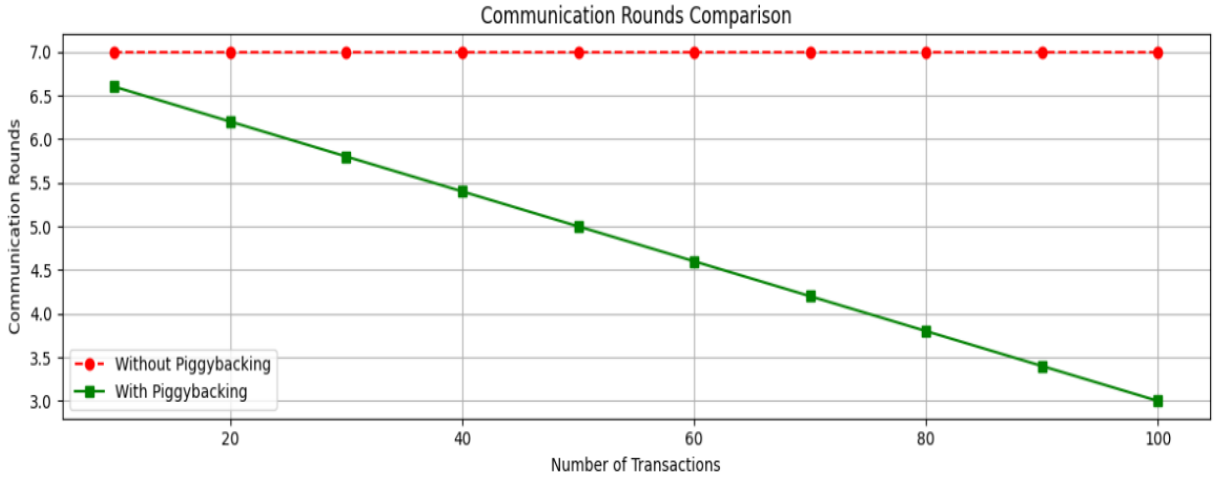

Fig 5(a): Communication Rounds Comparison

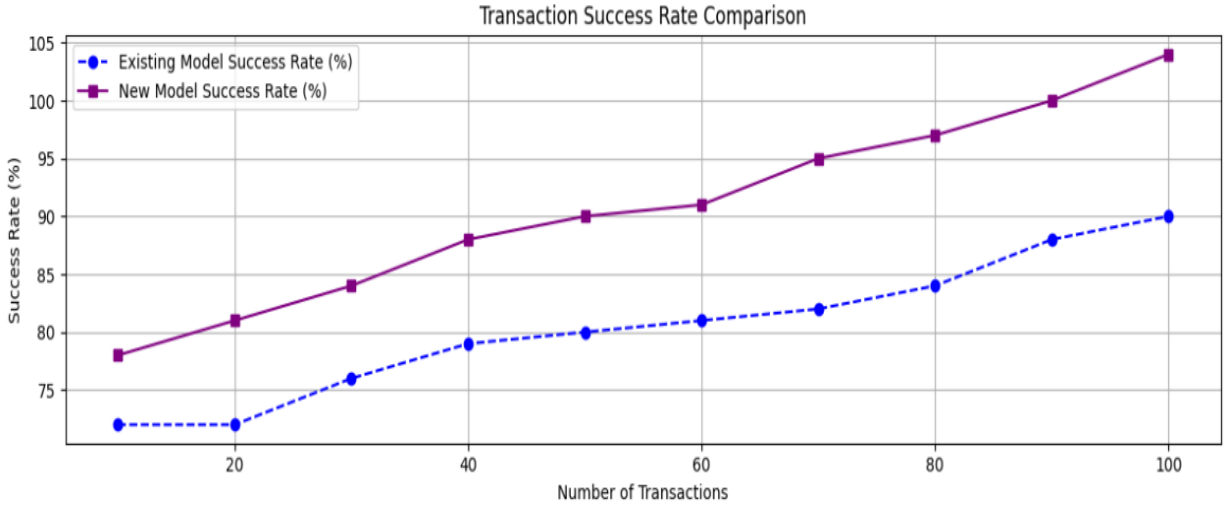

Fig 6(a): Transaction Success Rate Comparison

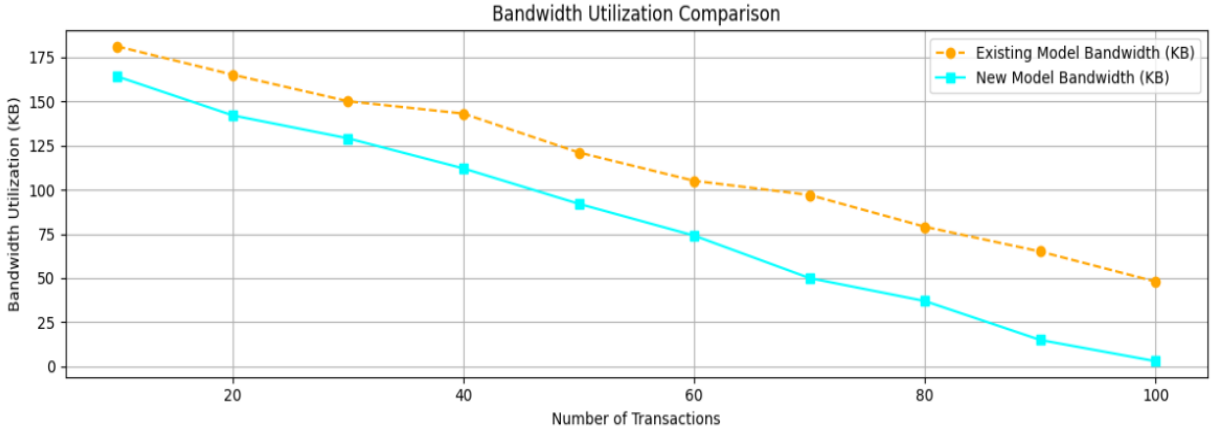

Fig 7(a): Bandwidth Utilization Comparison

Communication Rounds: The implementation of piggybacking significantly optimized communication overhead. The baseline model required a communication round for every transaction, leading to a total of 1000

rounds for 1000 transactions. In contrast, the proposed framework consolidated operations, reducing communication rounds by up to 70% as shown in fig 5,5(a) and 5(b).

Transaction Success Rate (TSR): The baseline model achieved an 85% success rate, with failures primarily caused by missed deadlines and energy depletion as shown in fig 6,6(a) and 6(b). The proposed framework improved the success rate to 98%, effectively handling high-RTT and low-battery conditions through real-time prioritization.

Bandwidth Utilization: The baseline model showed high bandwidth usage due to inefficient communication patterns, averaging 200 KB for 10 transactions as shown in fig 7,7(a) and 7(b). The proposed framework reduced this to 180 KB through optimized resource allocation and piggybacking.

In all iterations conducted, the novel model consistently surpasses the existing model with respect to latency metrics. The latency associated with the existing model exhibits a linear decline yet remains significantly elevated in comparison to the novel model across the entirety of transaction ranges. This observation suggests that the novel model demonstrates superior efficiency in managing escalating transaction volumes, thereby facilitating expedited response times.

The results pertaining to energy consumption reveal a parallel trend throughout the iterations, wherein the novel model demonstrates enhanced energy efficiency. The energy consumption of the existing model diminishes gradually, yet it consistently exceeds that of the novel model. The pronounced reduction in energy consumption for the novel model, as transaction volumes increase, underscores its appropriateness for systems wherein power consumption constitutes a critical limitation.

