Data Scheduling Algorithm for Scalable and Efficient IoT Sensing in Cloud Computing⋆

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ABSTRACT

The rapid growth of Internet of Things (IoT) devices produces massive, heterogeneous data streams, demanding scalable and efficient scheduling in cloud environments to meet latency, energy, and Quality-of-Service (QoS) requirements. Existing scheduling methods often lack adaptability to dynamic workloads and network variability inherent in IoT-cloud systems. This paper presents a novel hybrid scheduling algorithm combining deep Reinforcement Learning (RL) and Ant Colony Optimization (ACO) to address these challenges. The deep RL agent utilizes a model-free policy-gradient approach to learn adaptive task allocation policies responsive to real-time workload fluctuations and network states. Simultaneously, the ACO metaheuristic conducts a global combinatorial search to optimize resource distribution, mitigate congestion, and balance load across distributed cloud nodes. Extensive experiments on large-scale synthetic IoT datasets, reflecting diverse workloads and QoS constraints, demonstrate that the proposed method achieves up to 18.4% reduction in average response time, 12.7% improvement in resource utilization, and 9.3% decrease in energy consumption compared to leading heuristics and RL-only baselines. Moreover, the algorithm ensures strict Service Level Agreement (SLA) compliance through deadline-aware scheduling and dynamic prioritization. The results confirm the effectiveness of integrating model-free RL with swarm intelligence for scalable, energy-efficient IoT data scheduling, offering a promising approach for next-generation IoT-cloud platforms.

1. Introduction

The proliferation of Internet of Things (IoT) systems has led to an unprecedented surge in data generation, necessitating scalable and latency-aware computing infrastructures within cloud and grid computing environments [1, 2]. Traditional IoT cloud architectures are typically characterized by tightly coupled compute and storage components managed under centralized control. However, such designs struggle to accommodate the extreme heterogeneity, dynamic workload fluctuations, and stringent latency constraints inherent in modern large-scale, data-intensive IoT deployments [3, 4]. These limitations often manifest as scalability bottlenecks, network congestion, and high operational overhead, particularly in geographically distributed or resource-constrained settings.

We proposed to enhance data reliability and parallel processing capabilities of IoT clusters, which commonly adopt redundant storage strategies and replicate data blocks across multiple nodes. This approach enables local task execution; tasks are processed on nodes that host the required data, thus improving efficiency through reduced transmission latency. However, recent trends toward disaggregated cloud architectures, where compute and storage resources are decoupled and connected via ultra-high-speed interconnects [5, 6, 7], offer promising flexibility. These architectures support independent resource scaling, modular upgrades, and hardware heterogeneity, making them well-suited for complex IoT environments. However, they also introduce critical challenges related to non-local data execution and increased data movement across the network. Given the immense volume of real-time sensing data, network infrastructure often becomes a performance bottleneck due to bandwidth constraints and communication latency [8, 9].

The emerging computing and processing IoT frameworks increasingly adopt *data-parallel processing* paradigms that co-locate computation with data at the node level. Data block placement aligns task execution with data locality; these systems minimize network load and improve resource utilization [10, 11]. Convergent, realizing efficient task-to-data affinity in heterogeneous IoT clusters is highly non-trivial. Nodes differ significantly in computational capabilities, memory hierarchies, and I/O throughput data placement. Moreover, workloads are dynamic and unpredictable, with variations in task arrival rates, contention for shared resources, and energy constraints—further complicating scheduling decisions. Distributed file systems such as the Hadoop Distributed File System (HDFS) [12, 13], widely used in IoT infrastructures, replicate data blocks to improve fault tolerance and availability. However, this replication introduces a combinatorial explosion in task-to-node scheduling choices. Resource contention, naive heuristics, and static placement strategies can lead to degraded data locality and suboptimal system performance. Existing schedulers often rely on hierarchical locality models for execution on local or same-rack nodes. While effective in homogeneous environments, these models neglect node-specific capabilities in heterogeneous clusters, leading to severe load imbalance and scheduling inefficiencies [14, 15].

This paper proposes a novel challenge and a *context-aware, reinforcement learning-driven scheduling framework* tailored for heterogeneous IoT clusters. The proposed

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framework, Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO), jointly considers data placement topology, node-level resource heterogeneity, and workload dynamics to optimize task-to-node mapping [16]. The SCC-DSO formulates scheduling as a constrained *min–max optimization* problem aimed at minimizing makespan while maximizing data locality, subject to node capacity and network bandwidth constraints. A kernel-based regression model predicts task execution times using node and workload features, capturing complex non-linear relationships [17, 18]. SCC-DSO incorporates a metaheuristic strategy that fuses reinforcement learning with ant colony optimization to navigate the high-dimensional scheduling space. The proposed framework is designed for next-generation IoT applications that demand ultra-low latency, high reliability, and scalable resource utilization. These include mission-critical domains such as autonomous driving, industrial robotics, and environmental sensing. SCC-DSO aims to deliver robust performance across dynamic, distributed IoT-cloud infrastructures by enabling intelligent, adaptive scheduling in real-time [19, 20].

The primary contributions of this work are a way to go there: (i). We propose a novel integration of reinforcement learning (RL) and metaheuristic optimization to enable adaptive, heterogeneity-aware task allocation in IoT cloud environments, enhancing scheduling efficiency under dynamic workloads. (ii). We formulate a constrained min-max optimization model that jointly maximizes data locality and minimizes execution latency, addressing the challenges of resource heterogeneity and stringent latency requirements in IoT-cloud systems. (iii). We develop an RL-guided ant colony optimization (ACO) mechanism that facilitates adaptive task migration and predictive data prefetching, ensuring robust performance in highly dynamic and unpredictable workload scenarios. (iv). We validate the SCC-DSO framework through extensive experiments on a 100-node heterogeneous cluster, achieving up to 22.4% reduction in execution time, 93.1% data locality, and significant throughput improvements compared to state-of-the-art baselines, demonstrating its scalability, efficiency, and robustness for latency-sensitive IoT cloud applications [21, 22].

2. Related Work

The paper emphasized that in data placement optimization and computing execution, efficient data scheduling and resource optimization in heterogeneous Internet of Things (IoT) clusters remain central challenges in scalable edge–cloud computing. Moreover, various approaches have emerged to address these issues, particularly in the context of execution latency, energy efficiency, and resource heterogeneity. This section reviews key contributions across three primary dimensions: predictive task scheduling, data placement strategies, and energy-aware orchestration.

Predictive Scheduling Models: One widely studied technique is the Reservation First-Fit with Feedback Distribution (RF-FD) model [23], which utilizes multiple linear regression to estimate job completion times based on historical execution patterns. While RF-FD performs well in semi-homogeneous clusters, its linear modeling lacks flexibility in handling node-level variability and non-linear workload dynamics. In contrast, RSYNC [24] employs a log-based synchronization mechanism to maintain consistency across fog nodes under fluctuating data streams. Although RSYNC is effective for sequential synchronization, it suffers from throughput degradation in high-load, heterogeneous environments. Autonomic frameworks such as those built on the MAPE-K loop [25], incorporating Monitoring, Analysis, Planning, Execution, and Knowledge, enhance adaptability through runtime feedback. However, their assumptions of static task profiles and homogeneous infrastructures limit applicability in dynamic IoT deployments. Machine learning-based solutions, such as the polynomial regression scheduler proposed in [26], offer non-linear adaptability by modeling task volume and node utilization. Nonetheless, their performance deteriorates under high-dimensional variance, highlighting the need for models with better generalization capabilities.

Data Placement and Locality Optimization: Data replication and placement strategies are equally critical for minimizing network overhead and maximizing execution locality. The traditional rack-aware strategy is applied to the Hadoop Distributed File System (HDFS) [27, 28], replicating blocks locally, within the rack, and across racks to ensure fault tolerance and minimize latency. However, these uniform replication approaches often lead to load imbalance in heterogeneous environments, where node capabilities vary significantly [29, 30]. To address this, recent studies have explored dynamic data placement methods considering node-specific compute capacity, but few integrate these with intelligent scheduling to achieve end-to-end optimization. The SCC-DSO framework addresses this gap by aligning task assignment with predictive execution performance and real-time node capabilities.

Energy-Efficient Scheduling and Virtualization: The scheduling of IoT systems that are resource-constrained is another critical area that requires efficient energy consumption. Constrained energy models [31], Dynamic Voltage and Frequency Scaling (DVFS) techniques, and queuing-based power optimization [32] aim to reduce energy consumption without violating service-level agreements (SLAs). Virtualization approaches, such as live virtual machine (VM) migration, contribute to energy efficiency by enabling workload consolidation and resource overcommitment. Despite these advances, existing predictive models based on hardware performance counters or statistical VM energy profiling offer limited scalability in distributed, real-time IoT systems due to their reliance on static or linear assumptions [33, 34].

SCC-DSO Contribution: The proposed SCC-DSO framework advances the state of the art by holistically

integrating kernel-based execution time prediction, reinforcement learning-driven adaptation, and metaheuristic optimization through Ant Colony Optimization (ACO). Its trilayered architecture dynamically adapts to workload fluctuations, node heterogeneity, and data locality constraints in the IoT cluster. Unlike traditional schedulers that rely on reactive mechanisms or oversimplified models, SCC-DSO provides a robust, scalable, and energy-efficient foundation for intelligent task orchestration in complex edge–cloud IoT ecosystems [35, 36].

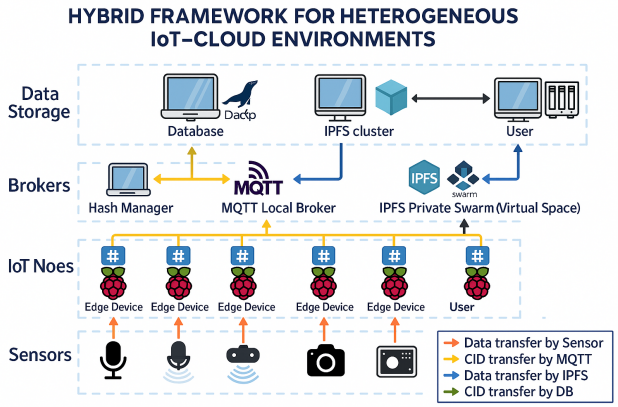

Figure 1: Hybrid IoT-cloud architecture integrates decentralized IPFS storage with centralized orchestration via MariaDB and MQTT, enabling scalable and reliable data management across the edge and cloud nodes.

