

PAPER 49 – A SURVEY OF LOAD-BALANCING SCHEMES FOR HETEROGENEOUS NETWORKS

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ABSTRACT

Load-balancing is a critical aspect of heterogeneous networks (HetNets) aimed at achieving optimal network performance, resource utilization, and improved user experience. This survey presents an overview of load-balancing schemes in HetNets, categorizing them into reactive, proactive, and hybrid approaches. Reactive algorithms, such as Cell Breathing, User Offloading, Game Theory-Based, and Reinforcement Learning algorithms, focus on balancing load and enhancing network performance. Proactive algorithms, including Prediction-based, Proactive Handover, and Traffic-aware Resource Allocation algorithms, anticipate future network conditions and take pre-emptive actions to optimize resource allocation. Hybrid algorithms combine proactive and reactive strategies to achieve a balance between prediction-based optimization and real-time adaptation. The study highlights the performance metrics used to evaluate these algorithms, along with the challenges and future research directions for each category. Furthermore, it discusses the potential applications of load-balancing in 5G networks, which include edge computing, dynamic network slicing, multi-connectivity scenarios, and integration with machine learning and artificial intelligence techniques. Understanding and optimizing HetNet load-balancing schemes are crucial for the successful deployment and operation of future 5G and beyond networks, contributing to enhanced network performance, improved user experience, and efficient resource utilization in diverse use cases.

KEYWORDS: load-balancing , heterogeneous networks, algorithm, deployment, performance, metrics.

1. INTRODUCTION

Heterogeneous deployments are mixed deployments consisting of macro, pico, femtocells and relay nodes (Hu & Qian, 2013). Heterogeneous networks have revolutionized network deployment, especially in rural and remote areas with tendencies for low return on investment (ROI) for the deployment of Macro Base stations (MBS) (McGuire, 2014). Some of the demands the evolving fifth-generation (5G) network seeks to address are enhanced data rate, improved capacity, reduced latency and better quality of service (QoS). Heterogeneous networks (HetNets) are an effective means to achieve these key objectives (Liang, 2017).

Traditionally, inhomogeneous cellular networks, mobile User Equipment (UE) aligns with networks that guarantee the best performance in terms of RSRP. In Heterogeneous networks, this would lead to an imbalance in the system which may overburden the MBS while keeping other associated BS underutilized (Adiline Macriga & Surya, 2012). An unbalanced load causes performance degradation. Thus, load-balancing ensures a balanced distribution of network load among the different cell tiers to ensure optimal utilization of network resources and improved users' quality of experience.

2. LOAD-BALANCING IN HETEROGENEOUS NETWORKS

Load-balancing is essentially used in heterogeneous deployments to manage network load across different cell tiers to ensure optimal utilization of network resources (Ye et al., 2013). Load-balancing distributes network load across tiers reducing congestion, enhancing capacity and improving user experience and network management efficiency. Thus UEs are connected to the cell with the highest available capacity and data rates, providing a better quality of service (Duan et al., 2014). Load-balancing algorithms in HetNets are based on whether they are reactive, proactive, or hybrid (Salhani, 2019).

3. REACTIVE LOAD-BALANCING ALGORITHMS

Reactive load-balancing algorithms in heterogeneous networks encompass occurrence-based approaches aimed at balancing load, reducing congestion, improving resource utilization, and enhancing overall network performance in heterogeneous cellular networks. Studies on reactive load-balancing algorithms in heterogeneous networks (HetNets) have focused on improving the performance and efficiency of these algorithms by incorporating new metrics and techniques (Ali et al., 2007). Reactive load-balancing algorithms are based on

distance-aware cell association; optimization-based approach; and reinforcement learning. Some of these approaches are highlighted as follows:

3.1 Cell Breathing Algorithm

Cell breathing algorithm (also referred to as the Cell Range Expansion, CRE Algorithm). The algorithm is used to dynamically modify cell sizes and optimize resource allocation for load-balancing. It strives to maintain a fair distribution of load across the HetNet infrastructure. Cell breathing algorithms make adaptive adjustments in cell sizes, power allocation, and handover decisions based on criteria such as traffic demand, cell capacity, and interference levels. Studies by (Siomina & Yuan, 2012; Nyembe, 2015; Sasikumar et al., 2016; Zhang et al., 2018; Bakuza et al., 2021) all showed improved network performance in terms of throughput, spectral efficiency, user experience, significant energy savings without compromising the quality of service. However, work requires a high level of coordination and signalling overhead, which impacts network scalability and complexity; and the performance may vary in different network conditions. Additionally, the studies may require additional infrastructure deployment and cost, especially for deploying new small cells.

3.2 User Offloading Algorithm

The Distributed Optimization approach in load-balancing involves users making offloading decisions locally based on their information and interactions with neighbouring users or base stations. The principle is to optimize resource allocation and load-balancing while minimizing interference and maximizing individual utility. Evaluation metrics for this approach include overall system throughput, fairness, user satisfaction, convergence speed, and resource utilization efficiency. Works by (Kim et al., 2012; Ali et al., 2015) have shown that there are challenges associated with achieving convergence in distributed decision-making, handling selfish user behaviour, dealing with limited local information, and ensuring fairness and efficiency in resource allocation. Future research in this area could focus on developing efficient distributed algorithms with provable convergence guarantees, integrating machine learning and artificial intelligence techniques, and exploring incentive mechanisms to foster cooperative behaviour among users. By addressing these challenges, the Distributed Optimization approach holds promising prospects for more effective and efficient load-balancing in heterogeneous networks.

3.3 Game Theory-Based Algorithm

The Game-Theoretic Power Allocation algorithm is based on the principle of modelling user-base station interactions as a non-cooperative game, where each user strategically selects power allocation to maximize their utility. The algorithm as demonstrated by (Li et al., 2015; Al-Zahrani et al., 2016) takes into account factors such as interference, channel conditions, and fairness. Performance metrics for this algorithm include overall system throughput, fairness index, user satisfaction, and convergence speed of the game. However, there are challenges associated with formulating the game model, handling incomplete or imperfect information, and finding equilibrium solutions in large-scale networks. Future research in this area could focus on developing more realistic and scalable game models, considering network dynamics and user behaviour, and addressing challenges related to practical implementation and convergence analysis. By addressing these challenges, the Game-Theoretic Power Allocation algorithm has the potential to enhance power allocation strategies in heterogeneous networks, leading to improved network performance and user experience.

3.4 Reinforcement Learning Algorithm

The Q-Learning-based load-balancing algorithm is a value-based method that estimates the value of state-action pairs to optimize decision-making in load-balancing scenarios. It follows the principle of learning the optimal value function, specifically the Q-value, through iterative updates based on observed rewards and transitions. The algorithm is evaluated using performance metrics such as average reward, convergence rate, and the ability to find optimal or near-optimal policies. However, (Kudo & Ohtsuki, 2013; Lee et al., 2021; Samson, 2022) have shown that there are challenges associated with value-based methods, including handling large state spaces, tuning hyperparameters, and addressing overestimation bias. Future research in this area could focus on improving sample efficiency, mitigating overestimation bias, and developing algorithms that can handle continuous state and action spaces. By addressing these challenges, Q-Learning and similar value-based approaches hold promising prospects for more effective and efficient load-balancing algorithms in various domains.

4. PROACTIVE LOAD-BALANCING ALGORITHMS

Proactive Load-balancing Algorithms offer promising approaches to optimize load distribution in HetNets. They anticipate the network load imbalance and take corrective actions before the network becomes congested leveraging on predictions, mobility patterns, and real-time traffic conditions to proactively manage network resources (Manzoor et al., 2019). Proactive Load-balancing algorithms are designed to be more proactive and efficient than reactive load-balancing techniques that only react to the network congestion after it occurs. There are several types of load-balancing algorithms that use the PLB approach:

4.1 Prediction-based Algorithms

Prediction-based load-balancing algorithms in HetNets aim to anticipate future network conditions and traffic patterns by leveraging historical data and prediction techniques. These algorithms proactively adjust resource allocation and offloading decisions to prevent congestion and optimize network performance. Evaluation metrics for these algorithms include network throughput, latency, fairness index, user satisfaction, and prediction accuracy. However, works by (Xiao et al., 2017; Manzoor et al., 2019; Gures et al., 2022) show that challenges exist in accurately predicting future network conditions, handling dynamic and unpredictable traffic patterns, and efficiently utilizing prediction models. Future research in this area focuses on improving prediction accuracy through advanced machine learning techniques, incorporating real-time feedback into prediction models, and developing adaptive algorithms that can dynamically adjust load-balancing strategies based on changing network conditions.

4.2 Proactive Handover Algorithms

Proactive handover algorithms in HetNets anticipate future changes in user mobility patterns and make early handover decisions to redistribute users across cells. These algorithms aim to prevent congestion and improve user experience by maintaining optimal cell associations. Performance metrics for proactive handover algorithms include handover success rate, handover delay, network capacity utilization, and user satisfaction. However, (Yoneya et al., 2015; Alhabo & Zhang, 2018; Bitonti & Tropea, 2020) show that challenges do exist in accurately predicting user mobility, efficient handover decision-making, minimizing handover delay, and addressing signalling overhead. Research advancements in this area focus on incorporating machine learning techniques for mobility prediction, developing distributed handover algorithms, addressing the impact of handover on user quality of service, and exploring context-aware handover strategies for heterogeneous networks.

4.3 Traffic-aware Resource Allocation Algorithms

Traffic-aware resource allocation algorithms in HetNets consider real-time traffic demands and dynamically allocate network resources to balance the load across cells. These algorithms proactively monitor traffic conditions and adjust resource allocation based on changing demand patterns, aiming to optimize network capacity and minimize congestion. Performance metrics for traffic-aware resource allocation algorithms include network throughput, fairness, congestion rate, resource utilization efficiency, and user satisfaction. However, (Gong et al., 2010; Fan & Ansari, 2018; De Schepper et al., 2019; Jahid et al., 2021) highlight the challenges in accurately estimating traffic demands, adapting resource allocation in real-time, handling heterogeneous traffic types, and considering the Quality of Service (QoS) requirements. Advances in this area focus on developing intelligent resource allocation algorithms that adapt to dynamic traffic patterns, incorporating machine learning for traffic prediction and classification, addressing QoS constraints, and considering energy efficiency in resource allocation.

5. HYBRID LOAD-BALANCING ALGORITHMS

Hybrid load-balancing algorithms offer a versatile approach to address the complexities of load-balancing in heterogeneous networks by combining proactive and reactive strategies, they aim to achieve a balance between prediction-based optimization and real-time adaptation (Fan & Ansari, 2018). While challenges do exist in threshold determination, learning algorithms, and centralized-distributed coordination, Advancements in machine learning techniques, optimization algorithms, and communication protocols can enhance the performance, scalability, and efficiency of load-balancing in heterogeneous networks. Some of the techniques for load-balancing in heterogeneous cellular networks are:

5.1 Threshold-based Hybrid Algorithms

Threshold-based hybrid load-balancing algorithms combine proactive and reactive approaches by setting thresholds for various performance metrics. These algorithms as shown by (Getnet et al., 2019) monitor network conditions and trigger load-balancing actions when the predefined thresholds are crossed. The principle is to

proactively adjust resource allocation based on predicted load conditions, while reactively responding to real-time network events. Performance metrics for threshold-based hybrid algorithms include network throughput, latency, fairness, load-balancing efficiency, and resource utilization. Challenges include selecting appropriate threshold values, handling sudden changes in network conditions, and ensuring timely and effective load-balancing decisions. Future research in this area focuses on adaptive threshold determination algorithms, intelligent threshold adjustment mechanisms, and incorporating machine learning techniques to enhance prediction accuracy and decision-making.

