International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
Article Received: *24 August 2023* ***Revised:*** *12 October 2023* ***Accepted:*** *28 October 2023*

A Tutorial on Cross-layer Optimization Wireless Network System Using TOPSIS Method

Dr. S. Nithya[1], Dr. T. Sathish Kumar[2], Gayatri Parasa[3], Shivakumar Nethani[4], Madhu Renamala[5]
[1]Department of Electrical and Electronics Engineering,SRMIST, Ramapuram,Chennai-89
Mail : nithisavidhina@gmail.com
[2]Associate Professor Department of Computer Science and Engineering Hyderabad Institute of Technology and Management, Hyderabad Mail : sathisht.cse@hitam.org
[3]Assistant Professor Department of CSE Koneru Lakshmaiah Education Foundation
Vaddeswaram, Andhra Pradesh, India – 522502 Mail : gayathriparasa20@gmail.com
[4]Assistant Professor, Department of CSE, Hyderabad Institute of Technology and Management, Hyderabad, Telangana, India. Mail : shivakumar.kumar093@gmail.com
[5]Department of CSE, MLR Institute of Technology ,Dundigal,Hyderabad.
Mail : msrao.renamala@gmail.com

Abstract

Each other, leading to issues such as interference, limited bandwidth, and varying channel conditions. These challenges require specialized optimization techniques tailored to the wireless environment. In wireless communication networks is to maximize the overall system throughput while ensuring fairness among users and maintaining quality of service requirements. This objective can be achieved through resource allocation optimization, where the available network resources such as bandwidth, power, and time slots are allocated to users in an optimal manner. Optimization-based approaches in wireless resource allocation typically involve formulating the resource allocation problem as an optimization problem with certain constraints.. These techniques provide practical solutions with reduced computational complexity, although they may not guarantee optimality. In summary, optimization-based approaches have been instrumental in studying resource allocation problems in communication networks, including the wireless domain. While techniques from the Internet setting have influenced the understanding of congestion control and protocol design, specific challenges in wireless networks necessitate tailored optimization techniques that account for interference, limited bandwidth, and varying channel conditions. power allocation problem in wireless ad hoc networks Cross-layer optimization refers to the process of jointly optimizing the allocation of resources across different layers of wireless networks, the interactions between different layers become more complex due to the shared medium and time-varying channel conditions. Nash equilibrium, where no user can unilaterally improve its own performance by changing its strategy. Game theory can capture the distributed nature of wireless networks and provide insights into the behavior of users in resource allocation scenarios Additionally, heuristics and approximation algorithms are often employed in wireless resource allocation due to the complexity of the optimization problems involved. In traditional cellular systems, each user is allocated a fixed time slot for transmission, regardless of their channel conditions. However, in opportunistic scheduling. Alternative parameters for **"**Data rate Ž kbps, Geographic coverage , Service requirements , cost " Evaluation parameter for **"**Circuit-switched cell, CDPD, WLAN, Paging, Satellite." **"**the first ranking training is obtained with the lowest quality of compensation.**"**

Keywords: "Data rate Ž kbps, Geographic coverage , Service requirements , cost ."

1. INTRODUCTION

By formulating the problem as a convex optimization problem, it becomes possible to find the globally optimal solution or near-optimal solutions with provable performance guarantees. Another approach is to use game theory, which provides a framework for analyzing the interactions among multiple users in a wireless network. Game-theoretic resource allocation models consider the selfish behavior of individual users and aim to achieve a Nash equilibrium, where no user can unilaterally improve its own performance by changing its strategy. Game theory can capture the distributed nature of wireless networks and provide insights into the behavior of users in resource allocation scenarios Additionally, heuristics and approximation algorithms are often employed in wireless resource allocation due to the complexity of the optimization problems involved. In traditional cellular systems, each user is allocated a fixed time slot for transmission, regardless of their channel conditions. However, in opportunistic scheduling, the available time slots are allocated to users based on their instantaneous channel quality. This optimization problem involves jointly considering the channel conditions, link data rates, and end-user data rates to maximize the overall system throughput or fairness. Another example is the power allocation problem in wireless ad hoc networks. In ad hoc networks, nodes communicate with each other directly without the need for a centralized infrastructure. The power allocation problem involves