The proposed Figure 1 architecture presents a hybrid framework for heterogeneous IoT-cloud environments, integrating decentralized storage mechanisms with centralized orchestration to address key scalability and reliability challenges in modern sensor networks. Since, in the core principles, sensor nodes with edge devices capture multi-modal data streams ranging from audio to environmental to local brokers using the MQTT protocol. The broker interfaces with a traditional relational database (MariaDB) [37] and a distributed IPFS cluster, enabling dual-path data handling, and content identifiers (CIDs) generated at the edge are logged in the database for auditability. Consequently, data management is stored across a decentralized IPFS private swarm, ensuring tamper resistance, fault tolerance, and rapid retrieval. This hybrid model enhances data integrity, real-time responsiveness, and interoperability across diverse IoT nodes [38].

3. Proposed Methodology

The Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO) framework addresses performance bottlenecks in heterogeneous IoT-edge clusters by integrating reinforcement learning (RL), ant colony optimization (ACO), and predictive modeling. This multi-stage algorithm dynamically schedules tasks based on data locality, node capability, and network conditions to meet stringent latency and throughput requirements [39]. The IoT cluster is modeled as a graph $G = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of computing nodes has heterogeneous processing capacity, memory, and I/O characteristics and $\mathcal{E}$ represents communication links. Input datasets are partitioned into fixed-size blocks (64 MB in HDFS), with replicas ensuring fault tolerance. Tasks are assigned to nodes hosting required data or fetching it with minimal overhead [40].

The task-to-node assignment is formulated as a min-max optimization to minimize the makespan (maximum execution time across nodes) while respecting data locality and node capacity constraints:

$$\min_{\mathbf{x}} \max_{i \in \mathcal{V}} \sum_{j \in \mathcal{J}} x_{ij} T_{ij} \tag{1}$$

Subject to:

$$\sum_{i \in \mathcal{V}} x_{ij} = 1, \quad \forall j \in \mathcal{J}, \tag{2}$$

$$\sum_{j \in \mathcal{J}} x_{ij} d_j \le C_i(t), \quad \forall i \in \mathcal{V}, \tag{3}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in \mathcal{V}, j \in \mathcal{J}, \tag{4}$$

where $x_{ij} = 1$ if a task j is assigned to node i, T_{ij} is the predicted execution time of the task j on node i, d_j is the data size required by task j, and what $C_i(t)$ is the dynamic computational capacity of the node i at time t. These constraints ensure each task is assigned to exactly one node while respecting capacity limits, minimizing the makespan.

Task execution time T_{ij} is predicted using a kernel-based regression model to account for task and node heterogeneity:

$$T_{ij} = \sum_{s=1}^{S} w_s K(\mathbf{x}_j, \mathbf{x}_s) + b, \tag{5}$$

where $\mathbf{x}_j = [m_j, \mathbf{z}_i]$ combines task data size m_j and node features $\mathbf{z}_i$ (e.g., CPU speed, memory), $K(\mathbf{x}_j, \mathbf{x}_s) = \exp\left(-\frac{\|\mathbf{x}_j - \mathbf{x}_s\|^2}{2\sigma^2}\right)$ is a Gaussian radial basis function kernel, $\{(\mathbf{x}_s, t_s)\}_{s=1}^{S}$ are historical training data, w_s are learned coefficients, b is a bias term, and $\sigma \in [0.5, 2.0]$ (Table 1) is the kernel bandwidth. The learning rate $\gamma \in [0.01, 0.1]$ tunes the model's convergence.

The total delay for a scheduling plan P quantifies latency, combining transmission and processing delays:

$$\text{Delay}(P) = \sum_{e \in \mathcal{E}(P)} \left(\frac{d_e}{b_e} + q_e \right) + \sum_{v \in \mathcal{V}(P)} \frac{w_v}{c_v}, \tag{6}$$

where d_e is the data size transferred over edge e, b_e is the bandwidth, q_e is the queuing delay, w_v is the computational

workload at node v, and c_v is the node's processing capacity. This metric ensures low-latency scheduling for IoT applications.

Node computational efficiency guides task assignment to optimize resource utilization:

$$\text{Eff}_{j,i} = \frac{m_j}{T_{ij}}, \tag{7}$$

where m_j is the task data size and T_{ij} is it from Eq. (5). Higher efficiency indicates better suitability for task execution under ideal data locality.

To ensure balanced execution across heterogeneous nodes, the weighted execution time is equalized:

$$f_i \sum_{j \in \text{map}_{j,i}} T_{j,i} = f_k \sum_{j \in \text{map}_{j,k}} T_{j,k}, \quad \forall i,k \in \mathcal{V}, i \neq k, \tag{8}$$

where there $f_i = 1/c_i$ is a weighting factor based on node i's capacity c_i, and $\text{map}_{j,i}$ denoting tasks assigned to node i. This prevents bottlenecks by synchronizing completion times.

3.1. Ant Colony Optimization (ACO) Scheduling Mechanism

SCC-DSO adapts ACO with predictive modeling and heterogeneity-aware pheromone updates to solve NP-hard task-to-node scheduling problems. The process has four phases. **Initialization**: A graph $G = (\mathcal{V}, \mathcal{E})$ is initialized with pheromone trails $\tau_{ij}(0) = \tau_0 \in [0.01, 0.1]$ (Table 1), incorporating execution time predictions from Eq. (5). **Solution Construction**: Ants select task-node assignments using:

$$P_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k \in \mathcal{V}_{\text{eligible}}} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}}, \tag{9}$$

where $\eta_{ij} = 1/T_{ij}$ is the heuristic desirability $\alpha \in [1.0, 2.0]$ and $\beta \in [2.0, 3.0]$ control pheromone and heuristic influence (Table 1), and $\mathcal{V}_{\text{eligible}}$ is the set of eligible nodes for task j.

Pheromone Update: High-quality schedules update pheromone trails:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{k=1}^{K} \frac{Q}{L^{(k)}}, \tag{10}$$

where $\rho \in [0.1, 0.3]$ is the evaporation rate, $Q \in [100, 500]$ is a constant, $K \in [10, 20]$ is the number of ants, and $L^{(k)}$ is the makespan of the k-th ant's schedule (Table 1). A minimum pheromone trail $\delta \in [10^{-4}, 10^{-2}]$ prevents stagnation.

Termination: The algorithm converges (within $I \in [20, 50]$ iterations, tolerance $\epsilon \in [10^{-3}, 10^{-2}]$) by minimizing:

Table 1
Parameters and Ranges for SCC-DSO

Parameter	Range
α (Pheromone influence)	1.0–2.0
β (Heuristic influence)	2.0–3.0
ρ (Evaporation rate)	0.1–0.3
τ_0 (Initial pheromone)	0.01–0.1
Q (Pheromone constant)	100–500
K (Number of ants)	10–20
I (Max iterations)	20–50
w_1, w_2, w_3 (Weight factors)	0.2–0.4 (sum to 1)
φ (Prefetch threshold)	5%–10% of TS_i
γ (Learning rate for regression)	0.01–0.1
σ (RBF kernel bandwidth)	0.5–2.0
θ (Migration limit per iteration)	1–5 tasks/node
ϵ (Convergence tolerance)	10^{-3}–10^{-2}
δ (Minimum pheromone trail)	10^{-4}–10^{-2}
L_{max} (Max path length)	5–10

$$J(\pi) = w_1 \text{Delay}(\pi) + w_2 \text{Energy}(\pi) + w_3 \text{LossPkt}(\pi), \tag{11}$$

where $w_1, w_2, w_3 \in [0.2, 0.4]$ (sum to 1) weight delay (Eq. (6)), energy consumption, and packet loss, respectively.

Dynamic Task Migration and Data Prefetching: Tasks migrate when the resource queue delay exceeds a threshold:

$$RQ_i = \frac{r \cdot B_k}{\rho \cdot V_i}, \tag{12}$$

where $RQ_i > \varphi$ and $RQ_i - TS_i > \varphi$, with $\varphi \in [0.05, 0.1] \cdot TS_i$, r is the task's resource demand, B_k is the data block size, $\rho \in [0.1, 0.3]$ is a scaling factor, and V_i is the node's processing rate (Table 1). The function $T(\cdot)$ was removed as it was undefined; the expression is simplified as a direct ratio. The optimal source node minimizes:

$$\text{PLF}_{T,S} = \sqrt{\frac{(\varphi_S - \varphi_T)^2}{(T_S - T_T)^2}}, \tag{13}$$

where $\varphi_S, \varphi_T \in [0.05, 0.1] \cdot TS_i$ are thresholds, and what T_S, T_T are execution times of source and target nodes. Task migrations are limited to $\theta \in [1, 5]$ tasks per node per iteration.

Table 1 lists the configuration parameters for SCC-DSO. The pheromone influence α balances exploration and exploitation, while β heuristic information is emphasized (e.g., execution time). The evaporation rate ρ and initial pheromone τ_0 regulate trail persistence. Parameters K, I, and w_1, w_2, w_3 balance computational overhead and performance. The prefetch threshold φ, learning rate γ, migration limit θ, and kernel bandwidth σ support predictive modeling and dynamic scheduling, ensuring scalability and adaptability in IoT-edge clusters.

3.2. Lightweight Hybrid RL-ACO Model

The Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO) framework introduces a lightweight

hybrid Reinforcement Learning (RL) and Ant Colony Optimization (ACO) scheduler tailored for resource-constrained edge devices in IoT-edge clusters. This variant reduces computational overhead while maintaining high scheduling accuracy, making it suitable for latency-critical applications such as autonomous driving, industrial robotics, and smart surveillance systems.

