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MH-Raft: an efficient and low-latency consensus algorithm for distributed systems via MOEA/D and hybrid hierarchical clustering

Key words: Consensus algorithm; Blockchain; Multi-objective optimization algorithm; Distributed systems

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Motivation

1. Although various Raft variants have addressed specific bottlenecks, they typically treat leader election and network topology as decoupled problems.
2. This separation leads to two major limitations: first, election optimizations often prioritize speed at the expense of leader stability; second, existing clustering methods lack the capability to adapt to dynamic node activity.
3. Consequently, there is a critical need for a unified framework that integrates multi-objective optimization to ensure leader quality with low complexity, while simultaneously employing dynamic and proximity-aware layering to enhance scalability.

Main idea

The MH-Raft algorithm proceeds as follows:

1. We introduce a leader node election methodology grounded in the multi-objective evolutionary algorithm based on decomposition (MOEA/D) optimization algorithm to elect the leader node.

2. We design an improved tightness value, which is combined with a hybrid clustering algorithm to determine the number of mediator nodes.

3. We design an adaptive clustering algorithm to cluster the remaining follower nodes.

4. We match the follower node groups and mediator nodes to complete the log synchronization process.

Method

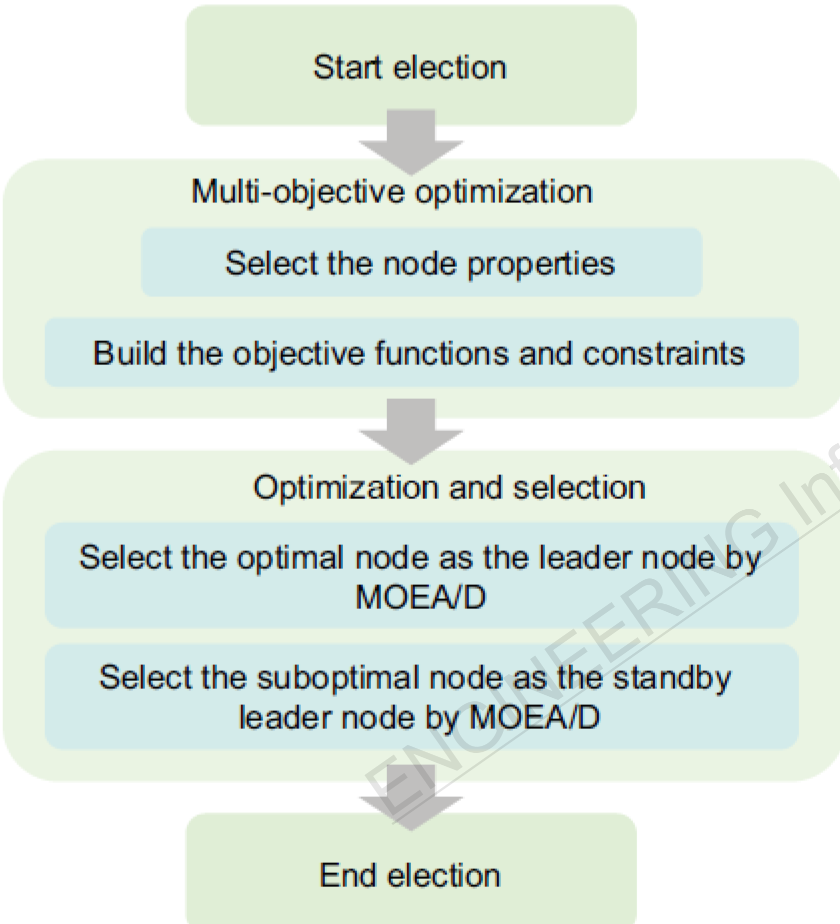

Fig. 3 Leader election of MH-Raft

1. Leader election based on MOEA/D. Initially, an objective function is formulated based on node attributes, incorporating relevant constraints. Subsequently, the MOEA/D algorithm is employed to obtain the optimal node, designated as the leader node, with the second best node serving as a backup. If the optimal node fails, the second-best node is elevated to the position of the leader, to ensure the continuity of normal operations.

Method (Cont'd)

2. Improved tightness values. This study aims to improve the definition of the tightness value to more accurately represent the relationship between follower nodes and the leader node, thereby facilitating the selection of more optimal mediator nodes.

We propose a revised definition of the tightness value as follows:

$$\mathrm{TN}_i = w_1 \frac{\mathrm{DN}_i}{\sum_{j=0}^{k-1} \mathrm{DN}_j} + w_2 \frac{\mathrm{AN}_i}{\sum_{z=0}^{k-1} \mathrm{AN}_z}.$$

Method (Cont'd)

3. Hybrid clustering algorithm for node grouping. We propose a hybrid clustering approach to ascertain the number of groups, which subsequently informs the selection of the number of mediator nodes. Ultimately, we identify a suitable clustering algorithm to facilitate the clustering of the mediator nodes.