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 24 August 2023 **Revised:** 12 October 2023 **Accepted:** 28 October 2023*

determining the optimal transmit power levels for each node to maximize the network capacity while satisfying certain quality of service constraints. This problem requires, the achievable data rates, and the power constraints of individual nodes. In both cases, the cross-layer optimization problems can be formulated as mathematical optimization problems. Various optimization techniques such as convex optimization, game theory, and dynamic programming can be applied resource allocation solutions. obtained from these optimization frameworks often exhibit a layered structure, where the optimization variables and constraints are organized in a layered manner, reducing the cross-layer coupling to a limited degree. By incorporating multiple layers into a unified optimization framework, cross-layer optimization approaches enable the exploitation of interdependencies and trade-offs between different layers, resulting in improved system performance and resource utilization in wireless networks. These approaches provide insights into the design of efficient resource allocation strategies and protocol parameters that can adapt to the dynamic wireless environment. levels and scheduling decisions of other links in the network.

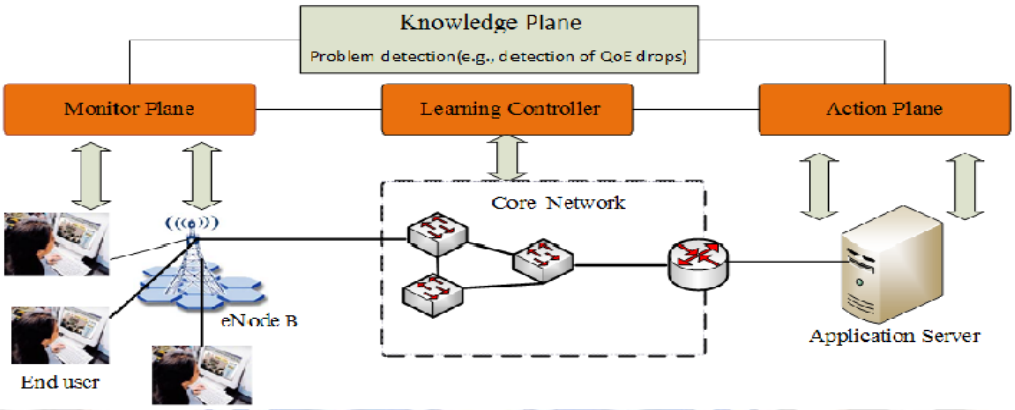

Figure 1 Wireless Network System.

2. MATERIALS AND METHODS

Data rate Ž kbps: Data rate Ž kbps Game-theoretic approaches consider the strategic behavior of users and aim to achieve Nash or other solution concepts that capture the equilibrium points in the network In summary, while convex programming, including Lagrange duality, plays an important role in decomposing and solving components of joint congestion control and scheduling problems in wireless networks, these problems often go beyond convexity. The non-convexities arising from interference and scheduling complexities require specialized optimization techniques, such as approximation algorithms, heuristics, and game theory, to tackle the challenges of resource allocation and optimization in wireless networks. Non convex optimization, such as convex relaxations, heuristics, and algorithms, are employed to tackle the non convex nature of the cross-layer control problem in wireless networks. The relationship between link capacity, power assignment, and transmission schedule in wireless networks introduces non convexities that pose challenges in finding optimal solutions.

Geographic coverage: Geographic coverage. Convex relaxations provide tractable solutions and can offer near-optimal results, although they may not guarantee global optimality. Heuristics and algorithms are another set of techniques commonly employed in non convex optimization problems. These techniques leverage problem-specific insights and explore the search space in a systematic manner to find good solutions. Examples include genetic algorithms, particle swarm optimization, simulated annealing, and ant colony optimization. While these techniques do not guarantee optimality, they can effectively navigate the non convex landscape and find satisfactory solutions.

Service requirements: Service requirements The scheduling component, in particular, involves solving a difficult non convex problem and often becomes the bottleneck in the overall solution process. To address these challenges, advanced techniques beyond convex programming are necessary. One approach is to use convex relaxations, which involve approximating the non convex problem with a convex one that can be efficiently solved Convex relaxations, heuristics, algorithms, and clean-slate designs are among the approaches used to satisfactorily solve the cross-layer control problem in wireless networks.

Cost: cost It provides insights into the long-term behavior and convergence properties of the system. Graph theory: Graph theory is utilized to model and analyze the connectivity, interference, and topology of wireless networks. It helps in understanding the relationships and dependencies between network elements and facilitates the design of efficient algorithms and protocols. Large deviations: Large deviations theory is employed to analyze rare events and extreme behaviors in wireless networks.