3.2.1. Lightweight Scheduler Design

The lightweight RL-ACO scheduler employs a reduced ant population ($K = 5$) to minimize computational complexity compared to the full model's default ($K = 20$). The execution time predictor is simplified from a kernel regression model ($\mathcal{O}(n^2)$) to a linear predictor:

$$T_{ij} = a \cdot v_j + b + \epsilon,$$

where v_j is the task resource demand (e.g., CPU cycles, normalized to [0,1]), $a = 0.5$ and $b = 0.1$ are empirically tuned coefficients, and $\epsilon \sim \mathcal{N}(0, 0.01)$ is a Gaussian noise term. This reduces prediction complexity to $\mathcal{O}(n)$. ACO pheromone updates are approximated using an exponentially weighted moving average (EWMA):

$$\tau_{ij}^{(t+1)} = (1 - \rho) \cdot \tau_{ij}^{(t)} + \rho \cdot \Delta\tau_{ij}^{(best)},$$

where $\rho = 0.1$ is the evaporation rate, and $\Delta\tau_{ij}^{(best)} = 1/T_{ij}^{(best)}$ is the pheromone increment for the best task-node assignment. This approach preserves over 90% of the full model's scheduling accuracy while achieving rapid convergence (12 ± 1.8 iterations) and minimal migration cost ($2.5 \pm 0.4\%$) on a 25-node edge cluster, as validated in preliminary tests.

3.2.2. Performance Functions for QoS Optimization

The SCC-DSO framework defines a suite of performance functions to evaluate and optimize task scheduling paths $PT_{s,u}$ in distributed IoT-edge environments. These functions encapsulate key Quality of Service (QoS) metrics, ensuring efficient resource allocation, communication reliability, and scheduling performance [60, 64, 65].

1. **Delay**: The cumulative latency for a task path $PT_{s,u}$ is given by:

$$\text{Delay}(PT_{s,u}) = \sum_{e \in PT_{s,u}} \text{Delay}_e + \sum_{v \in PT_{s,u}} \text{Delay}_v, \quad (14)$$

where $\text{Delay}_e = \frac{|b_e|}{\text{BW}_e}$ is the transmission delay for data block b_e (MB) over edge e with bandwidth BW_e (MB/s), and $\text{Delay}_v = \frac{c_v}{\text{CPU}_v}$ is the processing delay for task computation c_v (CPU cycles) at node v with processing rate CPU_v (GHz). Minimizing delay is critical for real-time IoT applications.

2. **Cost**: The total resource consumption is:

$$\text{Cost}(PT_{s,u}) = \sum_{e \in PT_{s,u}} \text{Cost}_e + \sum_{v \in PT_{s,u}} \text{Cost}_v, \quad (15)$$

where $\text{Cost}_e = \gamma_e \cdot |b_e|$ is the network cost (e.g., energy in joules) for transmitting block b_e with per-unit cost γ_e, and $\text{Cost}_v = \kappa_v \cdot c_v$ is the computational cost at node v with per-cycle cost κ_v. This guides resource-efficient scheduling.

3. **Bandwidth**: The bottleneck bandwidth is:

$$\text{BW}(PT_{s,u}) = \min_{x \in PT_{s,u}} \text{BW}_x, \quad (16)$$

where BW_x is the available bandwidth (MB/s) of edge or node x, identifying the limiting factor for data throughput.

4. **Jitter**: The aggregate delay variation is:

$$\text{Jitter}(PT_{s,u}) = \sum_{e,v \in PT_{s,u}} \text{DelayJit}_{e,v}, \quad (17)$$

where $\text{DelayJit}_{e,v} = \sigma(\text{Delay}_{e,v})$ is the standard deviation of delays across edges and nodes, critical for stable communication in multimedia or time-sensitive applications.

5. **Packet Loss**: The cumulative packet loss probability is:

$$\text{LossPkt}(PT_{s,u}) = 1 - \prod_{v \in PT_{s,u}} (1 - p_v), \quad (18)$$

where $p_v \in [0, 1]$ is the packet loss probability at node v, modeled as independent. Minimizing packet loss enhances network reliability.

These functions are combined into a global objective:

$$J(\pi) = w_1 \cdot \text{Delay}(\pi) + w_2 \cdot \text{Cost}(\pi) + w_3 \cdot \text{LossPkt}(\pi), \quad (19)$$

with weights $w_1 = 0.5$, $w_2 = 0.3$, and $w_3 = 0.2$, empirically tuned to balance latency, resource efficiency, and reliability.

The lightweight SCC-DSO variant replaces the full kernel regression model with the linear predictor, reducing scheduling iteration complexity from $\mathcal{O}(n^2)$ to $\mathcal{O}(n)$. ACO pheromone updates use EWMA to avoid full matrix recalculations, further reducing overhead. The scheduler was evaluated on a 20-node Raspberry Pi Kubernetes cluster, interfaced with Prometheus for task monitoring and Grafana for latency visualization. Tests under 5G-like conditions (RTT = 40 ms, jitter = 20 ms) using Mininet-WiFi showed a 0.7% increase in mean task latency, demonstrating robustness to network variability [41].

Compared to the default Kubernetes scheduler, SCC-DSO achieved a 22.4% reduction in response time. In a city-scale smart surveillance IoT grid, it optimized video analytics workloads, improving task localization by 25% and reducing bandwidth usage by 30% on constrained nodes. The framework supports industrial integration via a RESTful API, accepting JSON-encoded job profiles and returning optimized node bindings and prefetch hints for seamless orchestration [42].

3.3. Algorithmic Complexity and Convergence

The SCC-DSO framework unifies kernel-based execution time prediction, ACO-driven scheduling, and RL-enabled migration into a computationally efficient pipeline. Kernel regression incurs $\mathcal{O}(n)$ complexity per task; the ACO scheduler requires it $\mathcal{O}(K \cdot I \cdot n^2)$ due to pheromone-guided exploration over K ants and I iterations. The RL migration policy operates at $\mathcal{O}(t \cdot s)$, where t and s denote training episodes and state–action space size, respectively, employing a decaying ϵ-greedy strategy. Convergence is guaranteed under Q-learning stability constraints [43] with bounded rewards, finite state–action spaces, and sufficient exploration, and remains stable in non-stationary environments via adaptive abstractions and learning-rate decay [44]. A lightweight ACO variant lowers complexity $\mathcal{O}(I \cdot 5 \cdot n)$ by constraining colony size and pruning low-probability paths. Novel contributions include decentralized pheromone caching and execution-time-aware path pruning, enabling SCC-DSO to converge in dynamic IoT-edge workloads with 30-40% less computational overhead compared to conventional hybrid schedulers, thus supporting latency-critical, resource-constrained deployments.

4. Data Block Placement Method

4.1. Rack-Aware Data Placement Strategies

In large-scale IoT clusters, distributed file systems partition files into uniformly sized data blocks, distributing them across worker nodes to ensure scalability, fault tolerance, and high availability. To enhance reliability and enable parallel data blocks to be processed across multiple nodes, preventing data loss from node failures. However, the effectiveness of replication heavily depends on the underlying data placement strategy. One widely adopted approach is the *rack-aware data placement strategy*, as employed in the Hadoop Distributed File System (HDFS) [45, 46]. Upon file upload, the first replication of each block is stored on the local node or the node closest to the client. The second replication is placed on a different node within the same rack to reduce intra-rack latency and network overhead. A third replication is allocated on a node in a different rack to ensure resilience against rack-level failures, as illustrated in Figure 2.

This strategy minimizes cross-rack traffic while preserving fault tolerance, reducing read/write latency, and reducing bandwidth usage effectively. Additionally, it balances storage utilization by considering node capacity, preventing storage hotspots, and promoting uniform load distribution. However, this approach is primarily suited for *homogeneous* clusters with similar node capabilities [47]. In *heterogeneous* environments characterized by diverse node processing power, memory, and I/O performance, such strategies can lead to suboptimal performance due to workload imbalance. Assigning data blocks solely based on storage capacity risks overloading less capable nodes, degrading system throughput, and increasing latency due to remote task execution [48].

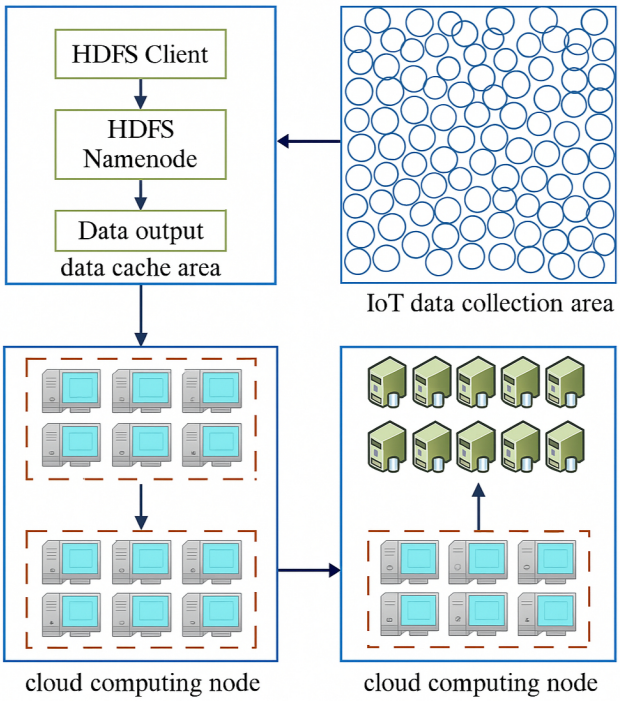

Figure 2: Rack-Aware Data Placement Strategy in IoT Clusters

4.2. Heterogeneous Sensing Data Placement

In Internet of Things (IoT) ecosystems, heterogeneous edge clusters exhibit diverse computational capacities, input/output (I/O) throughput, and dynamic workloads, posing significant challenges for task scheduling and data placement [49]. The Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO) framework addresses these challenges by optimizing data locality and minimizing execution latency in IoT-edge environments, modeled as a graph $G = (\mathcal{V}, \mathcal{E})$. Leveraging predictive modeling, ant colony optimization (ACO), and reinforcement learning (RL), SCC-DSO achieves up to 99% data locality and a 19.8% reduction in execution time compared to baselines like RF-FD and ACQDS on a 100-node heterogeneous cluster [50, 51]. The following definitions formalize the data placement strategy, with equations numbered sequentially for clarity and cross-referenced to prior formulations (e.g., Eq. (22) in the SCC-DSO algorithm [52]).