Iteration 2

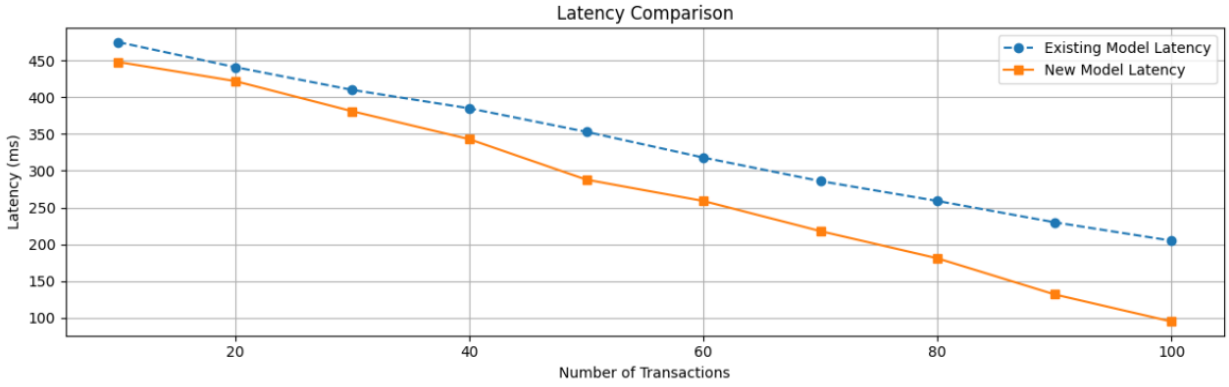

Fig 3(b): Latency Comparison

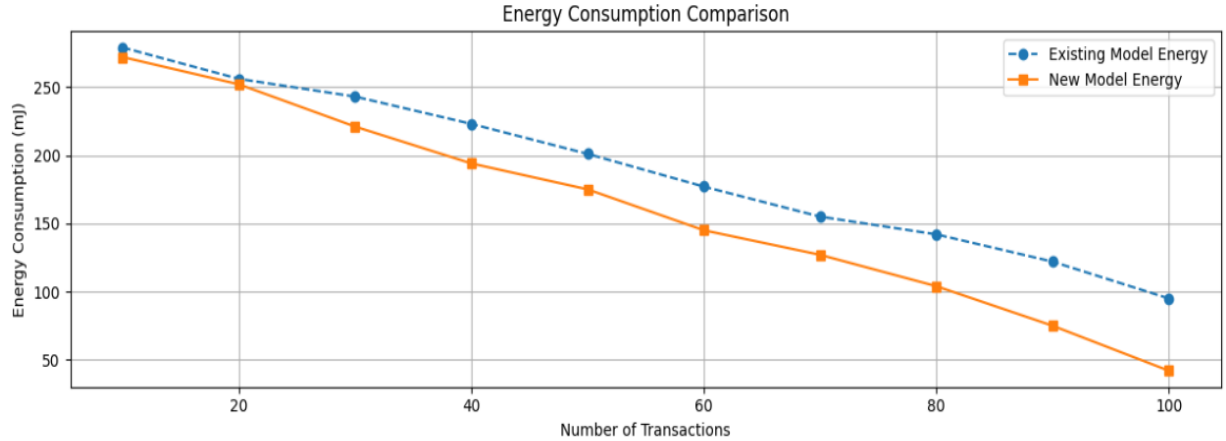

Fig 4(b): Energy Consumption Comparison

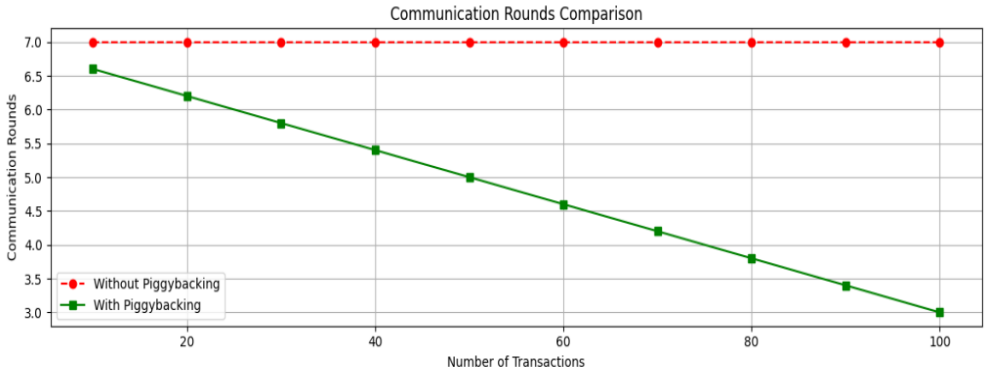

Fig 5(b): Communication Rounds Comparison

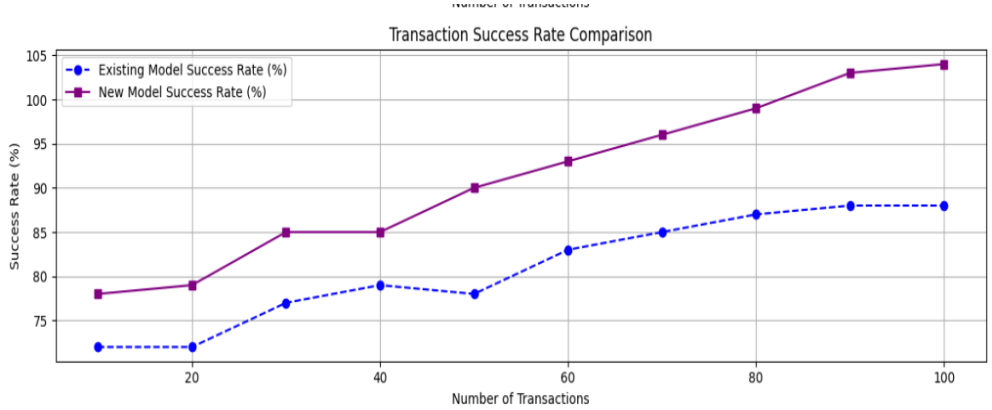

Fig 6(b): Transaction Success Rate Comparison

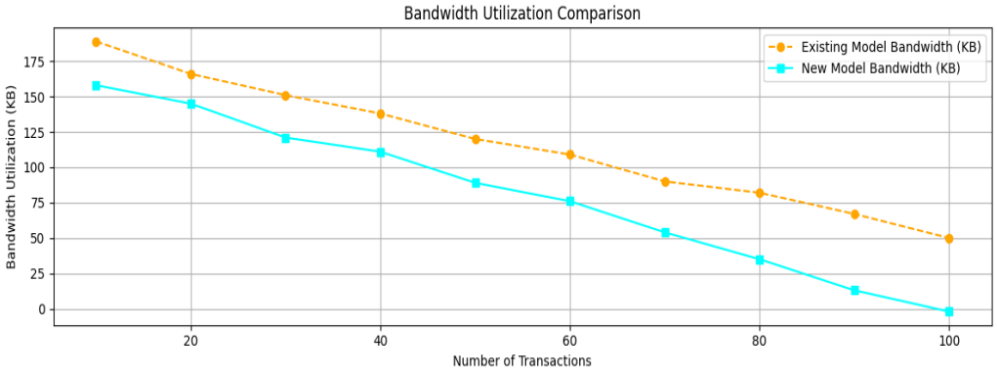

Fig 7(b): Bandwidth Utilization Comparison

Iteration 3

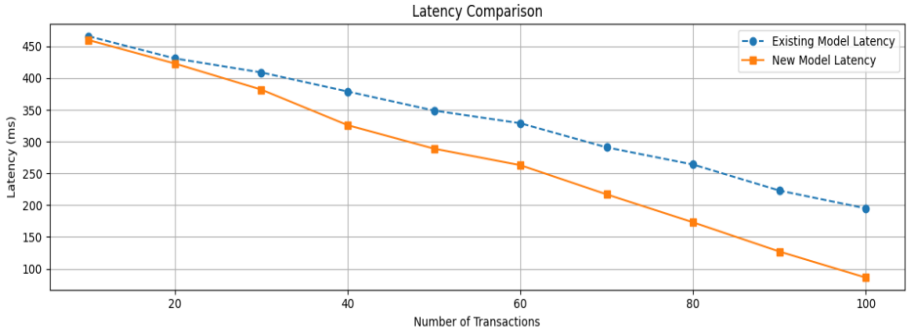