Circuit-switched cell: Circuit-switched cell In recent years, researchers have made significant progress in developing unified optimization frameworks that consider multiple layers and their interdependencies. These frameworks aim to jointly optimize the allocation of resources such as time, frequency, power, data rates, etc., across different layers of the wireless communication system. One example of a cross-layer optimization problem is the opportunistic scheduling problem in cellular networks.

CDPD: CDPD stands for Cellular Digital Packet Data. It enables the study of performance metrics under highly unfavorable conditions and provides insights into system resilience and robustness. Heavy-traffic limits: Heavy-traffic limits study the behavior of network systems under high loads or congestion. It helps in characterizing the system behavior and identifying bottlenecks, enabling the design of congestion control and resource allocation strategies. While the scope of cross-layer optimization is vast, this tutorial acknowledges that it is not possible to cover all subjects comprehensively due to space constraints. Instead, the focus is on providing readers with an overview of the main issues, challenges, and techniques in cross-layer optimization. The tutorial also highlights the main open problems in the field, encouraging further research and contributions from the community.

WLAN: WLAN stands for Wireless Local Area Network. These techniques provide alternative methods to address and optimize resource allocation in wireless communication systems In the field of cross-layer optimization in wireless networks, various mathematical and theoretical tools are employed to obtain realistic and efficient solutions to the control problem. These tools Convex programming: Convex optimization techniques are used to solve optimization problems with convex objectives and constraints. Convex programming provides tractable solutions for certain components of the cross-layer control problem.

Paging: Paging In addition to these optimization techniques, clean-slate designs have gained attention in wireless networks. Clean-slate designs refer to the approach of starting anew without being burdened by legacy systems. This approach allows for fresh perspectives and innovative solutions, as the constraints and limitations of existing systems are less prevalent in the wireless context. Clean-slate designs provide opportunities to rethink and optimize cross-layer control in wireless networks from the ground up. In summary, the nature of the relationship between link capacity, power assignment, and transmission schedule in wireless networks necessitates the use of advanced techniques beyond convex programming.

Satellite: Satellite the available time slots are allocated to users based on their instantaneous channel quality. This optimization problem involves jointly considering the channel conditions, link data rates, and end-user data rates to maximize the overall system throughput or fairness. Another example is the power allocation problem in wireless ad hoc networks. In ad hoc networks, nodes communicate with each other directly without the need for a centralized infrastructure. The power allocation problem involves determining the optimal transmit power levels for each node maximize the network capacity while satisfying certain quality of service constraints. This problem requires achievable data rates, and the power constraints of individual nodes. In both cases, the cross-layer optimization problems can be formulated as mathematical optimization problems.