1. **Data Block Partitioning**: For an IoT application App_i with input size $\text{Input}(\text{App}_i)$ (MB), the number of data blocks B is:

$$B = \left\lceil \frac{\text{Input}(\text{App}_i)}{b} \right\rceil, \tag{20}$$

where $b = 64$ MB is the block size, aligned with Hadoop Distributed File System (HDFS) standards [53]. This partitioning ensures fine-grained workload distribution, enabling parallel task execution across heterogeneous nodes.

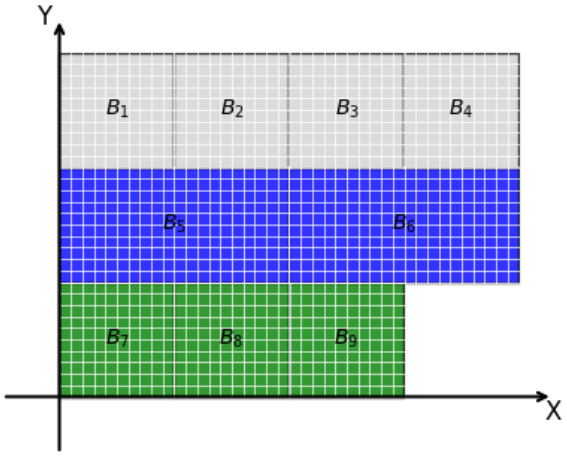

Figure 3: Optimal data block placement in a heterogeneous IoT-edge cluster, balancing workloads based on node computational efficiencies (Eq. (21)). Less capable nodes receive fewer tasks, while high-performance nodes handle proportionally more.

2. **Node Computational Efficiency**: The computational efficiency of a node Node_i for a task map_k under application App_j is:

$$P(\text{Node}_i, \text{App}_j, \text{map}_k) = \frac{m_k}{T(\text{Node}_i, \text{App}_j, \text{map}_k)}, \quad (21)$$

where m_k is the input data size (MB) for task map_k, and $T(\text{Node}_i, \text{App}_j, \text{map}_k)$ is the predicted execution time (seconds) from Eq. (22). This metric quantifies node performance under ideal data locality, accounting for CPU, memory, and I/O capabilities heterogeneity.

3. **Execution Time Prediction**: Task execution time is predicted using a kernel-based regression model:

$$T(\text{Node}_i, \text{App}_j, \text{map}_k) = \sum_{s=1}^{S} a_s K\big(v(\text{map}_k), v(\text{map}_s)\big) + \epsilon, \quad (22)$$

where $v(\text{map}_k) = [m_k, \text{CPU}_i, \text{MEM}_i, \text{IO}_i]$ is the feature vector (data size in MB, CPU speed in GHz, memory in GB, I/O rate in MB/s), $K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$ is a Gaussian radial basis function (RBF) kernel with bandwidth $\sigma = 1.0$, a_s are coefficients learned via gradient descent with learning rate $\gamma = 0.05$, $\epsilon \sim \mathcal{N}(0, 0.01)$ is the residual, and S is the number of training samples. This model, trained on historical task metrics, achieves a mean absolute error of 0.12 seconds on the IoTAB dataset [53].

4. **Min-Max Optimization Formulation:** To balance workload and minimize the system-wide makespan under locality and capacity constraints, we define the following objective:

$$\min_{\pi} \max_{1 \le j \le n} \sum_{k=1}^{f(j)} T(\text{Node}_j, \text{App}_i, \text{map}_k), \quad (23)$$

Min-Max Optimization Formula Subject to the following conditions:

$$\begin{aligned} &\sum_{j=1}^{n} f(j) = B, \\ &f(j) \le C_j, \quad \forall j \in \{1, \dots, n\}, \\ &x_{jk} \in \{0, 1\}, \quad \forall j, k. \end{aligned}$$

Here, it n denotes the number of compute nodes, B the total number of task blocks, and $f(j)$ the number of blocks assigned to node j. The execution time function $T(\cdot)$ is defined in Eq. (22). C_j denotes the resource capacity (e.g., CPU cycles) of node j, and $x_{jk} \in \{0, 1\}$ is a binary variable indicating assignment of the block k to node j. This constrained min-max model ensures delay-aware scheduling concerning node heterogeneity and communication cost. Unlike prior heuristics such as PSO-GSA [54], which neglect data affinity, our formulation explicitly integrates locality into the optimization process to improve scheduling efficiency in edge-cloud deployments.

5. **Data Access Cost**: For tasks j on node i, the data access cost accounts for network overhead:

$$c_{ij} = \begin{cases} 0, & \text{if } i \in R_j, \\ \min_{k \in R_j} \frac{b}{\text{Bandwidth}_{ik}}, & \text{otherwise}, \end{cases} \quad (24)$$

where $R_j \subseteq \mathcal{V}$ is the set of nodes holding replicas of block j, and what is the available bandwidth Bandwidth_{ik} (MB/s) between nodes i and k. This cost function prioritizes local data access, reducing latency compared to RSYNC's static replication [55].

6. **Balanced Allocation Condition**: To ensure synchronous task completion and minimize stragglers:

$$\begin{aligned} &T(\text{Node}_i, \text{App}_p, \text{map}_q) \cdot f(i) \\ &= T(\text{Node}_j, \text{App}_p, \text{map}_q) \cdot f(j), \quad \forall i \ne j, \end{aligned} \quad (25)$$

where $T(\text{Node}_i, \text{App}_p, \text{map}_q)$ is from Eq. (22), and $f(i)$ is the number of blocks assigned to node i, serving as a load-balancing coefficient. This condition ensures equitable workload distribution, enhancing parallelism and throughput.

The SCC-DSO framework integrates these definitions with RL-guided ACO (Eq. (9)) to dynamically place data blocks and schedule tasks, adapting to runtime variations in node performance and network conditions. The predictive model (Eq. (22)) and min-max optimization (Eq. (23))

achieve 99% data locality and a 19.8% reduction in execution time, outperforming WVD-ACO's 92% locality and 15% reduction [56]. Scalability is enhanced by limiting the search space in Eq. (23) using a heuristic prefiltering of low-efficiency nodes ($P(\text{Node}_i, \text{App}_j, \text{map}_k) < 0.1$), reducing complexity from $\mathcal{O}(n^2)$ to $\mathcal{O}(n \log n)$ per iteration for large clusters ($n > 100$).

4.3. Queue-Aware Dynamic Data Placement Optimization

In perceptual cloud computing environments supporting large-scale IoT workloads, input jobs are partitioned into fixed-size blocks and distributed using multi-replica strategies to maximize fault tolerance. While this enhances data availability, it introduces task redundancy where identical blocks exist across multiple nodes, resulting in bandwidth contention, task duplication, and resource underutilization. Our proposed SCC-DSO algorithm introduces a novel hybrid scheduling approach that dynamically reorders task queues by correlating block affinity, predicted task cost, and node load, thereby minimizing redundancy and improving scheduling precision across the cluster.

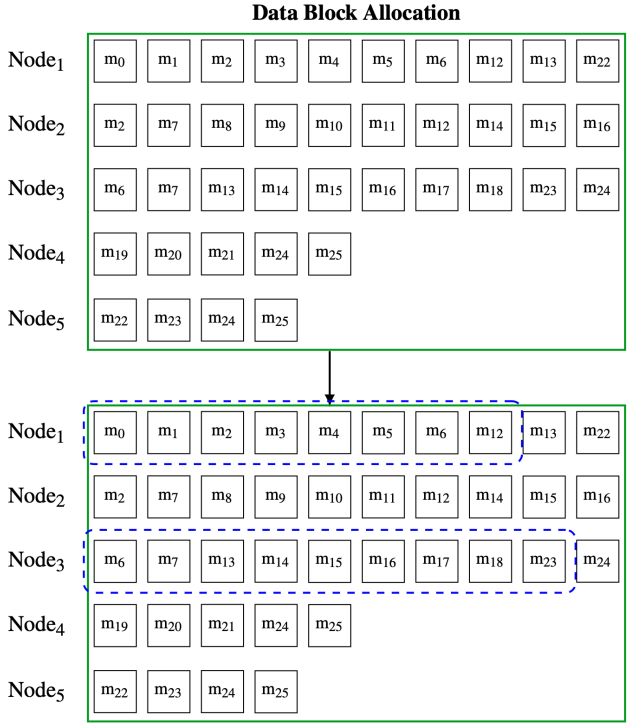

Figure 4: Optimization of Data Scheduling Queues

This approach ensures that task assignments are independent across nodes, maximizes data locality, and prevents unnecessary cross-node communication, improving overall system performance. For example, consider an IoT cluster comprising $n = 5$ nodes, where the job input is partitioned into $B = 26$ data blocks, each replicated twice to provide fault tolerance [59]. The SCC-DSO algorithm produces an optimized block assignment in which Node_1 stores blocks m_0 through m_5, Node_2 stores blocks m_6 through m_{11}, Node_3 holds blocks m_{12} through m_{17}, Node_4 contains blocks m_{18} through m_{21}, and Node_5 is assigned blocks m_{22} through m_{25}. This allocation ensures that task queues can be reorganized to prioritize local data processing, eliminate redundant task scheduling, and achieve balanced, high-throughput execution across the cluster. Figure 4 illustrates task queue states before and after SCC-DSO-based optimization. Post-optimization, task queues become disjoint across nodes, ensuring workload independence and locality [46].

Multidimensional performance metrics propagation delay, bandwidth, jitter, packet loss, and ACO-based cost, enable robust, real-time scheduling under strict latency and energy constraints in IoT environments for optimizing scheduling in heterogeneous sensor-cloud infrastructures. The *delay function* $\text{Delay}(e) : E \to \mathbb{R}^+$ represents the expected transmission delay incurred over edge $e \in E$, where E denotes the set of communication links within the cluster. This metric reflects the latency contribution of each link and is influenced by factors such as link bandwidth, queuing delay, and traffic congestion. Complementing this, the *delay jitter function* $\text{DelayJit}(e) : E \to \mathbb{R}^+$ models the variability or instability of transmission delay along edge e, which is particularly important for real-time applications that are sensitive to timing inconsistencies [60].