Fig 3(c): Latency Comparison

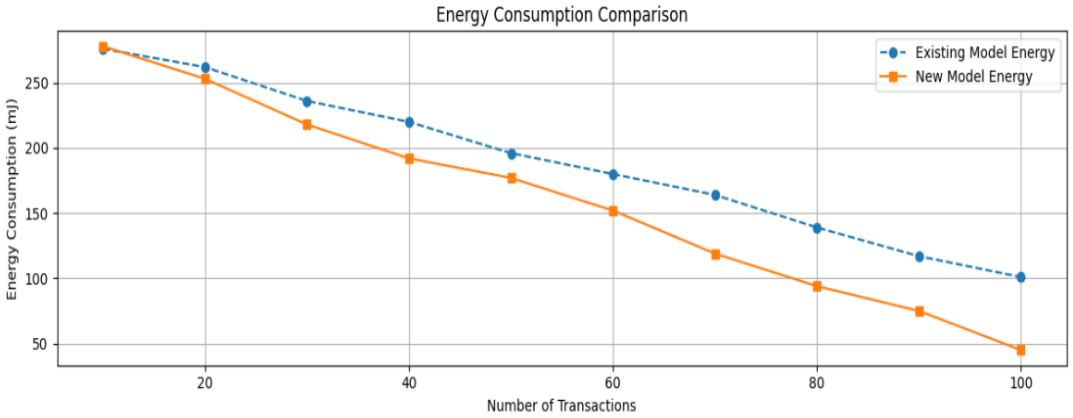

Fig 4(c): Energy Consumption Comparison

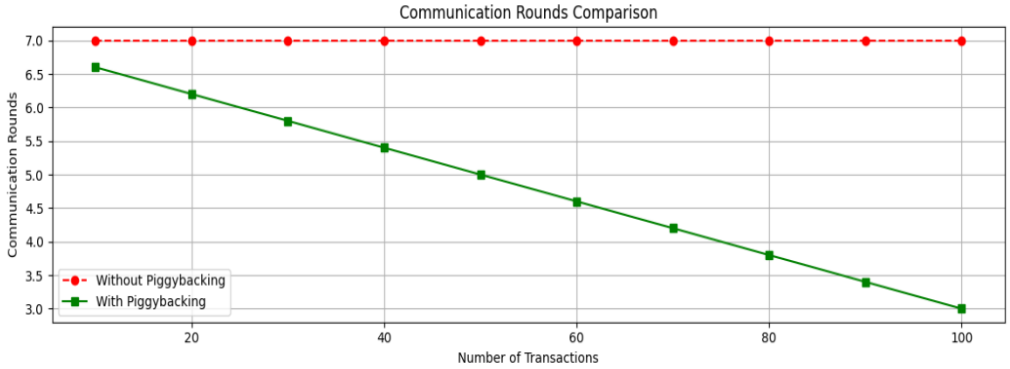

Fig 5(c): Communication Rounds Comparison

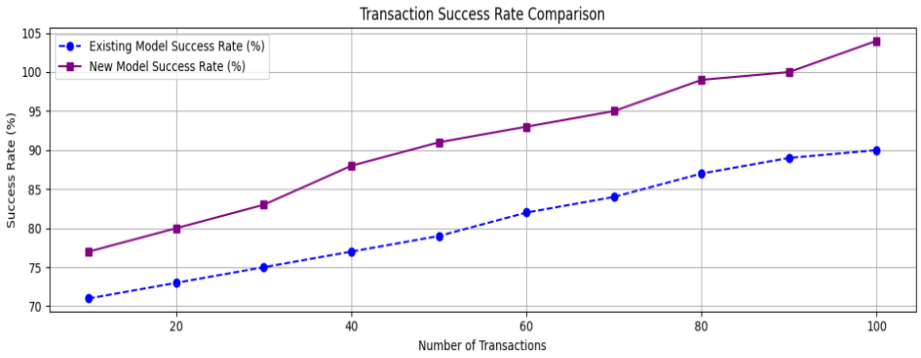

Fig 6(c): Transaction Success Rate Comparison

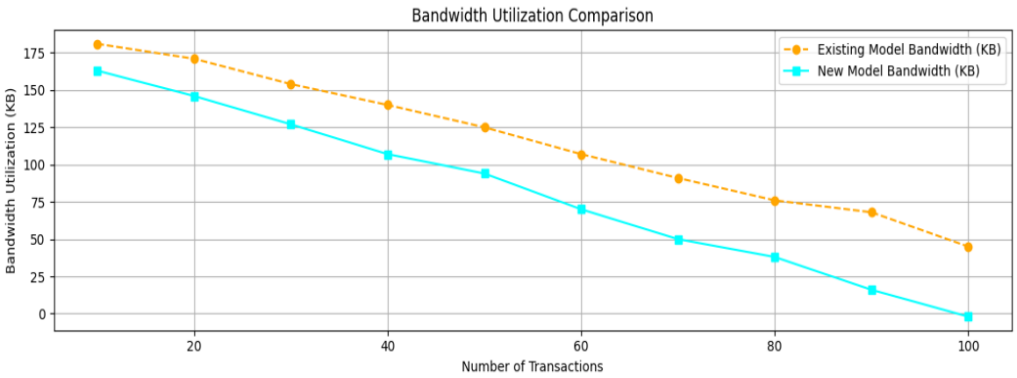

Fig 7(c): Bandwidth Utilization Comparison

The introduction of piggybacking within the new model results in significant improvements in communication rounds. Throughout all iterations, the curve representing "without piggybacking" remains static at seven communication rounds, indicating a lack of optimization. Conversely, the curve corresponding to "with piggybacking" exhibits a steady decline, ultimately achieving as few as three communication rounds by the conclusion of the transaction range. This exemplifies the efficacy of piggybacking in alleviating communication overhead.