Method: Global optimization. The dual decomposition framework combined with the method provides a distributed optimization solution that allows wireless network nodes to collaborate and achieve efficient resource allocation and management. In the framework, the original optimization problem is decomposed into smaller sub problems, with each node in the network responsible for optimizing its own performance based on local information. This decentralization enables nodes to make decisions independently without relying on a central controller, which is especially beneficial in large-scale and heterogeneous wireless networks. The dual decomposition technique is used to handle the constraints of the original optimization problem. By introducing Lagrange multipliers, the problem is transformed into a dual problem that can be solved in a distributed manner. Each node maintains local estimates of the Lagrange multipliers and exchanges them with neighboring nodes to coordinate their optimization decisions. The sub gradient method is employed to solve the dual problem iteratively. In each iteration, nodes compute their local sub gradients based on their current estimates of the Lagrange multipliers and exchange these sub gradients with their neighbors. By updating the Lagrange multipliers according to the received sub gradients, nodes can converge towards the optimal solution of the dual problem. The combination of the decomposition framework and the sub gradient method allows for efficient cross-layer optimization in wireless networks. Nodes can optimize their own performance while considering the impact on other layers of the network protocol stack. This enables the network to achieve global optimization, balancing the allocation of network resources, such as bandwidth or power, among different nodes and services. Overall, the framework provides an elegant approach for distributed optimization in wireless networks, offering scalability, flexibility, and the ability to handle the heterogeneity of modern wireless environments. It has become a standard technique in wireless networking research for achieving efficient resource management and improving overall network performance. scheduling, routing, power control, and congestion control. By applying the back-pressure principle within the framework, network nodes can make decisions based on the network's backlog, which represents the number of packets awaiting transmission. Nodes prioritize the transmission of packets that will reduce the backlog, thereby maximizing overall network throughput. This approach ensures that network resources are efficiently utilized and congestion is minimized. The framework, combined with the back-pressure principle, enables the design of distributed algorithms that adaptively adjust resource allocations based on changing network conditions. Nodes can make real-time decisions regarding transmission, routing, and scheduling by considering the current network backlog and local information. These decisions are made independently by each node, but they collectively contribute to achieving a globally optimal solution in terms of throughput and resource utilization. furthermore, the framework allows for the incorporation of additional constraints and objectives into the optimization problem. For example, quality-of-service requirements, fairness considerations, or energy efficiency objectives can be taken into account by introducing appropriate terms in the function. This flexibility enables the development of protocols that can cater to diverse application requirements and network scenarios. In summary, the combination of the framework, the method, and the back-pressure principle has significantly advanced the field of distributed optimization in wireless networks. These techniques provide a powerful approach for achieving global optimization, efficient resource allocation, and adaptive decision-making in large-scale and heterogeneous wireless environments. They have paved the way for the development of practical and scalable protocols that enhance network performance and satisfy various requirements. a distributed Newton's method for cross-layer optimization in wireless networks poses several challenges. First, computing the Hessian matrix is computationally expensive, especially in large-scale wireless networks. The Hessian matrix contains second-order derivatives and requires significant computational resources to be computed accurately. Additionally, in dynamic wireless environments where network conditions can change rapidly, maintaining an up-to-date and accurate Hessian matrix becomes challenging. Second, distributing the computation of the Hessian matrix and coordinating its updates across multiple nodes in the network is a non-trivial task. Since the Hessian matrix reflects the interdependencies between variables and constraints in the optimization problem, ensuring consistent and synchronized updates across nodes is crucial for convergence and correctness. Furthermore, the communication overhead incurred in exchanging the Hessian matrix information between nodes can be significant. In summary, while a distributed Newton's method holds the potential for faster convergence in cross-layer optimization for wireless networks by leveraging second-order information, its practical implementation poses significant challenges. Overcoming the computational burden of computing and maintaining the Hessian matrix, ensuring consistent updates and communication between nodes, and addressing the complexities of step size selection and regularization are important considerations in developing an effective and efficient distributed Newton's algorithm for wireless networks.

3. RESULT AND DISCUSSION

Table 1. A Tutorial on Cross-Layer Optimization in Wireless Network System data set.

	Circuit-switched cell	CDPD	WLAN	Paging	Satellite
Data rate Ž kbps.	66.7148	56.163	46.6867	2.87829	56.6793
Geographic coverage	25.1764	40.3557	29.5894	29.8822	40.3666
Service requirements	32.9132	33.7466	68.2108	11.7258	13.8024
cost	25.7729	45.5632	15.8539	34.9569	27.8912

Table 1 shows a tutorial on cross-layer optimization in wireless networks system Analysis method in WSM **“**Alternative preference: “Data rate Ž kbps, Geographic coverage, Service requirements, cost**” “**Evaluation preference: Circuit-switched cell, CDPD, WLAN, Paging, Satellite a tutorial on cross-layer optimization in wireless networks system .

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 24 August 2023 **Revised:** 12 October 2023 **Accepted:** 28 October 2023*