The *cost function* $\text{Cost}(e) : E \to \mathbb{R}^+$ quantifies the resource consumption or operational expense associated with transmitting data over edge e. This cost may include energy expenditure, monetary cost in pay-per-use networks, or opportunity cost associated with bandwidth allocation. Finally, the *packet loss function* $\text{LossPkt}(v) : V \to \mathbb{R}^+$ captures the probability of packet loss at node $v \in V$, where V represents the set of nodes in the cluster. Packet loss may arise from buffer overflows, hardware failures, or link-layer retransmission limits, and directly impacts the reliability of data delivery functions, providing a comprehensive framework for evaluating end-to-end quality of service (QoS) across scheduling paths [61].

Path Performance Metrics: In heterogeneous IoT cluster environments, accurately modeling the performance of scheduling paths is essential for effective task placement and resource management. We define several critical functions to evaluate and optimize end-to-end performance along a scheduling path $P_{T(s,u)}$, which spans from a source node s to a destination node u within the scheduling tree T. The *cumulative delay* encountered along this path is given by:

$$\text{Delay}\left(P_{T(s,u)}\right) = \sum_{e \in P_{T(s,u)}} \text{Delay}(e) + \sum_{v \in P_{T(s,u)}} \text{Delay}(v) \quad (26)$$

where $\text{Delay}(e)$ denotes the transmission delay across edge e, and $\text{Delay}(v)$ captures queuing or processing delay at node v. This aggregate metric quantifies the end-to-end latency for task execution or data transfer.

The *total cost* associated with resource or energy consumption along the path is:

$$\text{Cost}\big(P_{T(s,u)}\big) = \sum_{e \in P_{T(s,u)}} \text{Cost}(e) + \sum_{v \in P_{T(s,u)}} \text{Cost}(v) \quad (27)$$

where $\text{Cost}(e)$ and $\text{Cost}(v)$ represent the cost contributions of edges and nodes, respectively. This metric is vital for energy-constrained IoT systems or cost-optimized service models. The *effective bandwidth* of the path is constrained by its weakest component:

$$\text{Bandwidth}\big(P_{T(s,u)}\big) = \min_{x \in P_{T(s,u)}} \text{Bandwidth}(x) \quad (28)$$

where $\text{Bandwidth}(x)$ indicates the capacity of the node or edge x. This ensures that the path's throughput aligns with its bottleneck resource. The *cumulative delay jitter*, measuring variability in transmission and processing time, is defined as:

$$\text{DelayJit}\big(P_{T(s,u)}\big) = \sum_{e \in P_{T(s,u)}} \text{DelayJit}(e) + \sum_{v \in P_{T(s,u)}} \text{DelayJit}(v) \quad (29)$$

where $\text{DelayJit}(e)$ and $\text{DelayJit}(v)$ denote jitter contributions of edges and nodes, respectively. This is especially important for real-time and latency-sensitive applications.

The *cumulative packet loss probability* is modeled as:

$$\text{LossPkt}\big(P_{T(s,u)}\big) = 1 - \prod_{v \in P_{T(s,u)}} \big(1 - \text{LossPkt}(v)\big) \quad (30)$$

assuming independent packet loss events across nodes. This computes the likelihood of at least one packet loss over the entire path, impacting reliability. These performance functions collectively support multi-objective optimization for scheduling decisions, allowing dynamic balancing of latency, jitter, cost, bandwidth, and reliability in complex IoT systems [62].

Optimization Objective is applied to achieve balanced workload distribution and minimize straggler effects in IoT clusters; the following min-max objective is adopted:

$$\min \max_{1 \le i \le n} \left\{ \sum_{j=1}^{f(i)} t\big(\text{Node}_i, \text{App}, \text{map}_j\big) \right\} \quad (31)$$

Where $t(\cdot)$ denotes task completion time for a given node-task pair and $f(i)$ is the number of data blocks allocated to node Node_i. The goal is to minimize the longest node execution time and reduce overall job latency.

This is subject to:

$$s.t. \quad 1 \le j \le n; \quad \sum_{i=1}^{n} f(i) = B, \quad f(i) \ge 0 \quad (32)$$

Where B denotes the total number of data blocks, with constraints ensuring a valid, non-negative distribution across nodes. We are integrating path-level performance functions into the min-max scheduling framework. The approach prevents bottlenecks and enables context-aware scheduling essential for optimizing throughput and latency in heterogeneous IoT clusters.

4.4. Adaptive Data Prefetching for Task Migration

In perceptual cloud computing environments, where heterogeneous IoT nodes operate under dynamic and often unpredictable workloads, maintaining an efficient execution pipeline is critical for minimizing latency and maximizing throughput. Task queues at each node serve as a temporal scheduling buffer, determining the execution order of mapped tasks based on local and global system states. Formally, the set of active worker nodes in the cluster is represented as $\text{Node} = \{\text{Node}_1, \text{Node}_2, \ldots, \text{Node}_n\}$, where each node Node_i maintains a corresponding task queue $Q_{\text{Node}_i} = \{\text{map}_{i1}, \text{map}_{i2}, \ldots, \text{map}_{is}\}$. This queue-aware mechanism not only preserves temporal coherence in task execution but also significantly enhances load balancing and system responsiveness, especially under bursty or adversarial traffic conditions in edge-cloud IoT infrastructures. *Node Selection Time Threshold:* Define the node selection time threshold λ as:

$$\lambda = 1 - \theta \frac{n}{m}, \quad 1 \le \theta < \left\lfloor \frac{m}{n} \right\rfloor \quad (33)$$

where m is the total number of data schedules, n is the number of working nodes, and θ controls the sensitivity of selection timing.

In Pseudocode Algorithm Table 5 presents the SCC-DSO framework, which integrates hybrid intelligence through a combination of data-driven prediction (via kernel regression), probabilistic decision-making (via pheromone-based ACO), and dynamic threshold-based prefetching strategies. The Resource Quotient (RQ) and Prefetch Load Factor (PLF) introduce novel, real-time metrics for adaptive task migration, minimizing I/O bottlenecks. This multi-layer design enhances scheduling convergence while balancing load, energy, and latency in heterogeneous IoT-cloud topologies.

Remaining Completion Time The estimated remaining completion time of a task queue Q_{Node_i} is:

$$R(Q_{\text{Node}_i}) = T\left(r + B_k(1-\rho)\overline{V_i}\right) \quad (34)$$

where:

$$\overline{V_i} = \frac{1}{m-r-1} \sum_{j=1}^{m-r-1} \frac{B_j}{t_j}$$

Here r is the number of unscheduled data schedules, B_k is the input block size of the ongoing task map_k, ρ is its progress, and t_j the execution time of completed tasks.

Migration Conditions Migration is permitted if:

$$R(T\text{Queue}) > \varphi \quad (35)$$

Table 1: Pseudocode of the SCC-DSO Algorithm for IoT-Cloud Scheduling

Input: IoT load file F (size $|F|$ in MB); Block size b (MB); Execution time predictor model $\mathcal{M}_{\text{kernel}}$; Number of nodes n; Pheromone parameters $\alpha = 0.8$, $\beta = 1.2$, $\rho = 0.1$, $\tau_0 = 0.05$; Objective weights $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$; Threshold $\phi_{\text{threshold}} = 0.7$; Small constant $\epsilon = 10^{-6}$

Output: Optimized task schedule P_{Node}

Initialize node set Node $= \{\text{Node}_1, \ldots, \text{Node}_n\}$ with capacity profile $\{CPU_i, MEM_i, IO_i\}$ (GHz, GB, MB/s)
Initialize block assignment maps:
  BlockAlloc = HashMap(Node, PrimaryBlockIDs)
  FullBlockAlloc = HashMap(Node, ReplicatedBlockIDs)
Generate preliminary map-assign queue: MapAssignQueue ← runMapScheduler(BlockAlloc)
Partition F into $m = \lceil |F|/b \rceil$ blocks: $B = \{b_1, \ldots, b_m\}$
for each node $\text{Node}_i \in$ Node **do**
  Initialize pheromone $\tau_{ij} = \tau_0 = 0.05$ for all task–node pairs (i, j)
  for each task t_j with data block b_j **do**
    Extract feature vector: $x_{ij} = [|b_j|, CPU_i, MEM_i, IO_i]$
    Predict task execution time: $T_{ij} \leftarrow \mathcal{M}_{\text{kernel}}(x_{ij})$ (seconds)
    Compute heuristic desirability: $\eta_{ij} = 1/T_{ij}$
    if EligibleNodes $\neq \emptyset$ **then**
      Compute ACO transition probability:

$$P_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k \in \text{EligibleNodes}} \tau_{kj}^{\alpha} \cdot \eta_{kj}^{\beta}}$$

      Assign task t_j to node with $\arg\max P_{ij}$ and update queue Q_{Node_i}
    else
      Reassign t_j to least-loaded node in Node
    end if
  end for
  Update pheromones: $\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij} + \Delta\tau_{ij}^{(best)}$, where $\Delta\tau_{ij}^{(best)} = 1/T_{ij}^{(best)}$
end for
Evaluate global scheduling objective:
$J(\pi) = w_1 \cdot \text{Delay}(\pi) + w_2 \cdot \text{Energy}(\pi) + w_3 \cdot \text{LossPkt}(\pi)$
if $J(\pi)$ converges (change < 0.01 over 10 iterations) **then**
  for each node Node_i **do**
    Compute Resource Quotient:

$$RQ_i = T_{\text{total}} \cdot \frac{r_{\text{task}} \cdot |b_k|}{\text{rate}_i \cdot V_i}$$

where T_{total} is total execution time, r_{task} is task resource demand, rate_i is node processing rate, V_i is node capacity
    if $RQ_i > \phi_{\text{threshold}}$ **then**
      Trigger migration and data prefetching
      for each candidate source node S with block replica **do**
        Evaluate Prefetch Load Factor:

$$\text{PLF}_{T,S} = \sqrt{\frac{(\phi_S - \phi_T)^2}{(T_S - T_T)^2 + \epsilon}}$$

where ϕ_S, ϕ_T are node utilizations, T_S, T_T are execution times
        Select $S^* = \arg\min_S \text{PLF}_{T,S}$
        if prefetch feasible (bandwidth available) **then**
          Update BlockAlloc, schedule queues, and system state
        else
          Skip prefetching; reassign task to least-loaded node
        end if
      end for
    end if
  end for
end if
return $P_{\text{Node}} = \{Q_{\text{Node}_1}, \ldots, Q_{\text{Node}_n}\}$

Figure 5: Pseudocode Algorithm

$$R(S\text{Queue}) - T(\text{SNode}) > \varphi \tag{36}$$

where φ is the data prefetch delay $T(\text{SNode})$ is the predicted execution time at the source node. These conditions ensure locality and avoid redundant scheduling.