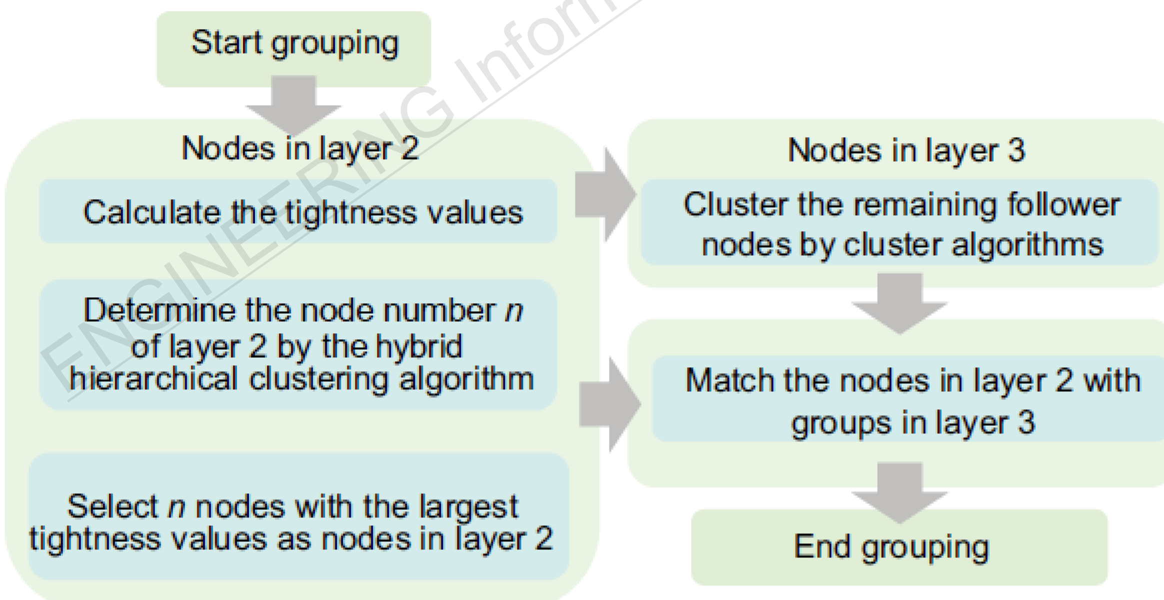

Fig. 4 Flowchart of node grouping

Major results

Leader election latency

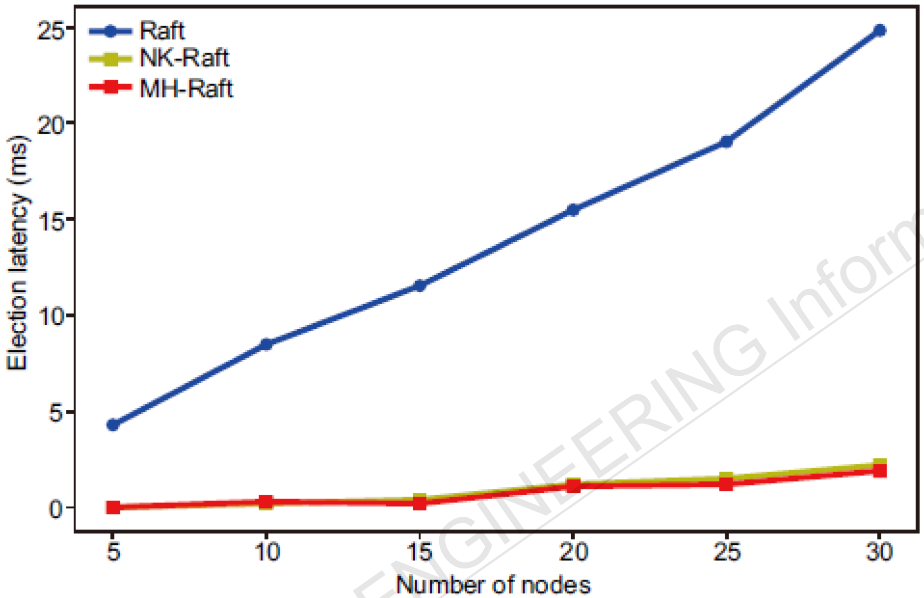

Fig. 6 Leader election latency of Raft, NK-Raft, and MH-Raft

Standard errors (SEs) for the leader election latency

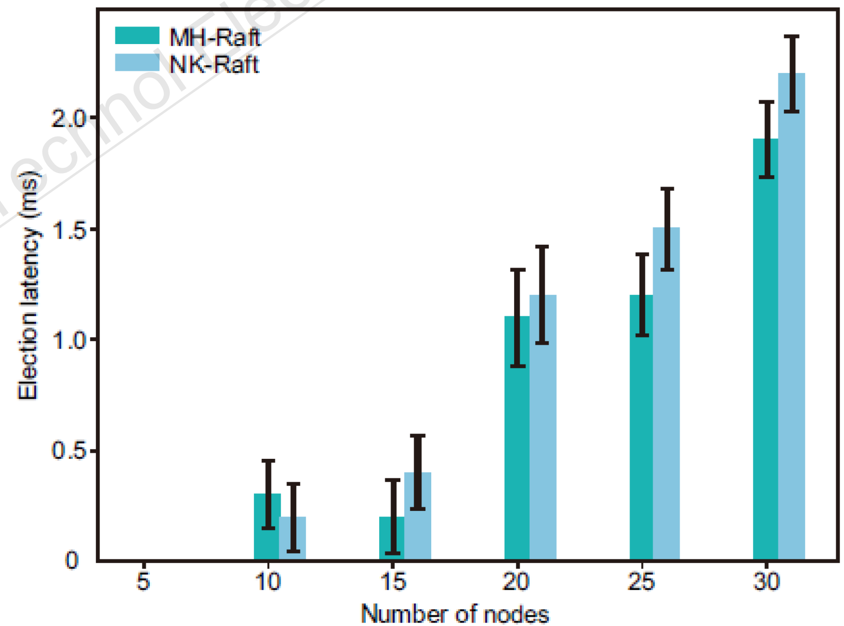

Fig. 7 SEs for the leader election latency of NK-Raft and MH-Raft

Major results (Cont'd)