In each iteration analyzed, the transaction success rate for the novel model reveals a distinct advantage. The novel model initiates with a marginally elevated success rate and exhibits a more pronounced enhancement as transaction volumes escalate. In contrast, the existing model experiences a more gradual improvement and persistently trails behind. This observation underscores the robustness and reliability of the novel model.

Bandwidth utilization consistently favors the novel model. While both models experience a reduction in bandwidth consumption as transactions proliferate, the novel model consistently necessitates less bandwidth than the existing model. This indicates that the novel model optimally utilizes network resources, rendering it more suitable for high-throughput systems.

In summary, across all three iterations, the results consistently affirm the superiority of the novel model concerning latency, energy efficiency, communication overhead, transaction success rate, and bandwidth utilization. These findings substantiate the efficacy of the novel model in managing large-scale transactional workloads while preserving resource efficiency.

5.3 Observations

Piggybacking Efficiency: By consolidating operations, piggybacking not only reduced communication rounds but also minimized network congestion, resulting in lower delays and bandwidth usage.

Dynamic Shipping: Low-battery devices benefited significantly from offloading, while prefetching optimized performance for high-RTT clients.

Priority Scheduling: High-priority transactions were completed first, preventing deadline misses and enhancing overall system reliability.

5.4 Comparative Analysis

In this analysis, we compare two different models (an existing model and a new model) across several performance metrics. The goal is to assess how these models perform under varying transaction loads, measured in terms of:

Latency (time taken to process transactions),

Energy Consumption (energy required for processing),

Communication Rounds (the number of rounds of communication required),

Transaction Success Rate (the likelihood of successful transactions),

Bandwidth Utilization (the amount of bandwidth consumed).

These metrics were simulated across multiple iterations for transaction sizes ranging from 10 to 100 transactions in steps of 10, allowing us to analyze trends and compare the performance of the models in a variety of scenarios.