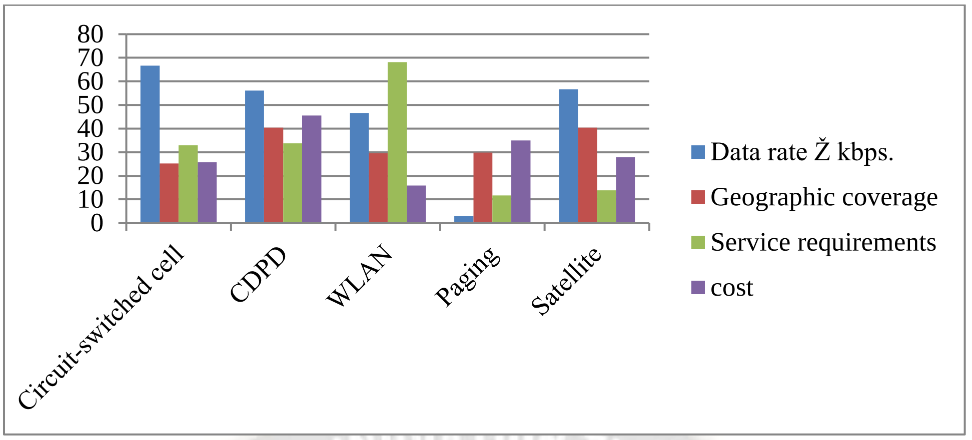

FIGURE 1. Data Set

Figure 1 Shows the in use: "Alternative preference: "Data rate Ž kbps, Geographic coverage, Service requirements, cost" "Evaluation preference: Circuit-switched cell, CDPD, WLAN, Paging, Satellite a tutorial on cross-layer optimization in wireless networks system data set".

TABLE 2. Performance value

	Circuit-switched cell	CDPD	WLAN	Paging	Satellite
Data rate Ž kbps.	1.00000	1.00000	0.68445	0.08234	1.00000
Geographic coverage	0.37737	0.00072	0.43379	0.85483	0.71219
Service requirements	0.49334	0.00060	1.00000	0.33544	0.24352
cost	0.38631	0.00081	0.23243	1.00000	0.49209

Table 2 It seems that the table 2 you provided includes different wireless communication technologies, such as Circuit-switched cell, CDPD (Cellular Digital Packet Data), WLAN (Wireless Local Area Network), Paging, and Satellite. The table includes several criteria or metrics for evaluating these technologies, namely data rate (in kbps), geographic coverage, service requirements, and cost. Each technology has been assigned a value for each criterion as seeing figure 2.

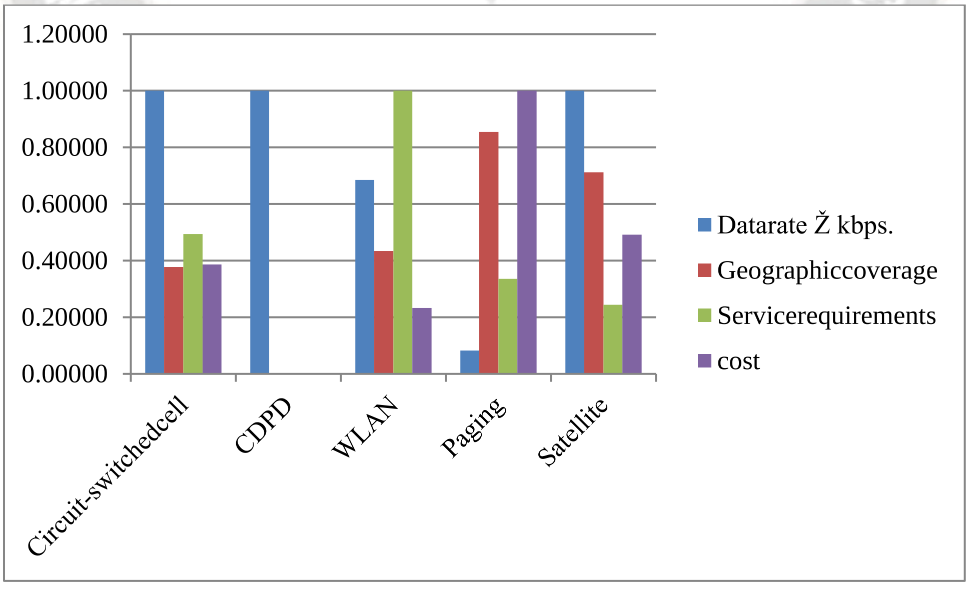

Figure 2. Shows the performance values

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 24 August 2023 **Revised:** 12 October 2023 **Accepted:** 28 October 2023*

Figur**e 2** It seems that the table 2 you provided includes different wireless communication technologies, such as Circuit-switched cell, CDPD (Cellular Digital Packet Data), WLAN (Wireless Local Area Network), Paging, and Satellite. The table includes several criteria or metrics for evaluating these technologies, namely data rate (in kbps), geographic coverage, service requirements, and cost. Each technology has been assigned a value for each criterion as seeing figure 2.