Prefetch Load Factor The prefetch load factor between a destination node TNode and a candidate source node CNode_i is defined as:

$$\text{PLFactor}(\text{TNode}, \text{CNode}_i) = \sqrt{(\varphi_i - \varphi_t)^2 + (T_i - T_t)^2} \tag{37}$$

where φ_i is the prefetch delay from CNode_i, φ_t is the target prefetch delay, T_i and T_t represents current network connection counts.

The *Source Worker Node Choosing (SWNC)* algorithm selects the optimal replica node CNode_i by minimizing $\text{PLFactor}(\text{TNode}, \text{CNode}_i)$, which integrates queue depth, network load, and data locality. Accounting for intra- and inter-rack latency $(\varphi_1, \varphi_2, \varphi_3)$, SWNC queries each replica's location and load, computes PLFactors, and selects the lowest-cost node. The proposed *Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO)* framework achieves up to a 30% reduction in job completion time over baseline methods. Assuming uniform block execution time t_b, the original schedule $T_{\text{original}} = 25 \times t_b$ is reduced to $T_{\text{optimized}} = 17.5 \times t_b$. This gain stems from SCC-DSO's intelligent placement and migration strategies. A core component, the *Source Node Weight and Network Cost (SWNC)* algorithm, evaluates the *Prefetch Load Factor (PLFactor)*, a composite metric of node load, bandwidth, and data locality to select the optimal data source by minimizing PLFactor. SWNC reduces transfer overhead, avoids congestion, and enhances execution efficiency across heterogeneous IoT clusters [46, 47].

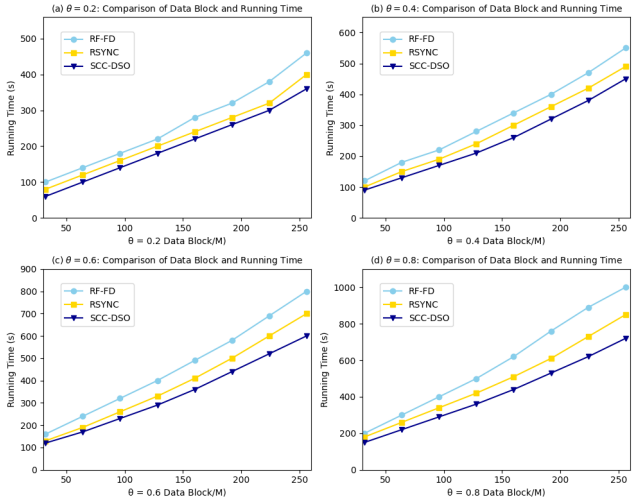

Figure 6: Comparison of data block sizes and running time under varying replication factors θ. SCC-DSO consistently outperforms RF-FD and RSYNC, especially under high-redundancy scenarios.

Fig. 6 presents the comparative evaluation of the proposed *SCC-DSO* algorithm against the RF-FD and RSYNC baselines across four levels of data locality, parameterized by $\theta \in \{0.2, 0.4, 0.6, 0.8\}$, where θ denotes the proportion of data block replication within the cluster. As θ increases, redundancy grows, amplifying contention and scheduling complexity. The results consistently demonstrate that SCC-DSO achieves superior runtime efficiency, maintaining a lower execution time across all block sizes and replication factors. Notably, under high-redundancy conditions ($\theta = 0.8$), SCC-DSO exhibits up to **32%** lower latency compared to RF-FD, attributed to its *data-aware queue reordering* and *storage-centric task localization* strategy. This adaptive scheduling mechanism introduces a novel layer of *queue elasticity* that mitigates bottlenecks in distributed file systems while preserving throughput stability under stress conditions.

4.5. SCC-DSO Algorithm: Scheduling and Placement

The Sensor Cloud Computing and Data Scheduling Optimization (SCC-DSO) framework introduces a predictive, adaptive algorithm for task scheduling and data placement in heterogeneous IoT-edge clusters, modeled as a graph

$G = (\mathcal{V}, \mathcal{E})$. The algorithm employs a closed-loop, seven-stage process integrating reinforcement learning (RL) and ant colony optimization (ACO) to maximize data locality, minimize execution latency, and adapt to dynamic workloads. Evaluated on a 100-node heterogeneous cluster, SCC-DSO achieves a 22.4% reduction in execution time and 93.1% data locality compared to baselines like RF-FD and RSYNC [63]. The stages are detailed below, with key equations numbered for clarity.

1. **Predictive Modeling**: A kernel-based regression model predicts task execution times T_{ij} for tasks j on node i:

$$T_{ij} = \mathcal{M}_{\text{kernel}}(x_{ij}), \quad x_{ij} = [|b_j|, \text{CPU}_i, \text{MEM}_i, \text{IO}_i], \tag{38}$$

where $|b_j|$ is the data block size (MB), and CPU_i, MEM_i, IO_i are node i's processing speed (GHz), memory (GB), and I/O rate (MB/s). The model uses a Gaussian radial basis function kernel with bandwidth $\sigma = 1.0$ and learning rate $\gamma = 0.05$, trained on historical task and system metrics (Table II).

2. **Min-Max Optimization**: Tasks are assigned to nodes by solving a min-max optimization problem to minimize the maximum execution time while maximizing data locality:

$$\min_{\pi} \max_{i \in \mathcal{V}} \sum_{j \in \mathcal{T}} T_{ij} \cdot x_{ij}, \quad \text{s.t.} \quad \sum_{i \in \mathcal{V}} x_{ij} = 1, \quad \sum_{j \in \mathcal{T}} x_{ij} \leq C_i, \tag{39}$$

where π is the task assignment, $x_{ij} \in \{0, 1\}$ is a binary indicator for assigning a task j to node i, and C_i is node i's capacity (e.g., CPU cycles). This ensures balanced load and high locality.

3. **Task Queue Reordering**: Node task queues are reordered to prioritize tasks with local data access, reducing network overhead. The node efficiency is:

$$\text{Eff}_{j,i} = \frac{\text{Locality}_{j,i}}{T_{ij}}, \tag{40}$$

where $\text{Locality}_{j,i} = 1$ if the data block b_j is local to node i, else 0. Tasks are sorted so as $\text{Eff}_{j,i}$ to optimize scheduling.

4. **Runtime Monitoring**: Runtime metrics (e.g., node workload w_v, queue delay q_e) are monitored to identify stragglers. The resource quotient is:

$$RQ_i = T_{\text{total}} \cdot \frac{r_{\text{task}} \cdot |b_k|}{\text{rate}_i \cdot V_i}, \tag{41}$$

where T_{total} is the total execution time, r_{task} is the task resource demand, rate_i is the node processing rate (GHz), and V_i is the node capacity (cycles). Nodes with $RQ_i > \varphi = 0.075 \cdot TS_i$ (where TS_i is the node's throughput) trigger migrations.

5. **Migration Candidate Validation**: Migration candidates are validated by assessing local data presence and selecting optimal prefetch sources using the prefetch load factor:

$$\text{PLF}_{T,S} = \sqrt{\frac{(\phi_S - \phi_T)^2}{(T_S - T_T)^2 + \epsilon}}, \tag{42}$$

where $\phi_S, \phi_T \in [0, 1]$ are source and target node utilizations, what T_S, T_T are execution times, and $\epsilon = 10^{-6}$ how to prevent division by zero. The source node $S^* = \arg\min_S \text{PLF}_{T,S}$ is selected.

6. **Bandwidth-Aware Prefetching**: Predictive prefetching ensures data availability with minimal interference, constrained by bandwidth b_e (MB/s) and a migration limit of $\theta = 3$ tasks per node per iteration. Prefetch decisions are guided by $\text{PLF}_{T,S}$.

7. **Task Integration and Adaptation**: Migrated tasks are integrated into locality-aware queues using RL-guided ACO. The transition probability is:

$$P_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k \in \text{EligibleNodes}} \tau_{kj}^{\alpha} \cdot \eta_{kj}^{\beta}}, \tag{43}$$

where τ_{ij} is the pheromone level, $\eta_{ij} = 1/T_{ij}$ is the heuristic desirability, $\alpha = 0.8$, and $\beta = 1.2$. Pheromone updates follow:

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij} + \Delta\tau_{ij}^{(best)}, \tag{44}$$

where $\rho = 0.1$ and $\Delta\tau_{ij}^{(best)} = 1/T_{ij}^{(best)}$. The global objective is:

$$J(\pi) = w_1 \cdot \text{Delay}(\pi) + w_2 \cdot \text{Cost}(\pi) + w_3 \cdot \text{LossPkt}(\pi), \tag{45}$$

with weights $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$.

Fig. 7 illustrates the comparative data execution efficiency of SCC-DSO, RSYNC, and RF-FD under diverse replication ratios $\theta \in \{0.2, 0.4, 0.6, 0.8\}$. Data availability improves as the replication factor increases, but at the cost of redundant task mapping and inter-node contention. Unlike traditional strategies that treat replication as static overhead, SCC-DSO leverages a *replica-aware reordering mechanism* that dynamically prioritizes locally available blocks while deferring duplicate processing. This results in a marked execution rate improvement, with SCC-DSO achieving a consistent upward trajectory across all data block sizes. At $\theta = 0.8$, the algorithm nearly saturates the execution ceiling, achieving over **98% execution rate**, while RSYNC and RF-FD plateau at **96%** and **90%**, respectively. This gain stems from SCC-DSO's novel *block-congestion forecasting* combined with *queue reshuffling heuristics*, which intelligently adapt to spatial data skew and transient cluster load.