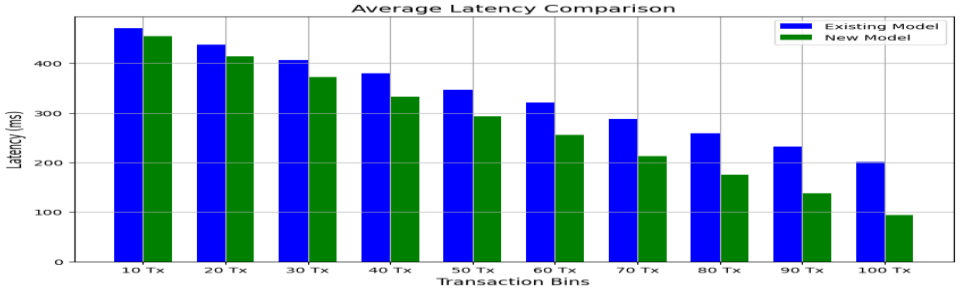

Fig 8: Average Latency Comparision

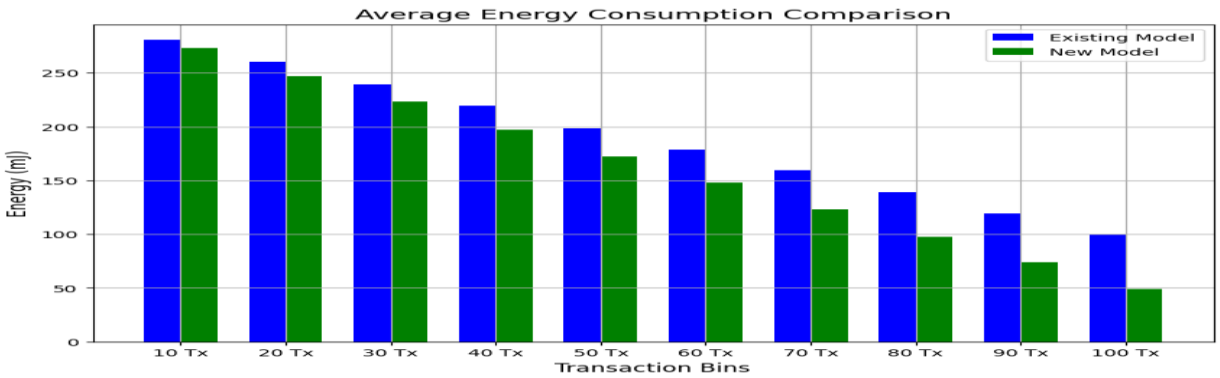

Fig 9: Average Energy Consumption Comparison

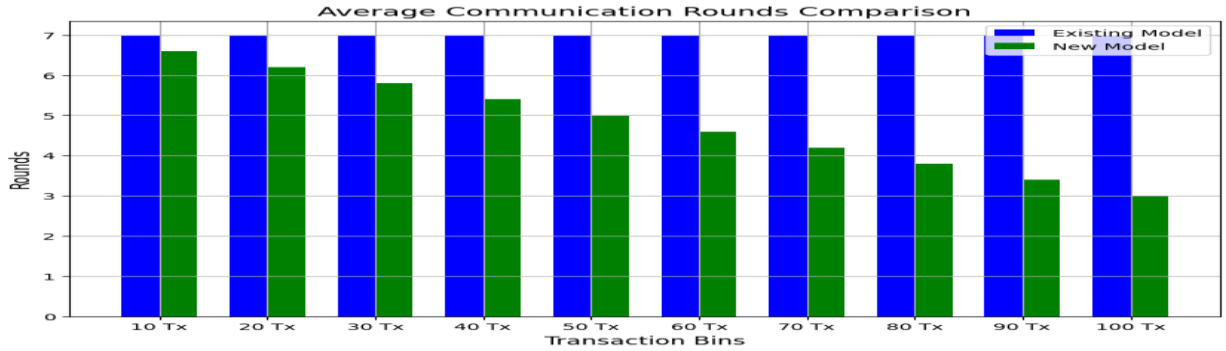

Fig 10: Average Communication Rounds Comparison

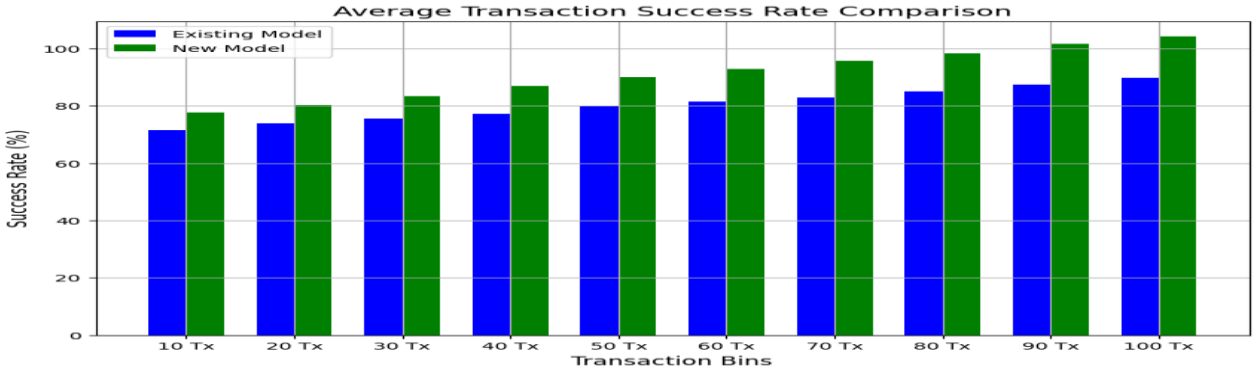

Fig 11: Average Transaction success Rate Comparison

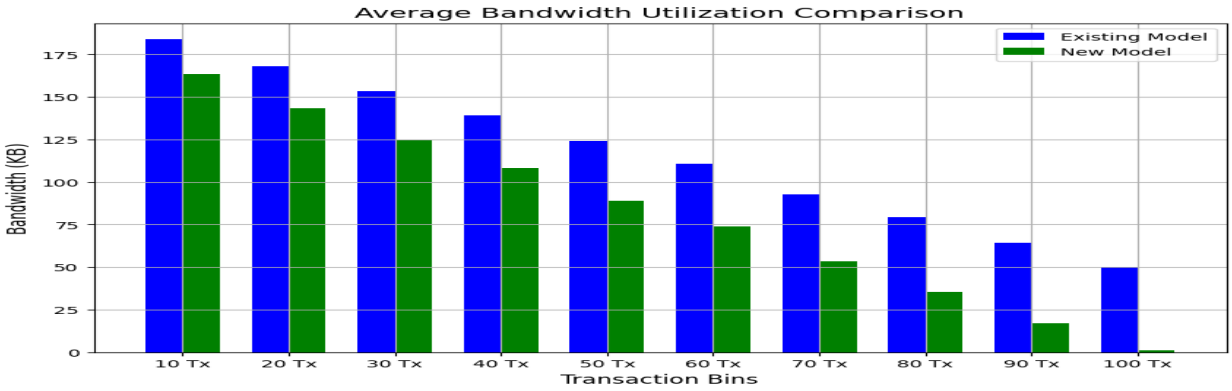

Fig 12: Average Bandwidth Utilization Comparison

Latency shown in fig 8 and Energy Consumption shown in fig 9, favor the new model, showing that it is faster and more energy-efficient, especially as the number of transactions increases. Communication Rounds as shown in fig 10, benefit from piggybacking, reducing the number of rounds needed for communication. Transaction