TABLE 3. Weightages

	Circuit-switched cell	CDPD	WLAN	Paging	Satellite
Data rate Ž kbps.	0.20	0.20	0.20	0.20	0.20
Geographic coverage	0.20	0.20	0.20	0.20	0.20
Service requirements	0.20	0.20	0.20	0.20	0.20
cost	0.20	0.20	0.20	0.20	0.20

Table 3. Shows Each technology or solution is represented by a row in the table, and the values in each row (0.20 for each category) seem to indicate equal weight or importance assigned to each criterion. However, without further context or information, it is difficult to determine the specific meaning or interpretation of these values.

Table 4 preference score.

	RANK
Data rate Ž kbps.	1
Geographic coverage	2
Service requirements	4
cost	3

The table 4 you provided includes several criteria for evaluating certain aspects related to data communication technologies. These values represent the scores or measurements assigned to each criterion. The data rate has a value of 0.56259, indicating a moderate level. The geographic coverage has a lower value of 0.14825, suggesting limited coverage. Similarly, the service requirements and cost have relatively low values of 0.11935 and 0.12909, respectively.

TABLE 5. Rank

Data rate Ž kbps.	0.56259
Geographic coverage	0.14825
Service requirements	0.11935
cost	0.12909

Table 5 **Shows** the in use: **"**Alternative preference: "Data rate Ž kbps:1th rank, Geographic coverage:2th rank, Service requirements:4^{th} rank , cost: 3th rank a tutorial on cross-layer optimization in wireless networks system.**"**

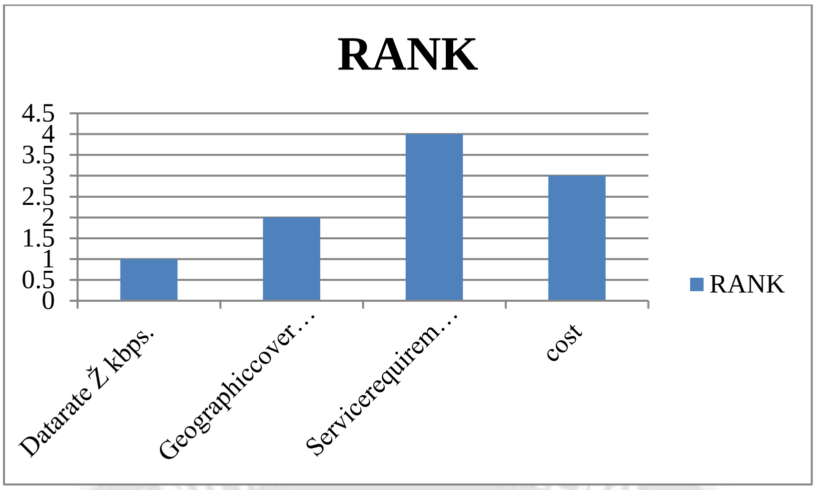

FIGURE 3. Rank

Figure 3 Shows the Data rate Ž kbps is 1th rank, Geographic coverage is 2nd rank, Service requirements is 4th rank , cost is 3th rank a tutorial on cross-layer optimization in wireless networks system.**"**

4. CONCLUSION

This complicates the distribution of Hessian-related computations among the network entities. As a result, developing distributed second-order algorithms for wireless networks becomes highly challenging. Researchers face the task of finding alternative approaches to handle the non-separable Hessian structure and devise techniques that are specifically tailored to the unique characteristics of wireless networks. Despite the difficulties, efforts are being made to address this issue and explore the development of distributed second-order algorithms in wireless networks. Researchers are actively investigating novel methodologies and algorithmic frameworks that can effectively handle the inherent interference and of the Hessian matrix in wireless settings. By advancing the understanding of distributed second-order algorithms and their applicability to wireless networks, these research endeavors aim to unlock the potential of leveraging second-order information for optimization tasks in wireless communication systems. Although the results in this area are currently limited, ongoing research holds promise for future breakthroughs and the development of more efficient optimization techniques for wireless Indeed, the problem structure in wireless networks differs significantly from, which poses challenges in applying techniques used for developing distributed second-order algorithms directly. In the context of distributed second-order algorithms, computing the primal and dual search directions usually involves decomposing the inverses of the Hessian matrix and a weighted matrix, and distributing these components to the network entities. However, in wireless networks, the Hessian's structure is non-separable due to the presence of inherent interference. Unlike networks where the Hessian matrix can be decomposed into separate components, wireless networks exhibit complex interference patterns that make such decomposition infeasible. This complicates the distribution of Hessian-related computations among the network entities. As a result, developing distributed second-order algorithms for wireless networks becomes highly challenging. Researchers face the task of finding alternative approaches to handle the non-separable Hessian structure and devise techniques that are specifically tailored to the unique characteristics of wireless networks. Despite the difficulties, efforts are being made to address this issue and explore the development of distributed second-order algorithms in wireless networks. Although the results in this area are currently limited, ongoing research holds promise for future breakthroughs and the development of more efficient optimization techniques for wireless networks. What is worse is that, not only are both the Hessian and weighted inversions cumbersome in large-scale wireless networks, the obtained inverses also have no structure in general. Hence, distributed computations of the Hessian and weighted inversion problems in wireless networks are far more difficult than their counterparts in networks You're correct. In large-scale wireless networks, the challenges related to distributed computations of the Hessian and weighted inversions are further exacerbated. Unlike networks where these inversions can still be computationally demanding but may have structures, in general, the inverses obtained in wireless networks lack such structures. Sparse structures are advantageous because they allow for more efficient computations by exploiting the patterns and reducing the computational burden. However, in wireless networks, the non-separable and interference-laden nature of the Hessian matrix and the weighted matrix result in dense inverses with no inherent. Consequently, distributed computations involving these dense inverses become significantly more challenging in wireless networks compared to networks. The increased computational complexity can impede the scalability and efficiency of distributed second-order algorithms designed for wireless networks.