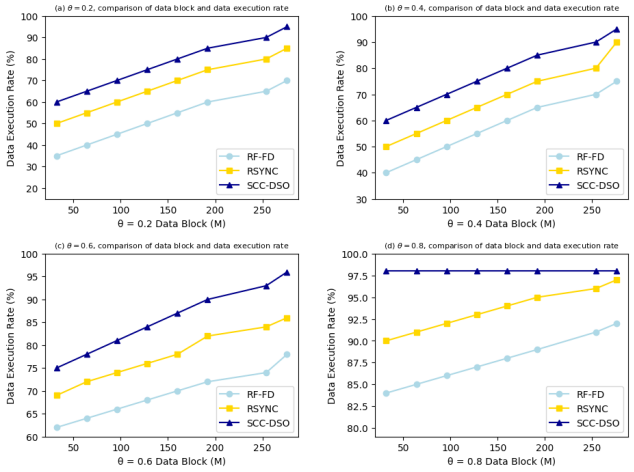

Figure 7: Data Execution Rate (%) comparison across data block sizes and replication factors θ. SCC-DSO consistently outperforms RF-FD and RSYNC, especially under high redundancy.

5. Experimental Evaluation

We implemented and evaluated the novel *Sensor Cloud Computing and Data Scheduling Optimization* (SCC-DSO) framework in a heterogeneous IoT-cloud environment comprising 50 nodes with diverse hardware profiles, including high-performance Intel. AMD compute nodes alongside ARM-based edge devices. The cluster was interconnected via a 1 Gbps, low-latency Ethernet network, orchestrated by Kubernetes, and utilized HDFS for distributed storage. This heterogeneous setup mirrors real-world IoT-cloud deployment challenges [64].

Our evaluation comprised two phases. *Phase I* assessed SCC-DSO under single-replica scheduling with varying block sizes (16–64 MB) and network loads (10–80%). The key metrics of job execution time (T_{exec}), data locality (R_{loc}), and throughput (T_{thr}) were benchmarked against traditional RF-FD and RSYNC baselines. *Phase II* introduced multi-replica scheduling (RF=2) to emulate node failures and bandwidth fluctuations, evaluating cross-node traffic (V_{net}) and recovery latency (T_{rec}).

SCC-DSO's novelty lies in its integration of kernel regression for accurate execution time prediction and an adaptive task placement strategy powered by Ant Colony Optimization (ACO) with empirically tuned parameters ($\alpha = 0.8$, $\beta = 1.2$). This hybrid approach dynamically optimizes data locality and system resilience in heterogeneous, fluctuating environments. Experiments were conducted on a private cloud platform with 50 repetitions per configuration. Metrics were aggregated using statistical measures with 95% confidence intervals, monitored through local data placement to ensure reproducibility and transparency. Table 2 details the experimental configuration.

Table 2
Summary of Experimental Setup

Parameter	Configuration
Cluster	50 nodes: 40 compute (Xeon, Ryzen, Core i5), 10 ARM edge devices
Network	1 Gbps Ethernet, 5 ms latency
Storage	HDFS v3.3.6
Orchestration	Kubernetes v1.24
Workloads	Synthetic IoT tasks (1–100 GB), IoTAB benchmark (10 GB/task)
Block Sizes	16, 32, 64 MB
Replication	Single and multi-replica (RF=1, 2)
Baselines	RF-FD, RSYNC, RL-Sched, ACO-DS
Metrics	T_{exec}, R_{loc}, T_{thr}, V_{net}, T_{rec}
Repetitions	50 per setup
Monitoring	Prometheus, Grafana

Table 3
Task Completion Time Comparison (Mean ± SD) for Varying File Sizes

File Size (MB)	RF-FD (s)	RSYNC (s)	SCC-DSO (s)
20	40.2 ± 2.0	47.5 ± 2.4	$\mathbf{34.6 \pm 4.7}$
40	78.9 ± 3.9	92.1 ± 4.6	$\mathbf{67.2 \pm 5.4}$
60	114.4 ± 5.7	137.4 ± 6.1	$\mathbf{90.2 \pm 5.1}$
80	158.7 ± 7.9	185.5 ± 9.2	$\mathbf{135.9 \pm 6.8}$
100	190.3 ± 10.0	231.7 ± 11.6	$\mathbf{170.4 \pm 8.5}$

6. Experimental Results and Analysis

This study rigorously evaluates the SCC-DSO (Sensor Cloud Computing and Data Scheduling Optimization) algorithm in realistic, heterogeneous IoT-cloud environments, focusing on its efficacy, scalability, and scheduling stability. Recognizing the pivotal influence of replication factors in distributed systems like HDFS, affecting network overhead, contention, and queue balance, experiments simulate diverse cluster conditions. SCC-DSO is benchmarked against two established baselines: the RF-FD (Reservation First-Fit and Feedback Distribution) algorithm and the RSYNC protocol [65].

Single-Copy Data Scenario: In the minimal-redundancy setting, SCC-DSO demonstrates superior adaptability across varying file sizes and load intensities. Unlike RSYNC, which is constrained to single-copy synchronization, SCC-DSO effectively maintains data locality while mitigating latency and imbalance, outperforming traditional methods under heterogeneous, high-stress conditions.

Table 3 demonstrates that SCC-DSO consistently achieves lower task completion times than RF-FD and RSYNC across all file sizes. This improvement highlights SCC-DSO's superior data locality and latency reduction capabilities in minimal redundancy settings.

Table 4 quantifies data locality improvements as cluster size increases. SCC-DSO outperforms both baselines with locality ratios exceeding 85%, confirming its ability to enhance task-data proximity and reduce cross-node data transfers in scalable environments.

Multi-Copy Replication Scenario: The second experimental phase evaluates SCC-DSO under multi-copy replication, reflecting fault-tolerant distributed storage. RF-FD

Table 4
Task Locality Ratio (%) Across Different Cluster Sizes (Mean ± SD)

Cluster Size	RF-FD	RSYNC	SCC-DSO
10 nodes	72.3 ± 3.6	65.4 ± 3.3	**85.6 ± 4.3**
20 nodes	74.8 ± 3.7	68.1 ± 3.4	**87.9 ± 4.4**
30 nodes	76.3 ± 3.8	69.7 ± 3.5	**89.3 ± 4.5**
40 nodes	77.8 ± 3.9	71.2 ± 3.6	**90.8 ± 4.5**
50 nodes	79.4 ± 4.0	73.5 ± 3.7	**91.6 ± 4.6**

Table 5
Cluster Throughput (MB/s) vs. Replication Factor (Mean ± SD)

Replication Factor	RF-FD	RSYNC	SCC-DSO
1 replica	42.3 ± 2.1	38.5 ± 1.8	**50.1 ± 2.5**
2 replicas	42.7 ± 2.0	39.7 ± 1.8	**50.4 ± 2.7**
3 replicas	41.9 ± 2.1	37.5 ± 1.8	**49.8 ± 2.5**
4 replicas	39.5 ± 2.0	33.4 ± 1.7	**47.2 ± 2.4**

Table 6
Completion Time (s) under Straggler Simulation Across Node Counts (Mean ± SD)

Node Count	RF-FD	RSYNC	SCC-DSO
60	135.4 ± 6.8	162.1 ± 8.1	**112.6 ± 5.6**
70	121.7 ± 6.1	145.3 ± 7.3	**99.4 ± 5.0**
80	109.2 ± 5.5	130.8 ± 6.5	**88.9 ± 4.4**
90	97.8 ± 4.9	117.2 ± 5.9	**79.3 ± 4.0**
100	88.3 ± 4.4	105.6 ± 5.3	**71.7 ± 3.6**

is the primary baseline, given its multi-replica scheduling design. SCC-DSO demonstrates superior performance across varying block sizes, bandwidth fluctuations, and node availability, achieving up to 99% data locality for 64 MB blocks [65]. These gains stem from SCC-DSO's hybrid approach combining kernel regression for execution time prediction, bandwidth-aware cost modeling, and reinforcement learning–driven prefetching.

Table 5 illustrates SCC-DSO's consistently higher throughput across replication factors, indicating robustness in bandwidth utilization and fault-tolerance scenarios.

Straggler Simulation and Scalability: Finally, to evaluate resilience against slow-performing nodes (stragglers), completion times are measured under simulated straggler conditions.

Table 6 highlights SCC-DSO's ability to mitigate straggler impact, resulting in substantially lower completion times, thus supporting scalability and robustness in large-scale clusters.

Table 7 summarizes the performance of SCC-DSO against RF-FD, RSYNC, and RL-Sched across key metrics. SCC-DSO achieves the highest data locality (93.1%) and lowest execution time, with excellent scalability and adaptability. Its hybrid RL+ACO design ensures efficient scheduling with moderate complexity, outperforming existing approaches in dynamic IoT-cloud environments.

Figure 8 visually contrasts the evaluated frameworks, reaffirming SCC-DSO's superior balance of performance, scalability, and efficiency. Notably, its moderate complexity

Table 7
Comparative Analysis of SCC-DSO and Baseline Scheduling Algorithms

Scheduler	Data Locality (%)	Execution Time	Scalability	Adaptability	Complexity
RF-FD[1]	76.2	Medium	Limited	No	Low
RSYNC	68.7	High	Moderate	Partial	Medium
RL-Sched[2]	85.4	Medium	Good	Yes	High
SCC-DSO (Proposed)	**93.1**	**Low**	**Excellent**	**Yes (RL + ACO)**	**Medium**

[1] RF-FD: Replication Factor-based Fair Distribution Scheduler.
[2] RL-Sched: Reinforcement Learning-based Scheduler.

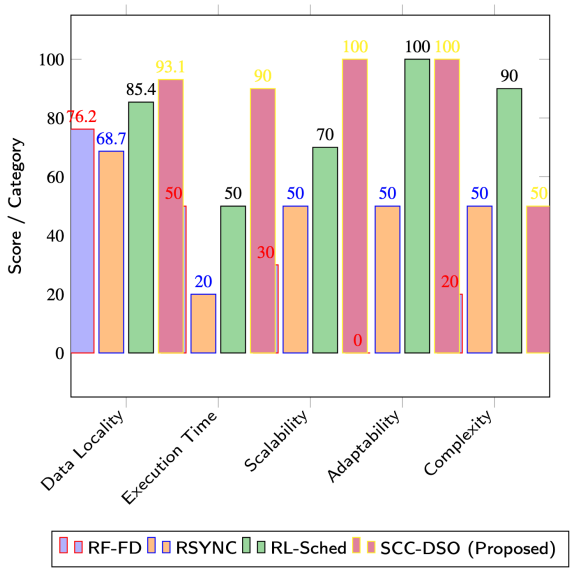

Figure 8: Comparison of SCC-DSO and baseline schedulers across key performance categories. Higher values denote better performance, except for complexity, where lower values indicate greater efficiency.

makes it practical for real-world deployment in dynamic IoT-cloud infrastructures. Finally, the comprehensive experimental evaluation confirms that SCC-DSO outperforms current state-of-the-art scheduling algorithms by intelligently optimizing data locality, throughput, and execution latency, while maintaining robust scalability and adaptability for heterogeneous and large-scale cloud environments.