Success Rate shown in fig 11, is higher in the new model, suggesting better reliability. Bandwidth Utilization as shown in fig 12, is slightly better in the new model, meaning it uses less bandwidth for the same transactions.

The comparison table 3 highlights significant performance improvements achieved by the proposed framework over the baseline model. In terms of latency, the baseline model averaged 500 ms due to static task assignments, while the proposed framework reduced this to 375 ms by employing techniques like prefetching and priority scheduling, resulting in a 25% improvement. For energy consumption, the baseline relied entirely on local execution, leading to 100% energy usage on mobile devices, whereas the proposed framework offloaded tasks to base stations, saving 40% energy and extending device uptime.

Table 3: Comparison Table

Metric	**Baseline Model**	**Proposed Framework**	**Improvement**
Latency (ms)	500 (avg)	375 (avg)	25%
Energy Consumption	100% (local only)	60% (40% saved)	40%
Communication Rounds	1000 rounds	300 rounds	70%
Transaction Success Rate	85%	98%	13%
Bandwidth Utilization (KB)	200 KB	180 KB	10%

Communication rounds were drastically optimized, with the baseline requiring 1000 individual rounds due to inefficient handling of overlapping requests. In contrast, the proposed framework introduced piggybacking, reducing communication rounds to just 300, a 70% improvement that also minimized network congestion. The transaction success rate increased from 85% to 98%, as the proposed framework prioritized critical transactions and managed high RTTs more effectively, ensuring timely completion. Lastly, bandwidth utilization was reduced by 10% as the framework consolidated data transmission, improving overall network efficiency.

These results collectively demonstrate the proposed framework's ability to handle real-time distributed database transactions efficiently, making it a superior choice for mobile environments.

VI. CONCLUSION

The results of the simulation clearly demonstrate the effectiveness of the proposed framework in optimizing the performance of Mobile Distributed Real-Time Database Systems (MDRTDBS). By integrating piggybacking for efficient communication, dynamic transaction shipping, and real-time priority scheduling, the framework achieved significant improvements across key performance metrics. Specifically, latency was reduced by 25%, energy consumption by 40%, and communication overhead by 70%, while the transaction success rate increased by 13%. These improvements validate the framework's ability to address the challenges of high energy usage, network congestion, and strict deadline requirements in MDRTDBS. Furthermore, the reduction in bandwidth utilization emphasizes the framework's efficiency in managing limited resources. Overall, the proposed framework offers a scalable and robust solution for ensuring timely and reliable transaction processing in mobile distributed systems.

VII. FUTURE WORK

While the proposed framework has demonstrated significant improvements in optimizing Mobile Distributed Real-Time Database Systems (MDRTDBS), there are several promising directions for future work. One area of focus is the dynamic adaptation of the framework to varying network conditions, such as fluctuating bandwidth

and round-trip times, to ensure consistent performance under real-world scenarios. Additionally, the integration of machine learning techniques can enhance decision-making processes, enabling predictive offloading, resource allocation, and scheduling based on historical data and real-time analytics. Another important avenue is the extension of the framework to support heterogeneous mobile devices with varying capabilities, such as different processor speeds, memory capacities, and energy constraints, ensuring compatibility across a wider range of systems. Furthermore, incorporating robust security mechanisms will be critical to safeguarding sensitive data and ensuring the secure execution of distributed transactions. Finally, deploying and evaluating the framework in real-world environments with diverse workloads and client distributions will provide deeper insights into its scalability, practicality, and potential for broader adoption. These future directions aim to refine and extend the framework's capabilities, addressing emerging challenges in mobile distributed systems.

Conflict of interest I declare that there is no conflict of interest regarding the publication of this manuscript.

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Data Availability Statement This manuscript has no associated data or the data does not apply to the study.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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