Addressing these challenges requires innovative approaches that can handle the dense and non-sparse nature of the inverses in wireless networks. Researchers are actively exploring techniques such as approximation methods, distributed matrix factorization, and exploiting structure-exploiting algorithms to alleviate the computational burden and enable more efficient distributed computations in wireless settings. While the difficulties associated with the lack of structure in the Hessian and weighted inverses in wireless networks pose significant challenges, ongoing research efforts aim to develop practical and scalable solutions. By finding ways to overcome these challenges, it will be possible to unlock the potential benefits of distributed second-order algorithms in optimizing wireless networks' performance and resource allocation.

REFERENCES

1. Lin, Xiaojun, Ness B. Shroff, and Rayadurgam Srikant. "A tutorial on cross-layer optimization in wireless networks." IEEE Journal on Selected areas in Communications 24, no. 8 (2006): 1452-1463.
2. Kushwaha, Bindeshwar Singh, and Pramod Kumar Mishra. "A Survey on Cross-Layer Optimization in Wireless Networks." J. Adv. Comput. Netw 10 (2022): 1-9.
3. Liu, Jia, Cathy H. Xia, Ness B. Shroff, and Hanif D. Sherali. "Distributed cross-layer optimization in wireless networks: A second-order approach." In 2013 Proceedings IEEE INFOCOM, pp. 2103-2111. IEEE, 2013.
4. Foukalas, Fotis, Vangelis Gazis, and Nancy Alonistioti. "Cross-layer design proposals for wireless mobile networks: a survey and taxonomy." IEEE Communications Surveys & Tutorials 10, no. 1 (2008): 70-85.
5. Miao, Guowang, Nageen Himayat, Ye Li, and Ananthram Swami. "Cross-layer optimization for energy-efficient wireless communications: a survey." Wireless Communications and Mobile Computing 9, no. 4 (2009): 529-542.
6. Fu, Bo, Yang Xiao, Hongmei Deng, and Hui Zeng. "A survey of cross-layer designs in wireless networks." IEEE Communications Surveys & Tutorials 16, no. 1 (2013): 110-126.
7. de Baynast, Alexandre, Petri Mähönen, and Marina Petrova. "ARQ-based cross-layer optimization for wireless multicarrier transmission on cognitive radio networks." Computer networks 52, no. 4 (2008): 778-794.
8. Shao, Ziyu, Minghua Chen, A. Salman Avestimehr, and Shuo-Yen Robert Li. "Cross-layer optimization for wireless networks with deterministic channel models." IEEE Transactions on Information Theory 57, no. 9 (2011): 5840-5862.
9. Devetsikiotis, Michael, Dzmitry Kliazovich, and Fabrizio Granelli. "Formal Methods in Cross-Layer Modeling and Optimization of Wireless Networks." (2007).
10. Kliazovich, Dzmitry, Michael Devetsikiotis, and Fabrizio Granelli. "Formal methods in cross layer modeling and optimization of wireless networks: State of the art and future directions." Networking and Telecommunications: Concepts, Methodologies, Tools, and Applications (2010): 410-436.
11. Jiang, Canming, Yi Shi, Xiaoqi Qin, Xu Yuan, Y. Thomas Hou, Wenjing Lou, Sastry Kompella, and Scott F. Midkiff. "Cross-layer optimization for multi-hop wireless networks with successive interference cancellation." IEEE Transactions on Wireless Communications 15, no. 8 (2016): 5819-5831.