Consensus latency

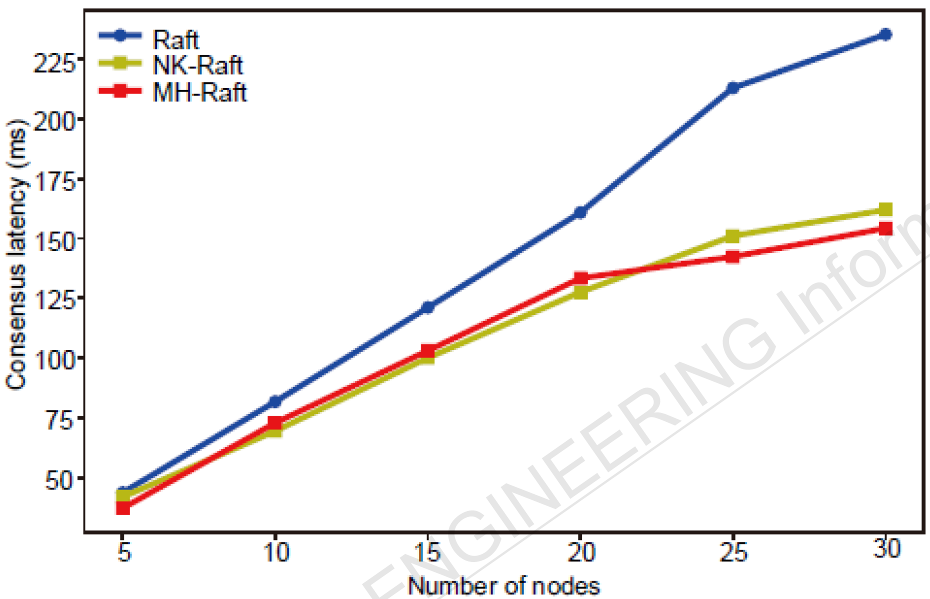

Fig. 8 Consensus latencies of Raft, NK-Raft, and MH-Raft

SEs for the consensus latency

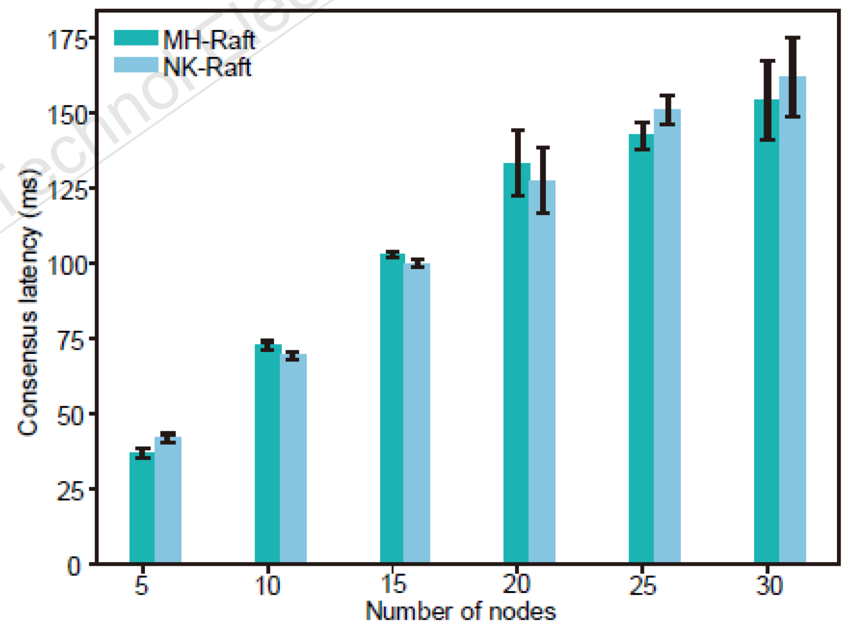

Fig. 9 SEs for the consensus latency of NK-Raft and MH-Raft

Major results (Cont'd)

Throughput

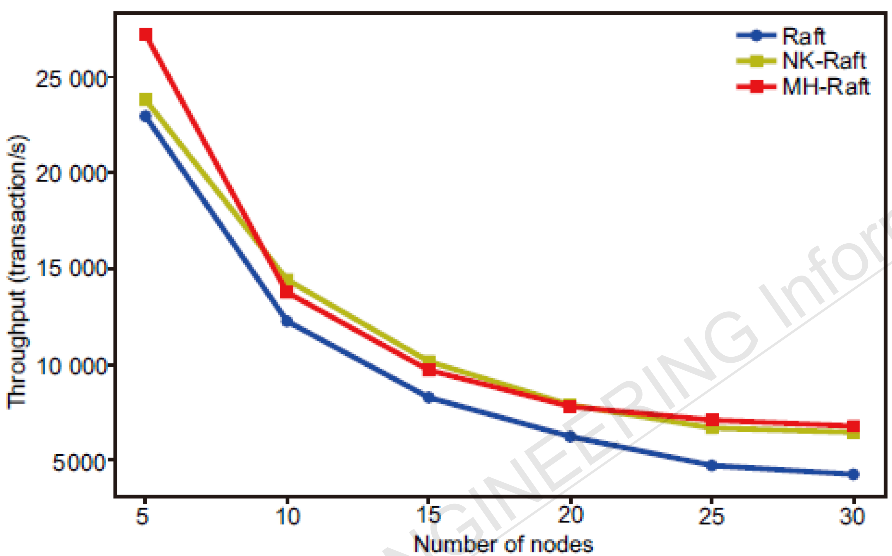

Fig. 10 Throughput of Raft, NK-Raft, and MH-Raft

SEs for the throughput

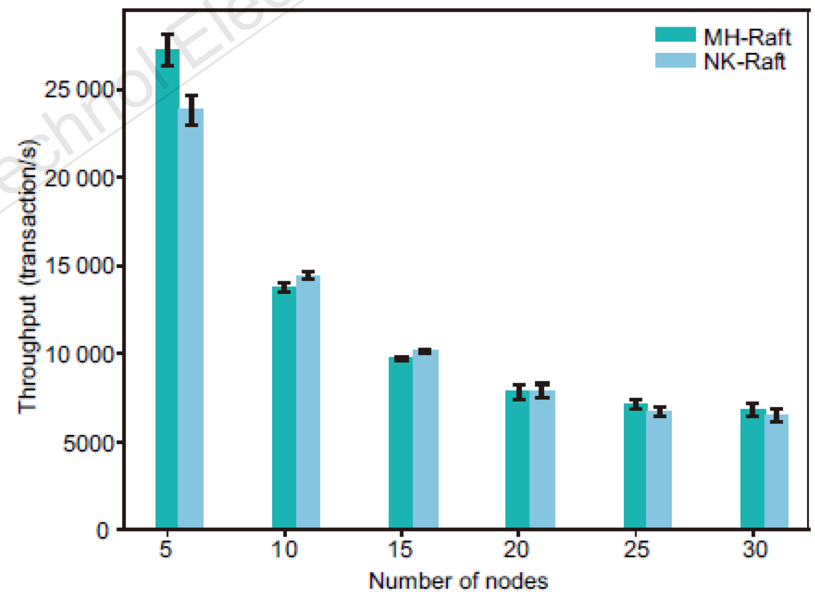

Fig. 11 SEs for the throughput of NK-Raft and MH-Raft

Conclusions

1. Experimental results show that the election latency is significantly reduced, the consensus latency is reduced by 14.87%–34.45% from small-scale to large-scale nodes, and the throughput is increased by an average of 30.43%.

2. This approach effectively bridges the gap between topological proximity and node fitness, providing a scalable and resilient solution for large-scale distributed consensus.

3. These findings indicate that the MH-Raft algorithm has potential advantages in real-world scenarios.

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