5.2 Learning-based Hybrid Algorithms

Learning-based hybrid load-balancing algorithms leverage both historical data and real-time network feedback to make load-balancing decisions. These algorithms employ machine learning techniques to learn from past experiences and adapt load-balancing strategies accordingly. The principle as shown by (Ichkov et al., 2016; Fletscher et al., 2019; Alsuhli et al., 2021; E. Kim et al., 2022) combine proactive learning from historical patterns with reactive learning from current network conditions. Performance metrics for learning-based hybrid algorithms include network throughput, fairness, convergence speed, learning efficiency, and adaptability. Challenges include handling high-dimensional and dynamic data, designing efficient learning algorithms, and addressing the trade-off between exploration and exploitation. Future research in this area focuses on developing advanced machine learning models, incorporating deep reinforcement learning techniques, and exploring transfer learning and federated learning approaches for load-balancing in heterogeneous networks.

5.3 Centralized-Distributed Hybrid Algorithms

Centralized-distributed hybrid load-balancing algorithms combine centralized control with distributed decision-making. These algorithms have a central controller that collects network information, performs load-balancing analysis, and distributes load-balancing decisions to individual cells or users. The principle utilizes the centralized controller for global load-balancing optimization while allowing distributed entities to make local load-balancing decisions. Performance metrics for centralized-distributed hybrid algorithms include network throughput, fairness, scalability, convergence speed, and coordination efficiency. Challenges include designing efficient communication protocols between the central controller and distributed entities, ensuring synchronization and consistency in load-balancing decisions, and addressing the overhead of centralized control (Mahmudah et al., 2016; Saadoun, 2019; Yuanita et al., 2016). Future research in this area focuses on developing efficient distributed load-balancing algorithms, exploring coordination mechanisms for the central controller and distributed entities, and investigating the impact of communication delays and network dynamics on load-balancing performance.

6. FUTURE APPLICATIONS IN 5G AND BEYOND

Load balancing plays a vital role in optimizing network performance and ensuring efficient resource utilization in 5G networks. As 5G technology continues to evolve, load-balancing techniques are expected to find applications in various areas. Prominent application is in the context of edge computing, dynamic network slicing, multi-connectivity scenarios, machine learning and artificial intelligence. Overall, load-balancing in 5G holds immense potential for future applications, contributing to enhanced network performance, improved user experience, and efficient resource utilization in diverse use cases (Duan et al., 2015; Tsirakis et al., 2017; Furqan et al., 2019; E. Kim et al., 2022).

7. CONCLUSION

Load-balancing is a crucial aspect of optimizing network performance and resource utilization in heterogeneous networks (HetNets) within the 5G ecosystem. This study presented an overview of load-balancing algorithms categorized into reactive, proactive, and hybrid approaches. Reactive algorithms, such as Cell Breathing, User Offloading, Game Theory-Based, and Reinforcement Learning algorithms, focus on dynamically balancing load and improving network performance. Proactive algorithms, including Prediction-based, Proactive Handover, and Traffic-aware Resource Allocation algorithms, anticipate network conditions and take preventive actions to optimize resource allocation. Hybrid algorithms combine proactive and reactive strategies to strike a balance between prediction-based optimization and real-time adaptation.

Despite advancements in load-balancing algorithms, some challenges need to be addressed in each category. Reactive algorithms require coordination and may have signalling overheads, while proactive algorithms face difficulties in accurately predicting network conditions and efficiently handling dynamic traffic patterns. Hybrid

algorithms aim to overcome the limitations of individual approaches and present promising prospects for load-balancing in HetNets.

Looking ahead, load-balancing in 5G networks holds great potential for future applications. It can be leveraged in edge computing scenarios to distribute computational tasks and network traffic efficiently, reducing latency and improving overall system performance. Dynamic network slicing can benefit from load-balancing techniques to allocate network resources effectively among different virtual network slices based on their varying demands. Load-balancing algorithms can also optimize traffic distribution in multi-connectivity scenarios, where devices connect to multiple access points or networks simultaneously and enhance user experience. Integration of load balancing with machine learning and artificial intelligence techniques can enable intelligent decision-making and real-time optimization based on network conditions.

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