12. Klügel, Markus, Mohammadhossein Mamduhi, Onur Ayan, Mikhail Vilgelm, Karl H. Johansson, Sandra Hirche, and Wolfgang Kellerer. "Joint cross-layer optimization in real-time networked control systems." IEEE Transactions on Control of Network Systems 7, no. 4 (2020): 1903-1915.
13. Akyildiz, Ian F., and Xudong Wang. "Cross-layer design in wireless mesh networks." IEEE Transactions on Vehicular Technology 57, no. 2 (2008): 1061-1076.
14. Edirisinghe, Ruwini, and Arkady Zaslavsky. "Cross-layer contextual interactions in wireless networks." IEEE Communications Surveys & Tutorials 16, no. 2 (2013): 1114-1134.
15. Srivastava, Vineet, and Mehul Motani. "Cross-layer design: a survey and the road ahead." IEEE communications magazine 43, no. 12 (2005): 112-119.
16. Baligh, Hadi, Mingyi Hong, Wei-Cheng Liao, Zhi-Quan Luo, Meisam Razaviyayn, Maziar Sanjabi, and Ruoyu Sun. "Cross-layer provision of future cellular networks: A WMMSE-based approach." IEEE Signal Processing Magazine 31, no. 6 (2014): 56-68.
17. Han, Chong, Josep Miquel Jornet, Etimad Fadel, and Ian F. Akyildiz. "A cross-layer communication module for the Internet of Things." Computer Networks 57, no. 3 (2013): 622-633.
18. Pudlewski, Scott, Nan Cen, Zhangyu Guan, and Tommaso Melodia. "Video transmission over lossy wireless networks: A cross-layer perspective." IEEE Journal of Selected Topics in Signal Processing 9, no. 1 (2014): 6-21.
19. Weeraddana, Pradeep Chathuranga, Marian Codreanu, Matti Latva-aho, and Anthony Ephremides. "Resource allocation for cross-layer utility maximization in wireless networks." IEEE Transactions on Vehicular Technology 60, no. 6 (2011): 2790-2809.
20. Weeraddana, Chathuranga, Marian Codreanu, Matti Latva-Aho, and Anthony Ephremides. "Resource allocation for cross-layer utility maximization in multi-hop wireless networks in the presence of self interference." In 8th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, pp. 70-75. IEEE, 2010.
21. Gatsis, Nikolaos, Alejandro Ribeiro, and Georgios B. Giannakis. "Cross-layer optimization of wireless fading ad-hoc networks." In 2009 IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 2353-2356. IEEE, 2009.

22. Conti, Marco, Enrico Gregori, and Giovanni Turi. "A cross-layer optimization of gnutella for mobile ad hoc networks." In Proceedings of the 6th ACM international symposium on Mobile ad hoc networking and computing, pp. 343-354. 2005.
23. Zheng, Xiaoying, Feng Chen, Ye Xia, and Yuguang Fang. "A class of cross-layer optimization algorithms for performance and complexity trade-offs in wireless networks." IEEE Transactions on Parallel and Distributed Systems 20, no. 10 (2008): 1393-1407.
24. Guan, Zhangyu, Lorenzo Bertizzolo, Emrecan Demirors, and Tommaso Melodia. "WNOS: An optimization-based wireless network operating system." In Proceedings of the Eighteenth ACM International Symposium on Mobile Ad Hoc Networking and Computing, pp. 241-250. 2018.
25. Kumwilaisak, Wuttipong, Yiwei Thomas Hou, Qian Zhang, Wenwu Zhu, C-CJ Kuo, and Ya-Qin Zhang. "A cross-layer quality-of-service mapping architecture for video delivery in wireless networks." IEEE Journal on selected areas in communications 21, no. 10 (2003): 1685-1698.
26. Hsu, Cheng-Hsin, and Mohamed Hefeeda. "Cross-layer optimization of video streaming in single-hop wireless networks." In Multimedia Computing and Networking 2009, vol. 7253, pp. 21-33. SPIE, 2009.