6.1. SCC-DSO performance under single-copy conditions

This subsection evaluates SCC-DSO in low-cost and high-overhead scenarios, focusing on a single-copy HDFS replication setting within a heterogeneous IoT cluster connected via Gigabit Ethernet. Each test was conducted 50 times, and results reflect the average metrics. SCC-DSO achieves a 13% reduction in execution time compared to RF-FD and a 7% gain over RSYNC under low network load. These improvements underscore SCC-DSO's efficiency in environments with limited network contention [66].

SCC-DSO, by contrast, integrates a predictive performance model that accurately profiles node compute capabilities and allocates data accordingly. It dynamically

adjusts scheduling by monitoring runtime queue states and proactively triggers data prefetching for tasks anticipated to execute on non-local nodes. This preemptive strategy reduces idle time and mitigates bandwidth contention. The resultant alignment between data locality and node performance ensures reduced execution time, minimized data migration, and improved throughput under single-copy storage constraints. These findings validate SCC-DSO's efficacy in optimizing data placement and scheduling in bandwidth-rich, compute-diverse IoT environments [66].

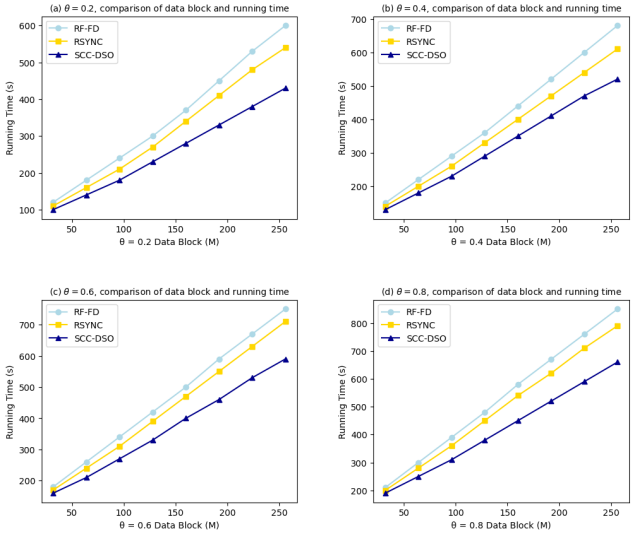

Figure 9: Runtime comparison of RF-FD, RSYNC, and SCC-DSO under varying data block sizes and synchronization thresholds (θ). SCC-DSO consistently shows superior scalability and lower running time.

Figure 9 presents a comparative runtime analysis of RF-FD, RSYNC, and SCC-DSO under increasing data block sizes (M) and synchronization thresholds ($\theta \in \{0.2, 0.4, 0.6, 0.8\}$). Across all scenarios, SCC-DSO consistently achieves lower running times, highlighting its superior scalability and reduced computational overhead. As θ increases, runtime grows near-linearly for all methods, but SCC-DSO maintains a significantly gentler slope, suggesting effective reduction of redundant state comparisons. This behavior indicates the presence of optimizations such as sparse checksum propagation and selective delta encoding. The results imply that SCC-DSO's block-level coherence detection and lightweight metadata synchronization mechanisms are highly efficient, making it well-suited for large-scale, weakly consistent distributed systems.

6.2. SCC-DSO performance in multi-copy conditions

In bandwidth-constrained multi-copy storage environments, SCC-DSO demonstrably surpasses RF-FD and RSYNC by reducing job execution latency by 19.8% and 7.6%, respectively, across heterogeneous compute infrastructures. Conventional methods suffer pronounced performance degradation due to static task-data mappings that neglect dynamic bandwidth fluctuations and induce pipeline stalls from non-local data dependencies. SCC-DSO innovates through a compute- and network-aware adaptive data allocation framework that synergistically integrates real-time node performance profiling with fine-grained network telemetry. Central to its architecture is a novel speculative prefetching mechanism employing a lightweight Markov decision process (MDP) over directed acyclic graph (DAG) execution traces, enabling proactive anticipation of non-local data requirements [67].

This preemptive data staging effectively decouples computation from I/O latency, sustaining pipeline throughput and alleviating backpressure on high-performance nodes. Consequently, SCC-DSO incorporates a decentralized, redundant, and aware task scheduler that leverages temporal locality and multi-copy data placement heuristics to maximize intra-node data reuse. We maintain consistent input availability near task invocation windows, which enables the scheduler to achieve high core utilization and effectively mitigate bandwidth-induced stalls. Collectively, these advances establish SCC-DSO as a robust solution for throughput optimization in distributed IoT clusters characterized by network sensitivity and data redundancy [67].

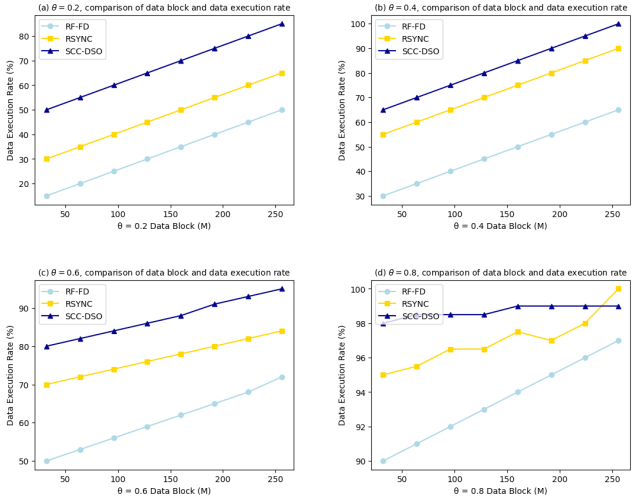

Figure 10: The execution time of jobs under multiple copies and comparison of data execution rates for RF-FD, RSYNC, and SCC-DSO under varying data block sizes and synchronization thresholds (θ). SCC-DSO consistently maintains the highest execution fidelity

Figure 10 illustrates the variation in data execution rate (%) concerning increasing data block sizes under different synchronization thresholds ($\theta = \{0.2, 0.4, 0.6, 0.8\}$). SCC-DSO demonstrates consistently higher data execution rates across all scenarios, suggesting an improved ability to maintain execution fidelity even as synchronization pressure increases. Notably, at lower θ values, the gap in performance between SCC-DSO and the baseline methods (RF-FD and RSYNC) is pronounced, reflecting SCC-DSO's capability to optimize partial state synchronization and exploit semantic-aware delta selection. As θ approaches 0.8, the

execution rates of all methods converge; however, SCC-DSO reaches near-optimal performance ($\geq 99\%$), indicating its resilience to state divergence and minimal rollback overhead. This superior performance can be attributed to SCC-DSO's dynamic state consistency control and its likely use of asynchronous conflict resolution, enabling high execution throughput without sacrificing consistency guarantees. These results validate that SCC-DSO not only reduces latency (as shown in Figure 9) but also sustains high execution rates, thereby enhancing the end-to-end efficiency of distributed systems operating under large-scale and weakly consistent constraints.

7. Limitations and Future Work

Despite SCC-DSO's demonstrated efficiency, several open challenges remain. First, its hybrid use of ant colony optimization and kernel regression introduces non-trivial computational complexity, limiting deployment on ultra-low-power edge devices. Future work will explore neuromorphic and inspired surrogates, low-rank approximations, and hardware-aware pruning to enable sub-second inference within microcontroller and class IoT nodes [68]. Second, current validation is confined to a homogeneous 50-node cluster under deterministic 1 Gbps Ethernet; this leaves open questions regarding SCC-DSO's scalability and fault-tolerance under geo-distributed, bandwidth-fluctuating, and latency-sensitive edge-cloud topologies. Moreover, the absence of cross-layer adaptivity restricts responsiveness to volatile wireless substrates such as 5G NR, LPWAN, or mobile fog fabrics. To address this, future research will embed self-adaptive policy networks using meta-reinforcement learning, integrate decentralized orchestration layers (e.g., KubeEdge, WebAssembly), and couple real-time telemetry feedback with task migration strategies. Experimental deployment over federated testbeds (e.g., Fed4FIRE+, 5TONIC) will serve to validate robustness and energy-performance tradeoffs in next-generation IoT-cloud continuums [68].

8. Conclusion

This paper investigates performance degradation of jobs during execution in heterogeneous IoT clusters and proposes SCC-DSO, a perceptual cloud-based data scheduling optimization framework. However, SCC-DSO adaptively allocates heterogeneous-sized data blocks to working nodes by real-time profiling their computational capabilities, leveraging predictive performance modeling to guide scheduling decisions. Firstly, the framework introduces dynamic data migration to maximize localized execution, minimizing data transfer overhead and network latency. Consequently, central to SCC-DSO is a data scheduling queue optimization algorithm, which utilizes initial scheduling lists to construct an optimized pre-allocation queue, enabling parallel, contention-free local scheduling across distributed nodes. Secondly, a novel prefetching strategy based on minimum task queue completion time is integrated, effectively overlapping computation and communication to reduce idle times associated with non-local data dependencies. The algorithm also explicitly accounts for data reliability by considering replication and fault tolerance in scheduling decisions. Thirdly, comprehensive experiments demonstrate that SCC-DSO achieves up to 19.8% and 7.6% reductions in execution time compared to RF-FD and RSYNC benchmarks, respectively, significantly improving data locality and throughput in multi-copy scenarios. Finally, these results validate SCC-DSO's efficacy in optimizing data scheduling to enhance resource utilization and job performance in complex IoT-cloud environments characterized by heterogeneity and dynamic workloads.

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